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DATA ENVELOPMENT ANALYSIS AND PERFORMANCE MEASURMENT

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Data Envelopment Analysis and Performance Measurement

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PREFACE: A MESSAGE FROM THE LOCAL ORGANIZERS

On behalf of the Organizing Committee I am delighted to welcome you all to the 11th International conference on Data Envelopment Analysis (DEA2013) at Ondokuz Mayıs University in Samsun, Turkey. Samsun is a leading city of modern Turkey with about one million citizens which is on the black sea cost.

Turkey has strategic importance for the world with its developing democracy, dynamic economy, strategic location and important regional role. Over the last decade, Turkey has achieved a serious stability leading to its security problems better and better. Therefore, as well as developed countries, the countries in the region have positive attitudes towards Turkey's wish to be an intersection center of the energy distribution that provides the energy flow between Eurasia.

In every modern country, one of the indispensable elements of policies of booming economy, energy, health, education, transportation, finance and banking, perhaps the most prominent one, is using its own resources productively and effectively. Since our country has made significant progress in these areas in recent years, these issues have been selected as the main theme of DEA2013.

Through the DEA, a performance evaluation technique, it is achieved successfully in these (and other) areas the effective use of resources, the determination of efficiency and performance. We are delighted that this conference hosted over 200 participants for 145 submissions from 43 countries of the world. The Conference will take three days and DEA had been discussed by eminent scientists in terms of both the practical and theoretical contexts with their presentations.

I wish our country, which unites the continents and, which has become the scene of a number of civilizations throughout the history, would possess a function that brings together all the countries against global issues.

We are very glad to see many people in this conference from all around World.

Professor Hasan BAL
Chair of the Organizing Committee

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A NEW CONSTRAINED DATA ENVELOPMENT ANALYSIS APPROACH WITH CORRELATION COEFFICIENTS FOR BALANCED WEIGHT DISTRIBUTION

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ABSTRACT

Data Envelopment Analysis (DEA) which is applied to evaluate the relative efficiency of decision making units (DMU), is a mathematical programming approach. The efficiency in the classical DEA is "the ratio of the sum of the weighted outputs to the sum of weighted inputs". In order to obtain the maximum efficiency score for each DMU under evaluation, different weights are assigned to the inputs and outputs of the DMU. Classical DEA models allow weight flexibility. Thus, zero weights can be assigned to some important inputs and outputs of the DMU. In this case, such inputs and outputs will be ignored in the evaluation and will be found unrealistic results. Weight restrictions are utilized to eliminate the problem. Input and output variables in the production process are associated with the degree of correlations between these variables. Previous papers didn't consider the relationship between inputs and outputs.

In this study, the weights are defined by correlations between input and output variables. So, the new DEA models constrained with correlation coefficients (CCRCOR and BCCCOR) are developed. The CCRCOR and BCCCOR models and other known DEA models were applied on some datasets in the literature. The results were compared with the Spearman rank test. According to the results, the CCRCOR and BCCCOR models provided a more balanced weight distribution than the other models.

***Keywords**: BCCCOR, CCRCOR, Correlation Coefficient, Data Envelopment Analysis, Weight Restrictions.*

INTRODUCTION

Data Envelopment Analysis (DEA) is a method which is used to measure the efficiencies of DMUs with multiple inputs and outputs. It calculates weights to the inputs and outputs by assigning the maximum efficiency score for a DMU under evaluation. So, it allows the weight flexibility. Hence, zero weights and unreasonable results sometimes can be obtained. In order to avoid this situation, the weight restrictions are used in DEA. A review with the weight restrictions methods was presented by Allen et al. [1]. Weight restrictions can be divided into four main groups:

a. Direct weight restrictions (Dyson and Thanassoulis [2], Beasley [3], Roll et al. [4]): Numerical limits on the input and output weights are imposed by the restrictions.

b. Cone Ratio model (Charnes et al. [5, 6], Kornbluth [7]): The model can be used as a CCR model that evaluates the same DMUs with transformed data [8].

c. Assurance Region (AR) (Thompson et al. [9]): AR can be divided into two groups as AR1 and AR2 in DEA. The limit values for AR1 are dependent on the levels of input and output variables. AR1 is a special case of Cone Ratio model [10]. AR2 imposes restrictions on the ratio between input and output variables.

d. Virtual input and output weight restrictions (Wong and Beasley [11]): In this approach, the contribution of a variable to the total efficiency is determined by the level of input or output times the weight.

In this study, we developed the new DEA models constrained with correlation coefficients (CCRCOR and BCCCOR). So, the weights are defined by correlations between inputs and/or outputs. The CCRCOR and BCCCOR models and the other DEA models were applied on the dataset. The obtained results were compared with the Spearman rank test. From the results, we can say that CCRCOR and BCCCOR models provide a more balanced weight distribution than the other DEA models.

CHARNES COOPER RHODES (CCR) MODEL

CCR model was developed in 1978 by Charnes et. al. [12]. It is a model which is based on the assumption of constant returns to scale. CCR model can be input or output oriented. The choice of input or output oriented models depends on the proporties of Data Making Units (DMUs) in the production process. The input oriented model minimizes the using of inputs for a given level of outputs. The output oriented model maximizes the producing of outputs for a given level of the inputs.

BANKER CHARNES COOPER (BCC) MODEL

BCC Model was developed in 1984 by Banker et al. [13]. The main difference between BCC model and CCR model is to add the variable of u_0 to the input oriented model and the variable of v_0 in the output oriented model to obtain convexity. So, the BCC model is based on the variable returns to scale assumption.

ASSURANCE REGION (AR) APPROACH (CCRAR, BCCAR)

AR approach was first applied to select "best site" for the location of a high-energy physics laboratory by Thompson et al. [9]. Then, Charnes et al. (1990) developed Cone Ratio approach, which combines limits on the input and output weights [5]. The use of a priori restrictions on weights, taking into the relative importance of inputs and outputs during the production process, is allowed to merge the opinions of experts. The CCRAR Model and the BCCAR Model are achieved by adding the weight restrictions into the CCR Model and the BCC Model, respectively.

DEA WITH ANALYTICAL HIERARCHY PROCESS (AHP)

AHP Method was developed by Saaty [14]. A preference matrix of the binary preferred coefficients is created in this method. The consistency of the preference matrix is measured. Mostly, a priori information or value judgments in DEA cannot be easily achieved. Thus, the AR bounds must be defined using expert opinions. In order to collect expert opinions to determine the AR bounds in DEA, the AHP was first used by Zhu [15].

The Input Oriented CCRAHP Model is given in Equation (1) [17].	The Input Oriented BCCAHP Model is seen in Equation (2) [17].

<table>
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$$\max \theta_0 = \sum_{r=1}^{s} u_r y_{r0}$$

st. $\sum_{i=1}^{m} v_i x_{i0} = 1$ (1)

$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad (j = 1,\ldots,n)$

$a_{i,i+1} v_{i+1} - v_i \leq 0, \ (i = 1,\ldots,m-1),$

$k_{i,r}\, u_r - v_i \leq 0, \ (i = 1,\ldots,m), \ (r = 1,\ldots,s)$

$t_{r,r+1} u_{r+1} - u_r \leq 0, \ (r = 1,\ldots,s-1),$

$u_1, u_2, \ldots, u_s \geq 0 \ , \ v_1, v_2, \ldots, v_m \geq 0$

</td>
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$$\max \theta_0 = \sum_{r=1}^{s} u_r y_{r0} - u_0$$

st. $\sum_{i=1}^{m} v_i x_{i0} = 1$ (2)

$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0, \ (j = 1,\ldots,n)$

$a_{i,i+1} v_{i+1} - v_i \leq 0, \ (i = 1,\ldots,m-1),$

$k_{i,r}\, u_r - v_i \leq 0, \ (i = 1,\ldots,m), \ (r = 1,\ldots,s)$

$t_{r,r+1} u_{r+1} - u_r \leq 0, \ (r = 1,\ldots,s-1),$

$u_1, u_2, \ldots, u_s \geq 0, \ v_1, v_2, \ldots, v_m \geq 0, \ u_0 \ \ \textit{free.}$

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In the Equations (1) and (2), $a_{i,i+1}$ is the AHP binary preference coefficient between the i 'th and (i+1)' th input variables.

$k_{i,r}$ is the AHP binary preference coefficient between the i 'th input and the r' th output variables.

$t_{r,r+1}$ is AHP binary preference coefficient between the r'th and (r+1)' th output variables.

A NEW CONSTRAINED DEA APPROACH WITH CORRELATION COEFFICIENTS (CCRCOR-BCCCOR MODELS) (MECIT AND ALP) [16, 17]

In the classical DEA models, the weights, which assign the maximum efficiency score of the DMU under evaluation, are chosen randomly. In this situation, sometimes unreasonable results are obtained. The inputs and outputs are related to each other in the production process. In the study, the relationship was projected in the rate of correlation between the variables. So, the weights were calculated.

The weight restrictions with correlation coefficients can be seen in Equation (3) [16,17].

$$
\begin{array}{lll}
c_{i,i+1} v_{i+1} - v_i \leq 0 & (i = 1,\ldots,m-1), & \\
p_{i,r}\, u_r - v_i \leq 0 & (i = 1,\ldots,m), & (r = 1,\ldots,s) \qquad (3) \\
b_{r,r+1} u_{r+1} - u_r \leq 0 & (r = 1,\ldots,s-1), & \\
u_1, u_2, \ldots, u_s \geq 0, & v_1, v_2, \ldots, v_m \geq 0 &
\end{array}
$$

The Input Oriented CCRCOR Model is given in Equation (4) [16,17].	The Input Oriented BCCCOR Model is seen in Equation (5) [17].

$\max \theta_0 = \sum_{r=1}^{s} u_r y_{r0}$ st. $\sum_{i=1}^{m} v_i x_{i0} = 1$ (4) $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad (j = 1,...,n)$ $c_{i,i+1} v_{i+1} - v_i \le 0, \ (i = 1,..., m-1)$, $p_{i,r}\ u_r - v_i \le 0, \ (i = 1,..., m), \ (r = 1,..., s)$ $b_{r,r+1} u_{r+1} - u_r \le 0, \ (r = 1,..., s-1),$ $u_1, u_2,..., u_s \ge 0$, $v_1, v_2,..., v_m \ge 0$	$\max \theta_0 = \sum_{r=1}^{s} u_r y_{r0} - u_0$ st. $\sum_{i=1}^{m} v_i x_{i0} = 1$ (5) $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \le 0, \ (j = 1,...,n)$ $c_{i,i+1} v_{i+1} - v_i \le 0, \ (i = 1,..., m-1)$, $p_{i,r}\ u_r - v_i \le 0, \ (i = 1,..., m), \ (r = 1,..., s)$ $b_{r,r+1} u_{r+1} - u_r \le 0, \ (r = 1,..., s-1),$ $u_1, u_2,..., u_s \ge 0$, $v_1, v_2,..., v_m \ge 0$ u_0 *free.*

In the Equations (4) and (5), $c_{i,i+1}$ is the correlation coefficient between the i 'th and (i+1)' th input variables.

$p_{i,r}$ is the correlation coefficient between the i 'th input and the r' th output variables.

$b_{r,r+1}$ is the correlation coefficient between the r'th and (r+1)' th output variables.

AN APPLICATION

In this section, the data set was taken from Cooper et al. [8]. Here, the numbers of doctor and nurse in the hospital are inputs. The outpatient and inpatient in the hospital are outputs. So, we have got two inputs and two outputs in this study. Total 14 hospitals are the DMUs.

RESULTS AND DISCUSSIONS

The hospital efficiency scores obtained by these DEA models are given in Table 1. As it can be seen, all efficient hospitals have a score of unity. The number of efficient DMUs and zero weights for the CCRCOR and other models are seen in Table 2. We didn’t find zero weights for any of the input and output variables by using the CCRCOR model and the CCRAR model. So, balanced weight distribution was obtained with the CCRCOR model. The CCRCOR model is an objective model. So, preference information is not needed. But, CCRAR model is a subjective method. It needs preference information. So, the CCRCOR model is superior to the CCRAR model. A comparison of the BCC and the other models can be found in Table 3. In this table, we see the total numbers of efficient DMUs and zero weights obtained by using these models. As it is seen in Table 3, the number of zero weights using the BCCOR model is greatly reduced. In Table 4, maximum correlation is between the CCR and CCRCOR models. The Spearman’s Rho equals to 0.911 between the CCR and CCRCOR models. The CCRCOR model is the closest to CCR model for the ranking of efficient DMUs. Similarly, maximum correlation is between the BCC and BCCCOR models in Table 4. The Spearman's Rho equals to 0.879 between the BCC and BCCCOR models. The BCCCOR model is close to the BCC model in efficiency ranking.

Table 1. The hospital efficiency scores obtained from the DEA models

Hospital	CCR Efficiency Score	CCRAR Efficiency Score	CCRAHP Efficiency Score	CCRCOR Efficiency Score	BCC Efficiency Score	BCCAR Efficiency Score	BCCAHP Efficiency Score	BCCCOR Efficiency Score
H1	0,954560	0,925715	0,924660	0,947096	1	1	1	1
H2	1	1	1	1	1	1	1	1
H3	1	1	0,997747	1	1	1	1	1
H4	0,701828	0,634423	0,560697	0,563968	0,851160	0,837071	0,851160	0,851160
H5	0,826964	0,819869	0,777661	0,798866	0,845358	0,837339	0,786986	0,813037
H6	1	1	1	1	1	1	1	1
H7	0,844089	0,802941	0,745741	0,744496	0,862006	0,814176	0,790080	0,776565
H8	1	0,872323	0,836157	0,917538	1	0,874758	0,856856	0,943572
H9	0,994563	0,982302	0,968070	0,980167	0,995639	0,987171	0,971449	0,983327
H10	1	1	1	1	1	1	1	1
H11	0,912515	0,849426	0,821492	0,855666	0,918927	0,854544	0,822069	0,858051
H12	0,968954	0,930476	0,874901	0,877738	1	0,940836	0,877678	0,919465
H13	0,785919	0,740374	0,666224	0,646535	0,794119	0,745799	0,669496	0,648371
H14	0,974226	0,928811	0,791207	0,825040	1	1	0,881082	1
The Number of Efficient DMUs	5	4	3	4	8	6	5	6

Table 2. The number of efficient DMUs and zero weights for the CCRCOR and other models

Models	The Number of Efficient DMUs	The Number of Zero Weights			
		u_1	u_2	v_1	v_2
CCR	5	10	1	6	3
CCRAR	4	0	0	0	0
CCRAHP	3	0	1	0	0
CCRCOR	4	0	0	0	0

Table 3. The number of efficient DMUs and zero weights for the BCCCOR and other models

Models	The Number of Efficient DMUs	The Number of Zero Weights				
		u_1	u_2	u_0	v_1	v_2
BCC	8	7	5	3	7	3
BCCAR	6	2	2	1	0	0
BCCAHP	5	1	2	3	0	1
BCCCOR	6	1	2	0	0	1

Table 4. Spearman's rank correlation test for the models

	Spearman's Correlation Coefficient			
Model	CCR	CCRAR	CCRAHP	CCRCOR
CCR	1	0,898	0,883	0,911
Sig. (2-tailed)	0,000	(0,000)	(0,000)	(0,000)
	BCC	BCCAR	BCCAHP	BCCCOR
BCC	1	0,874	0,841	0,879
Sig. (2-tailed)	0,000	(0,000)	(0,000)	(0,000)

CONCLUSIONS

The CCRCOR and BCCCOR models decrease both the number of efficient DMUs and the number of zero weights. So, a balanced weight distribution is achieved by the CCRCOR and BCCCOR models which add weight restrictions with correlation coefficients into the CCR and BCC models, respectively.

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A NOVEL DEA APPROACH TO ASSESS INDIVIDUAL AND OVERALL EFFICIENCIES IN TWO-STAGE PROCESSES

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ABSTRACT

In the DEA context, a two-stage production process assumes that the first stage transforms external inputs to a number of intermediate measures, which then are used as inputs to the second stage that produces the final outputs. In the additive approach, the overall efficiency of the production process is defined as a weighted average of the efficiencies of the individual stages. As the weights are assumed functions of the DEA multipliers, they derive endogenously by the optimization process and are different for each evaluated unit. In this paper, we first show that the above assumption made for the weights unduly bias the efficiency assessments in favor of the second stage and we present an unbiased approach to assess the efficiencies of the two stages in an additive two-stage DEA framework. Then, we use the envelopment variants of the individual stages as models to develop a two-phase procedure, which enables the derivation of the efficient frontier at a minimum distortion of the intermediate measures.

Keywords: *Data Envelopment Analysis (DEA); Two-stage DEA; Projections; Efficient frontier.*

INTRODUCTION

Data Envelopment Analysis (DEA) (Charnes et al.,1978) is a widely used technique for evaluating the performance of peer decision making units (DMUs) that consume multiple inputs to produce multiple outputs. In conventional DEA a single stage production process is assumed, which transforms inputs to final outputs, ignoring the internal structure of the decision making units. However, there is an increasing literature body that is devoted to the efficiency assessment in multistage production processes. Castelli et al. (2010) provide a comprehensive categorized overview of models and methods developed for different multi-stage production architectures. In this paper, we focus on the typical architecture of a two-stage production process, which assumes that the external inputs entering the first stage of the process are transformed to a number of intermediate measures which are then used as inputs to the second stage that produces the final outputs.

Seiford and Zhu (1999) studied such a production process in the banking sector by treating the two stages independently, i.e. without assuming any relationship between the two stages. Kao and Hwang (2008) introduced the multiplicative approach that takes into account a series relationship of the two stages. They developed a model that decomposes the overall efficiency to the product of the efficiencies of the two stages. Their approach is based on the reasonable assumption that the virtual intermediate measures are the same, no matter if they are considered as outputs of the first stage or inputs to the second stage. Chen et al. (2009) introduced the additive efficiency decomposition. They decompose the overall efficiency of the production process to a weighted average of the efficiencies of the individual stages. Their modeling approach assumes that the weighting of the two stages derives endogenously by the optimization process.

Notably however, that the assumption made for the weights unduly bias the efficiency assessments in favor of the second stage.

Our paper focuses on an alternative approach in two-stage DEA under the common assumption of the series relationship of the two stages. The selection of different orientations for the two stages enables us to aggregate the efficiency measures of the two individual stages in a bi-objective linear programming framework. Our model estimates simultaneously optimal efficiency scores for the two stages, which then are used to calculate the overall efficiency of the production process, by selecting the aggregation method a posteriori. Thus our method, as opposed to the aforementioned decomposition approaches, is considered as a composition approach. Then we present a two-phase procedure to derive the efficient frontier at a minimum distortion of the intermediate measures.

THE ADDITIVE DECOMPOSITION APPROACH: A CRITICAL REVIEW

Assume n DMUs ($j=1,...,n$), each using m external inputs $X_j=(x_{ij}, i=1,...,m)$, in the first stage to produce q outputs $Z_j=(z_{pj}, p=1,...,q)$ from that stage. The outputs obtained from the first stage are then used as inputs to the second stage to produce s final outputs $Y_j=(y_{rj}, r=1,...,s)$. The vectors $v=(v_1,...,v_m)$, $w=(w_1,...,w_q)$ and $u=(u_1,...,u_s)$ are variable weights associated with the external inputs, the intermediate measures and the final outputs, respectively whereas e_j^o, e_j^1, e_j^2 denote the overall, the first stage and the second stage efficiency of unit *j*.

Chen et al. (2009) introduced the additive decomposition approach; its major characteristic is that apart from the definition of the efficiency of the two individual stages, it premises the definition of the overall efficiency (1) together with a model to decompose the overall efficiency to the stage efficiencies (2). Then, the efficiency scores of the two stages, for each unit, derive as offspring of the overall efficiency.

$$e_j^o=\frac{uY_j+wZ_j}{vX_j+wZ_j}, \qquad e_j^1=\frac{wZ_j}{vX_j},\ e_j^2=\frac{uY_j}{wZ_j} \tag{1}$$

$$\frac{uY_j+wZ_j}{vX_j+wZ_j}=t_j^1\frac{wZ_j}{vX_j}+t_j^2\frac{uY_j}{wZ_j}, \qquad t_j^1+t_j^2=1 \tag{2}$$

$$t_j^1=\frac{vX_j}{vX_j+wZ_j}, \qquad t_j^2=\frac{wZ_j}{vX_j+wZ_j} \tag{3}$$

In effect, the overall efficiency is *a weighted arithmetic average* of the stage efficiencies. The weights (3) are obtained by solving the system (2) for t_j^1 and t_j^2. Particularly, as the weights are functions of the virtual measures, they depend on the unit being evaluated and, obviously, they generally differentiate from one unit to another. On the basis of the above definitions, the linear model (4) has been proposed to assess the overall efficiency of the evaluated unit j_0. Once an optimal solution (v^*, w^*, u^*) of model (4) is obtained, the overall efficiency and the stage efficiencies are calculated by the following equations (5).

$$
\begin{aligned}
& e_{j_0}^o = \max uY_{j_0} + wZ_{j_0} \\
& s.t. \\
& vX_{j_0} + wZ_{j_0} = 1 \\
& uY_j - wZ_j \le 0,\ j = 1,\dots,n \\
& wZ_j - vX_j \le 0,\ j = 1,\dots,n \\
& v \ge 0, w \ge 0, u \ge 0
\end{aligned}
\tag{4}
$$

$$
\begin{aligned}
e_{j_o}^o &= u^* Y_{j_0} + w^* Z_{j_0} \\
t_{j_0}^1 &= v^* X_{j_0}, \quad t_{j_0}^2 = w^* Z_{j_0} \\
e_{j_o}^1 &= \frac{w^* Z_{j_0}}{v^* X_{j_0}} = \frac{t_{j_0}^2}{t_{j_0}^1} \\
e_{j_o}^2 &= \frac{e_{j_o}^o - t_{j_0}^1 e_{j_o}^1}{t_{j_0}^2} = \frac{u^* Y_{j_0}}{w^* Z_{j_0}}
\end{aligned}
\tag{5}
$$

The overall efficiency $e_{j_0}^o$ is obtained as the optimal value of the objective function in (4), the weight $t_{j_0}^1$ is obtained as the optimal virtual input, the weight $t_{j_0}^2$ is obtained as the optimal virtual intermediate measure, the efficiency of the first stage $e_{j_0}^1$ is given by the ratio of the two weights, whereas the efficiency of the second stage $e_{j_0}^2$ is obtained as offspring of $e_{j_0}^o, e_{j_0}^1$. In Chen et al. (2009), the definition of the overall efficiency, as in (1), is implicit. Explicit is, however, the definition of the weights (3), which is made for the sake of linearization of the efficiency assessment model, in the form of (4). The argument given for the weights is that they represent the relative contribution of the two stages to the overall performance of the DMU. The "size" of each stage, as measured by the portion of total resources devoted to each stage, is assumed to reflect their relative contribution to the overall efficiency of the DMU. However, as long as the weights derive from the optimal solution of (4), they depend on the DMU being evaluated and, generally, they are different for different DMUs. Thus, the "size" of a stage is not an objective reality, as it is viewed differently from each DMU. But this is not the only peculiarity emerging from the definition of the weights. Indeed, from the definition of the weights (3), as well as form (5) holds that $\frac{t_j^2}{t_j^1} = \frac{wZ_j}{vX_j} = e_j^1 \le 1$ i.e. $t_j^2 \le t_j^1$. Thus, the efficiency decomposition in model (4) is biased in favor of the second stage, as the efficiency assessments are always made by imposing to the first stage a greater or equal weight than the weight assigned to the second stage. This is a major drawback of the additive decomposition method.

THE COMPOSITION APPROACH: A REVERSE PERSPECTIVE

Consider the output-oriented CRS model (6) for the first stage and the input-oriented CRS model (7) for the second stage, where the same intermediate weights are assumed for both stages. Appending the constraints $uY_j - wZ_j \le 0, j = 1,\dots,n$ to model (6) and the constraints $wZ_j - vX_j \le 0, j = 1,\dots,n$ to model (7) we derive two augmented models for the first and the second stage respectively.

1st Stage – Output Oriented | 2nd Stage – Input Oriented | Single-Objective Linear Program

$$
\begin{aligned}
&\frac{1}{e^1_{j_0}} = \min vX_{j_0} \\
&s.t. \\
&wZ_{j_0} = 1 \qquad\qquad (6) \\
&wZ_j - vX_j \le 0,\ j = 1,\dots,n \\
&v \ge 0, w \ge 0
\end{aligned}
$$

$$
\begin{aligned}
&\max uY_{j_0} \\
&s.t. \\
&wZ_{j_0} = 1 \qquad\qquad (7) \\
&uY_j - wZ_j \le 0,\ j = 1,\dots,n \\
&w \ge 0, u \ge 0
\end{aligned}
$$

$$
\begin{aligned}
&\min vX_{j_0} - uY_{j_0} \\
&s.t. \\
&wZ_{j_0} = 1 \qquad\qquad (8) \\
&uY_j - wZ_j \le 0,\ j = 1,\dots,n \\
&wZ_j - vX_j \le 0,\ j = 1,\dots,n \\
&v \ge 0, w \ge 0, u \ge 0
\end{aligned}
$$

Notice that an optimal solution of model (6) is also optimal in the augmented model. Analogously, an optimal solution of model (7) is also optimal in the augmented variant. The augmented models have common constraints and, thus, can be jointly consider in a bi-objective linear program. The basic model (8) derives by aggregating the two objective functions additively. Once an optimal solution (u^*, v^*, w^*) of model (8) is obtained, the efficiency scores for unit j_0 in the first and the second stage are respectively $\hat{e}^1_{j_0} = 1/v^* X_{j_0}$ and $\hat{e}^2_{j_0} = u^* Y_{j_0}$. Having the stage efficiency scores, the overall efficiency can be computed either as a simple or as a weighted average, with the weights given a priori commonly for all the units. Hence, our approach can be considered as "neutral", as opposed to the Chen's et al. (2009) one, where the unit under evaluation assigns its own weights to the efficiency scores of the two individual stages. The essential characteristic of our method is that the overall efficiency is derived from the stage efficiencies (composition approach), whereas, under the decomposition frameworks (Chen et al, 2009 and Kao and Hwang, 2008) the stage efficiencies derive from the overall efficiency.

Comparing the efficiency scores derived from model (8) with those obtained by Chen et al. (2009) method, on randomly generated data as well as on data sets reported in the literature, showed that they differ significantly. It is conceivable that the overall efficiency scores cannot be compared directly. Moreover, as post-optimality analysis verified, model (8) yields unique efficiency scores.

DERIVING THE EFFICIENT FRONTIER

An issue worth mentioning is the inability of two-stage DEA models to derive the efficient frontier, i.e. to provide sufficient information on how to project the inefficient units on the DEA frontier. As mentioned by Chen et al. (2010) the standard DEA technique of adjusting the inputs and outputs by the efficiency scores cannot yield a frontier projection under the concept of a two-stage process neither in their additive approach nor in Kao and Hwang's (2008) multiplicative approach. They addressed this issue by developing alternative models, under the framework of Kao and Hwang (2008), which generated a set of new inputs, outputs and intermediate measures that constituted efficient projections. Unfortunately, the aforementioned technique cannot be applied in the additive framework. Recently, Chen et al. (2013) noticed that the envelopment and the multiplier forms are two types of network DEA models, which use different concepts of efficiency. Consequently, the envelopment forms of network DEA models should be used for determining the frontier projection for inefficient DMUs while the multiplier models for estimating efficiency scores.

In our approach, the envelopment (dual) form of our basic model (8) does not provide adequate information to project the units onto the efficient frontier. To address the deficiencies discussed above, we apply a reverse technique by selecting an input orientation for the first stage (9) and an output orientation for the second stage (10). Appending the constraints of model (9) to model (10), and vice versa, we derive two augmented models for the first and the second stage respectively which have common constraints; hence they enable us to jointly consider them as a bi-objective linear program. Accordingly, by aggregating the two objective functions additively, we derive the following single-objective linear program (11).

1st Stage – Input Oriented	2nd Stage – Output Oriented	Phase I	Phase II
$\begin{array}{l} \min \theta_1 \\ s.t. \\ X\lambda \le \theta_1 X_0 \quad (9) \\ Z\lambda \ge Z_0 \\ \lambda \ge 0 \end{array}$	$\begin{array}{l} \max \theta_2 \\ s.t. \\ Y\mu \ge \theta_2 Y_0 \quad (10) \\ Z\mu \le Z_0 \\ \mu \ge 0 \end{array}$	$\begin{array}{l} \min \theta_1 - \theta_2 \\ s.t. \\ X\lambda \le \theta_1 X_0 \\ Y\mu \ge \theta_2 Y_0 \\ Z\lambda \ge Z_0 \quad (11) \\ Z\mu \le Z_0 \\ \lambda \ge 0, \mu \ge 0 \\ \theta_1 \le 1, \theta_2 \ge 1 \end{array}$	$\begin{array}{l} \max M(es^- + es^+) - (e\alpha + e\beta) \\ s.t. \\ X\lambda + s^- = \theta_1^* X_0 \\ Y\mu - s^+ = \theta_2^* Y_0 \\ Z\lambda + \alpha - \beta \ge Z_0 \quad (12) \\ Z\mu + \alpha - \beta \le Z_0 \\ \lambda \ge 0, \mu \ge 0 \\ s^+ \ge 0, s^- \ge 0 \\ \alpha \ge 0, \beta \ge 0 \end{array}$

Notice that model (11) in Phase I yields the independent efficiency scores θ_1^*, θ_2^* for the two stages, which then they are passed in Phase II. Once optimal λ*'s and μ*'s are obtained from the Phase II model (12), the efficient projections for the external inputs and the final outputs derive as $\hat{X}_0 = \sum_{j\in J} X_j \lambda_j^*$, $\hat{Y}_0 = \sum_{j\in J} Y_j \mu_j^*$, with adjusted intermediate measures $\hat{Z}_0 = Z_0 - \alpha^* + \beta^*$, where α^*, β^* are the vectors of the optimal values of the deviation variables in (12). The vectors of deviation variables α and β are used to yield new intermediate measures at a minimum distortion of the original ones, while M is a large positive number that gives priority in defining the max-slack solution with respect to the external inputs and the final outputs. The rationale is that as the intermediate measures are debatable between the two stages, they should undergo minor changes from their initial state. Such an issue, is not taken into account in other projection methods (Chen et al. 2010, 2013), where the new estimated intermediate measures differ substantially from their original values and depend on the orientation assumed. The experiments show that the projections render the units efficient.

CONCLUSIONS

We showed in this paper that the additive decomposition approach introduced by Chen et al (2009) biases the efficiency assessments in favor of the second stage. Then we introduce the composition approach to two-stage DEA. In principle, we differentiate from the additive decomposition approach in that we estimate first optimal and unbiased efficiency scores for the two stages, which are then aggregated additively as a simple or a weighted average to obtain the overall efficiency. Further, having obtained the individual efficiency scores, one might consider different aggregation schemes. Moreover, we introduce a two-phase procedure to derive the efficient frontier. The novelty of this two-phase approach is that, when projecting the inefficient units on the frontier, the adjusted intermediate measures are as close as possible to their original values, an issue that is not taken into consideration in other approaches. Recapping, the proposed composition approach provides insight where the conventional DEA models do not fully access, by yielding neutral and unique stage efficiencies (the true efficiency scores) and the efficient frontier.

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A REVIEW ON ARASH METHOD IN DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Arash Method (AM) is a new technique in Data Envelopment Analysis (DEA), which estimates the performance of Decision Making Units (DMUs) with flexible linear programming based on Additive DEA model (ADD). It is simultaneously able to discriminate technically efficient DMUs and/or inefficient ones without using statistical techniques, super-efficiency methods or requiring additional information in the case of weight restrictions. It simultaneously benchmarks both inefficient and technically efficient DMUs. AM is also able to measure the cost-efficiency of DMUs when cost information is available. It can be extended as a non-linear programming to have all the properties of linear AM and all capabilities of the Slack Based Measure (SBM) model. A practical definition based on AM score not only can find the best technically efficient DMUs, where small errors are introduced in their input values even if data are accurate, but it also provides an assurance that "small" errors in the measurement of input quantities did not result in "large" errors in the calculation of the efficiency index, which prompted introducing the axioms of continuity. This study clearly discusses about the capabilities of AM in comparison with most of previous DEA models with some numerical examples.

***Keywords**: Data Envelopment Analysis, Arash method, Efficiency, Benchmarking, ranking.*

INTRODUCTION

Data Envelopment Analysis (DEA) is a non-parametric method to estimate the production frontier of Decision Making Units (DMUs) with multiple inputs and multiple outputs. It proposed by Charnes et al. [1] based on the earlier work of Farrell [2]. Full details on the description of DEA techniques and models can be seen in [3-8]. Recently, Khezrimotlagh et al. [9] identified the flaw in the Pareto-Koopmans definition of efficiency, and depicted some shortcomings in the base of DEA techniques to benchmark and rank DMUs. They proposed a robust DEA technique called Arash Method (AM) with a practical definition to remove the shortcomings [9]. Soon later, they proved that AM is able to measure cost-efficiency of DMUs [10], and proposed a non-linear AM which not only has all the capabilities of Slack Based Measure model (SBM) [11-13], but it is also able to discriminate technically efficient and inefficient DMUs concurrently. AM was also extended to measure the performance of DMUs inclusive non-controllable data [14] and integer-valued data [15] as well as estimating the production frontier and measuring the sensitivity of DMUs' efficiency [16]. In this paper, AM is introduced and its capabilities and properties are illustrated with some numerical examples and clear figures. The simulations were performed using Microsoft Excel Solver and Lingo11/win64 as it required simple linear programming.

THE PARETO-KOOPMANS DEFINITION OF EFFICIENCY

Once the input and output variables are identified for a set of DMUs, a Production Possibility Set (PPS) is produced by DEA axioms [1, 17] and its frontier called the Farrell frontier is considered to estimate the production frontier. Then, the location of a DMU within the PPS is compared to the Farrell frontier in order to calculate its efficiency as well as benchmark and rank DMUs. Moreover, DMU $A(x, y)$ is more efficient than DMU $A'(x', y')$, if the value of y/x is greater than the value of y'/x'. The Pareto-Koopmans' definition of efficiency declares that a DMU is to be rated as fully (100%) efficient (referred to as 'technical efficiency' in economics) on the basis of available evidence if and only if the performances of other DMUs do not show that some of its inputs or outputs can be improved without worsening other inputs or outputs [9]. Therefore, DMUs on the Farrell frontier are called fully (100%) efficient by this definition and other DMUs are called inefficient. However, Khezrimotlagh et al. [9] identified that it is not appropriate to call a technically efficient DMU "100% efficient". They proved that the Pareto-Koopmans definition of efficiency is only able to identify technically efficient DMUs and a technically efficient DMU may neither be efficient nor be more efficient than inefficient ones. Moreover, the DEA techniques and models could be classified into two groups [18]. The first group did not require information from the decision makers such as super-efficiency and cross-evaluation models [19-23]. The second group required some information about data such as allocation models and weight restrictions [24-29]. The Pareto-Koopmans definition of efficiency is not also valid for the second group. For instance, a DMU was called fully efficient DMU whereas its efficiency score might have been less than all other DMUs' efficiency scores by the cost-efficiency model. In order to depict the shortcoming in Pareto-Koopmans definition of efficiency obviously, let us suppose that there are five DMUs with one input and one output according to Table 1 and Figure 1 in Variable Returns to Scale (VRS) [17].

Table 1: Example of five DMUs inclusive one input and one output.

DMU	x	y	Pareto-Koopmans definition	Efficiency (y/x)
A	2	2	100% Efficient	1
B	3	9	100% Efficient	3
C	10	10	100% Efficient	1
D	3	8.7	Inefficient	2.9
E	3.3	9	Inefficient	2.7

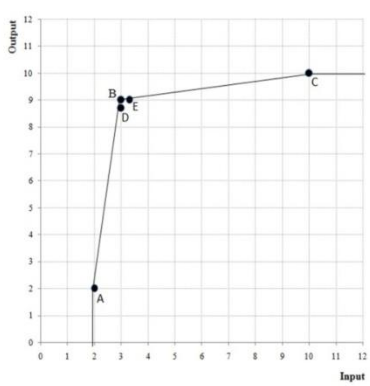

Figure 1: The VRS Farrell frontier.

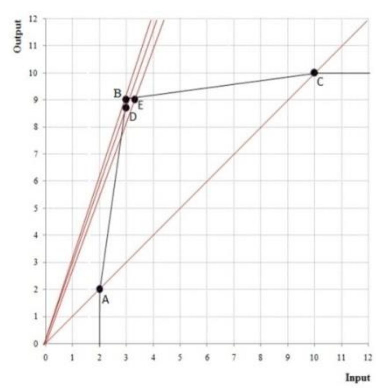

Figure 2: The measurement of DMUs'

efficiency.

From Figure 1 and the forth column of Table 1, the technically efficient DMUs A, B and C are fully (100%) efficient by Pareto-Koopmans definition of efficiency, however, none of DMUs A and C are more efficient than other inefficient DMUs D and E as can be seen in Figure 2 and the last column of Table 1. In other words, the technically efficient DMUs A and C are more inefficient than inefficient DMUs D and E. This simple clear example obviously proves that the Pareto-Koopmans definition of efficiency is not valid to call a technically efficient DMU as fully (100%) efficient. Since the DEA construction was supposed on the Pareto-Koopmans definition, there was a need to reconsider the base of DEA. Therefore, Khezrimotlagh et al. [9] proposed a robust technique called Arash Method (AM) and a new definition of efficiency in order to remake the structure of DEA and simultaneously cover the purpose of both mentioned groups [10, 12-16].

ARASH METHOD (AM)

Let us consider the DMUs A and B in Table 1. As can be seen, B has only one unit input higher than A, however, the output of B is quite greater than the output of A. This suggests that A should increase one unit of its input to produce the same output as B, in order to improve its efficiency significantly. This tactic can be discussed for B and C, by decreasing one unit of C's output in order to use less than one third of C's input and improve its efficiency sharply. The basic DEA models are not able to offer these suggestions, because the purpose of basic DEA techniques is only to decrease input and/or increase output. Although, the second group of DEA models may not have this shortcoming, they require the necessary information of data. However, as it will be discussed AM is able to remove this shortcoming of basic DEA models either the necessary information are available or not. For instance, let us consider the virtual DMU A' in a neighbourhood of A with one greater unit in input. Now the technique of non-redial Additive DEA model (ADD) [30] clearly suggests the location of B on the Farrell frontier as a target for A'. Then the ratio of the efficiency score of A and the efficiency score of B, that is, $1/3 = 0.\overline{3}$, is defined as a measure to identify the validity of suggested target when one unit error is introduced in the input of A. If this measure is less than 1, it says that the suggested target has the greater efficiency score than that of A, and A should be benchmarked to B. If the score is equal or greater than 1, the suggested target has the same or less efficiency score than the efficiency score of A, and A has a good efficient combination by the considered error. In this example, the virtual DMUs in the neighbourhood of A which has an input with a small value greater than the input of A, are not benchmarked to A. This phenomenon illustrates that A has not a good efficient combination in its data in comparison with other available DMUs. The above discussion can also be demonstrated for C when the virtual DMUs are considered with a small value of output less than that of C. In contrast, every virtual DMU in the neighbourhood of B with greater value in input and/or with less value in output is strongly suggested to B, which shows that B has a good efficient combination in its data among other available DMUs. Therefore, B can only be called as fully efficient DMU among these DMUs where a small error is introduced in its data. This technique is called AM when a small error is introduced in input values, and is called the Kourosh Method (KM) when a small error is introduced in output values. The combination of both methods is called the Kourosh and Arash Method (KAM) [16]. In order to illustrate the Arash Method, suppose that there are n DMUs ($\text{DMU}_i, i = 1,2,\dots,n$) with m non-negative inputs ($x_{ij}, j = 1,2,\dots,m$) and p non-negative outputs ($y_{ik}, k = 1,2,\dots,p$), such that, at least one of the inputs and one of the outputs of each DMU are not zero, and there is no i that $x_{ij} = 0$, for all $j = 1,2,\dots,m$. Assume that DMU_l ($l = 1,2,\dots,n$) is evaluated, w_j^- and w_k^+ are the user specified weights obtained through values judgments, $\boldsymbol{\varepsilon} = (\varepsilon_1^-, \varepsilon_2^-, \dots, \varepsilon_m^-)$, $\varepsilon_j^- \geq 0$, s_j^-'s and s_k^+'s are non-negative slacks, for $j = 1,2,\dots,m$ and for $k = 1,2,\dots,p$. Table 2 illustrates the linear and non-linear $\boldsymbol{\varepsilon}$-AM in Variable Returns to Scale (VRS) [3]. If the weights w_j^- and w_k^+ are unknown, they can be defined as $1/x_{lj}$ and $1/y_{lk}$ where $x_{lj} \neq 0$ and $y_{lk} \neq 0$, or N_j and M_k where $x_{lj} = 0$ and $y_{lk} = 0$, for $j = 1,2,\dots,m$ and $k = 1,2,\dots,p$, respectively. The N_j and M_k can be non-negative real numbers related to the goals of the DMUs. If $\varepsilon_j^- > 0$, for some $j = 1,2,\dots,m$, and $A_{\boldsymbol{\varepsilon}}^* < 1$ for a DMU, $\boldsymbol{\varepsilon}$-AM proposes that the DMU changes its data to the new $\boldsymbol{\varepsilon}$-AM target. Otherwise, that is, $A_{\boldsymbol{\varepsilon}}^* \geq 1$, $\boldsymbol{\varepsilon}$-AM warns the DMU to avoid changing its data, because it may decrease its efficiency. The efficiency index of non-linear AM is not greater than that of linear AM and it always belongs to $(0,1]$. If $\varepsilon = 0$, the non-linear AM is SBM [12, 13]. If $\varepsilon_j^- = \varepsilon/w_j^-$, $w_j^- = 1/x_{lj}$, for $j = 1,2,\dots,m$ and $\varepsilon > 0$, $w_k^+ = 1/y_{lk}$, for $k = 1,2,\dots,p$, the effects on the Farrell frontier depend on the DMUs' data, however, as ε_j^- is defined with $\varepsilon \times \min\{x_{ij}: x_{ij} > 0, \text{for } i = 1,2,\dots,n\}$, for $j = 1,2,\dots,m$, there are the same effects on the Farrell frontier to assess the performance of each DMU. By replacing $\sum_{i=1}^n \lambda_i y_{ik} - s_k^+ = y_{lk} - \varepsilon_k^+,\ \forall k$, with $\sum_{i=1}^n \lambda_i y_{ik} - s_k^+ = y_{lk},\ \forall k$, and adding the constrains $x_{lj} - s_j^- \geq 0, \forall j$ and $y_{lk} + s_k^+ - 2\varepsilon_k^+ \geq 0, \forall k$, AM is extended to KAM [16].

Table 2: Linear and non-linear Arash models in VRS.

	Linear $\boldsymbol{\varepsilon}$-AM	Non-linear $\boldsymbol{\varepsilon}$-AM
Models	$\max \sum_{j=1}^m w_j^- s_j^- + \sum_{k=1}^p w_k^+ s_k^+$, Subject to $\sum_{i=1}^n \lambda_i x_{ij} + s_j^- = x_{lj} + \varepsilon_j^-, \forall j$, $\sum_{i=1}^n \lambda_i y_{ik} - s_k^+ = y_{lk},\ \forall k$, $\sum_{i=1}^n \lambda_i = 1$, $\lambda_i \geq 0,\ \forall i$, $s_j^- \geq 0,\ \forall j$, $s_k^+ \geq 0,\ \forall k$.	$A^* = \min \dfrac{1 + \sum_{j=1}^m W_j^-(\mathrm{E}_j - s_j^-)}{1 + \sum_{k=1}^p W_k^+ s_k^+}$, Subject to $\sum_{i=1}^n \lambda_i x_{ij} + s_j^- = x_{lj} + \mathrm{E}_j,\ \forall j$, $\sum_{i=1}^n \lambda_i y_{ik} - s_k^+ = y_{lk},\ \forall k$, $\sum_{i=1}^n \lambda_i = 1$, $\lambda_i \geq 0,\ \forall i$, $s_j^- \geq 0,\ \forall j$, $s_k^+ \geq 0,\ \forall k$.
Targets and Scores	Targets: $\begin{cases} x_{lj}^* = x_{lj} + \varepsilon_j^- - s_j^{-*}, \forall j, \\ y_{lk}^* = y_{lk} + s_k^{+*}, \forall k, \end{cases}$ Score: $A^* = \dfrac{\sum_{k=1}^p w_k^+ y_{lk} / \sum_{j=1}^m w_j^- x_{lj}}{\sum_{k=1}^p w_k^+ y_{lk}^* / \sum_{j=1}^m w_j^- x_{lj}^*}$,	Targets: $\begin{cases} x_{lj}^* = x_{lj} + \mathrm{E}_j - s_j^{-*}, \forall j, \\ y_{lk}^* = y_{lk} + s_k^{+*}, \forall k, \end{cases}$ where $W_j^- = w_j^- / \left(\sum_{j=1}^m w_j^- x_{lj}\right)$, $\mathrm{E}_j = \varepsilon_j / w_j^-$, and $W_k^+ = w_k^+ / \left(\sum_{k=1}^p w_k^+ y_{lk}\right)$.

If the potential increase of outputs, that is, s_k^+'s, are eliminated in the linear AM objective and the score is considered as $A^* = \sum_{j=1}^{m} w_j^- x_{lj}^* / \sum_{j=1}^{m} w_j^- x_{lj}$, the cost-efficiency outcome is the same as the result of ε-linear AM when ε is large enough [10]. Similarly AM can be extended to the Kourosh Method (KM) to measure the revenue-efficiency. The combination of KM and AM, called the Kourosh and Arash Method (KAM) is also able to measure the profit efficiency. If the constraints $s_j^- \leq \varepsilon_j^-$, for $j = 1,2, \dots, m$, are added to the AM constraints, AM is able to measure the performance evaluation of DMUs inclusive non-controllable data. By replacing the inequality '$\leq$' and '$\geq$' instead equality '$=$' in the first and second constraints of AM, respectively, and adding the constraints $s_j^- \in \mathbb{Z}$ and $s_k^+ \in \mathbb{Z}$, AM is able to benchmark and rank DMUs inclusive integer valued data [15]. In this case, the epsilons can be defined in the set of integer numbers to have the integer results. They can also be defined in the set of real values by adding the constraints $x_{lj} - s_j^- \geq 0, \forall j$, and considering the targets as $x_{lj}^* = x_{lj} - s_j^{-*}, \forall j$ and $y_{lk}^* = y_{lk} + s_k^{+*}, \forall k$. From these changing and the proposed PPS of KAM the points with integer values which are very close to the Farrell frontier can be suggested even they were infeasible by the basic DEA PPS. A practical definition to characterize best technically efficient DMUs is as follows [13-16]:

Definition: A technically efficient DMU is efficient with $\boldsymbol{\varepsilon}$ degree of freedom ($\boldsymbol{\varepsilon}$-DF) in inputs if $A_0^* - A_{\boldsymbol{\varepsilon}}^* \leq \delta$. Otherwise, it is inefficient with $\boldsymbol{\varepsilon}$-DF in inputs. The proposed amount for δ is $10^{-1}\varepsilon$ or ε/m.

The minimum values of input and output are 2 for DMUs in Table 2, therefore, $\varepsilon_j^- = 2\varepsilon$. Table 3 illustrates the results of AM, KM and KAM when ε is 0, 0.1 and 0.5. Here, 0-AM is the same as 0-KM and 0-KAM. As can be seen, 0.1-AM clearly discriminates between DMUs A and B and depicts that A is less efficient than inefficient DMUs D and E with 0.1-DF by the scale of the non-zero minimum input. This means that the technically efficient DMU A in comparison with other technically efficient DMUs B and C, should increase its input to find a better place on the Farrell frontier. Likewise, 0.1-KM discriminates B and C, and suggests that C should decrease its output to get a more efficient place on the Farrell frontier. These findings clearly represent that KAM moves the technically efficient DMUs toward the economically part of the Farrell frontier.

Table 3: The results of $\boldsymbol{\varepsilon}$-AM, $\boldsymbol{\varepsilon}$-KM and $\boldsymbol{\varepsilon}$-KAM for DMUs in Table 1.

DMU	0-AM	0.1-AM	0.5-AM	0.1-KM	0.5-KM	0.1-KAM	0.5-KAM
A	1.0000	0.5882	0.2222	0.9091	0.6667	0.5556	0.2000
B	1.0000	0.9333	0.6667	0.9783	0.9000	0.9130	0.6000
C	1.0000	0.9800	0.9000	0.8600	0.3000	0.8400	0.2000
D	0.9667	0.9022	0.6444	0.9457	0.8700	0.8826	0.5800
E	0.9091	0.8485	0.6061	0.8893	0.8182	0.8300	0.5455

NUMERICAL EXAMPLES

Khezrimotlagh et al. [13] considered 18 DMUs with five inputs and two outputs to depict the differences between linear AM (L.AM) and non-linear AM (NL.AM) and SBM when ε is 0, 0.0001, 0.001, 0.01 and

0.1. Figure 5 depicts the results of these models clearly where $\varepsilon_j^- = \varepsilon/w_j^-$, $w_j^- = 1/x_{lj}$, for $j = 1,2,\dots,m$ and $\varepsilon = 0.1$, $w_k^+ = 1/y_{lk}$, for $k = 1,2,\dots,p$,. For instance, inefficient DMU A16 is more efficient than technically efficient DMUs $A06$, $A11$, $A13$, $A10$, $A14$, $A08$, $A15$, $A03$, $A07$ and $A04$. Non-linear AM also discriminates the differences between $A01$, $A02$ and $A05$ in comparison with Linear AM in constant returns to scale. There are also a number of good examples in [15, 16, 31] which identify the robust technique of AM in comparison with current DEA techniques to assess the performance evaluation of DMUs inclusive integer-valued and non-controllable data whether the necessary information of data is available or not. In other words, the technique of AM is able to cover many subjects regarding DEA.

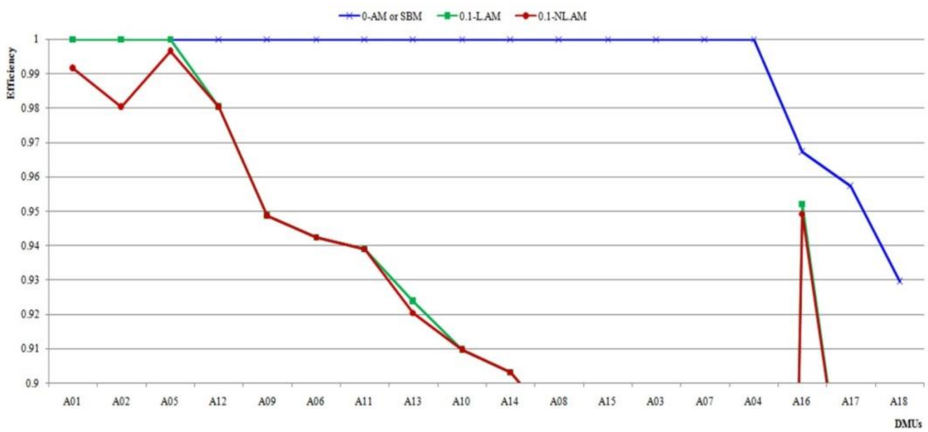

Figure 5: Differences between L.AM and NL.AM and SBM.

CONCLUSIONS

This paper illustrates the short history on Arash Method (AM) and its capabilities to estimate the performance evaluation of DMUs with multiple inputs and outputs as well as benchmark and rank DMUs.

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A ROBUST DATA ENVELOPMENT ANALYSIS MODEL FOR RANKING: A CASE OF HOSPITALS OF TEHRAN

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ABSTRACT

The current study is devoted to Data Envelopment Analysis (DEA) model with uncertain data for performance assessment of hospitals. The importance of health care is growing world-wide, and the health sector is receiving a good proportion of public funds. As health-care costs are increasing, efforts have been made to assess efficiency of hospitals. DEA has proven to be an effective and versatile tool for health care efficiency measurement, and its application has spread throughout the world. Despite many DEA approaches, there are few studies considering the uncertainty in data, and the unknown distribution of the random data together. The method is used in this article has been suggested by Sadjadi & Omrani(2008) based on the novel robust optimization approach proposed by Bertsimas et al.(2003). This paper provides a measurement of Tehran hospitals efficiency utilizing Crisp DEA and Robust DEA, and compares the results to show the effects of uncertain data on the performance of DEA outputs. The results represent that the robust DEA approach can be reasonably reliable method for efficiency estimation and ranking strategies.

Keywords: *Data Envelopment Analysis, Robust Optimization, Hospital efficiency*.

INTRODUCTION

In the contemporary world, the main concerns of managers include determining organizations success in utilizing the extant facilities, comparing their performance, identifying inefficient organizations, distinguishing the source of inefficiency, analyzing their strengths and weaknesses and providing appropriate solutions to improve their status. Nowadays, in the developing approach, increasing capacity is not sufficient, but efficiency increment and productivity improvement in existing capacity is the major part of development plans. Given the importance of the healthcare systems in the social, economical, political and cultural sustainable development, paying special attention to this part is not only an ethical but also a social and economical issue. Hospital is considered as the main consumer in the healthcare sector, and a large share of GDP and healthcare budget is allocated to this part. In order to improve the quality and accessories of hospital services, it is crucial to take some actions in the way of preventing or reducing waste of the resources allocated to this sector of healthcare systems. Hundreds of studies that examine the efficiency of health services are conducting in countries such as Finland, Netherlands, England, U.S., Norway and Sweden. Evidence from these studies indicate that technical inefficiency in these systems is remarkable. Although several techniques such as SFA, regression with fixed effects and simple rates exist to estimate best activities, DEA is preferred. DEA is a method which assesses decision making units, and specifies the extent to which the observed performance is closed to its potential. Despite criticisms from some health economists (Newhouse, 1994), Lebenstein considered DEA as primary method for measuring and partitioning X-inefficiency (Leibenstein & Maital, 1992). Theoretical development with this approach began by the works of Charnes et al. (1978) in assessing the efficiency of decision making units. The first application of DEA in healthcare dates to Nunamaker and Lewin works in evaluating the performance of nursing services in 1983. Since then DEA has been used widely in measuring hospital technical efficiencies in the US and other parts of the world at different levels of DMUs. For instance, Sherman (1984) was the first one in evaluating overall hospital efficiency by applying DEA. By 1997, Hollingsworth et al. (1999) reported 91 DEA studies in health care. DEA applications in health have increased during the last two decades, and as access to information technology has improved, the quality of studies has grown too (ozcan et al, 2008). A review study of O'Neill et al (2008) showed that the number of DEA studies in measuring hospital efficiency is remarkably different between Europe countries and US. Their paper also indicates that most studies are input based models, because managers have more controls over inputs. Hollingsworth et al (2008) concluded in their studies that basic techniques in performance analysis in healthcare are DEA and SFA. In 80% of frontier analysis, nonparametric analysis have been used, in 8% Malmquist index, and in 18% SFA and other parametric technique have been used. Ying Chu NG (2011), in a paper based on five years data, examined efficiency of china’s hospital using input-oriented DEA. In this study, he has applied non-parametric Malmquist index in addressing productivity changes. Brown & Pagan (2006), Harrison and Sexton (2006), and Harrison, Coppola, and Wakefield (2004) have examined hospitals nationwide in the 1990s using input-oriented DEA yielding efficiency scores of 0.68 to 0.79. Ferrier et al (2006) analyzed 170 hospitals in Pennsylvania with output-oriented DEA and found that most inefficiency was due to pure technical inefficiency. Three studies have been conducted in the developing countries, addressing technical and scale efficiency in African hospitals; Kirigia, Emrouznejad, and Sambo (2002) concluded that 26% of district level hospitals in Kenya were technically inefficient. A study relying on samples obtained from 17 hospitals in Ghana found that they suffered from serious pure technical and scale inefficiency (Osei et al., 2005). In conventional Data Envelopment Analysis, it is assumed that all data values are specified. However, the observed values of inputs and outputs in real-world problems are imprecise and vague. Furthermore Ben-Tal and Nemirovski in a survey study on benchmark problems indicated that a small perturbation on data could lead to infeasible solutions. Thus, in many cases, the result of ranking could be unreliable, particularly when the efficiency score of a DMU is close to another. Recent advances on robust optimization have made it possible to develop some robust DEA models. Sadjadi and Omrani (2008) are believed to be the first who developed the DEA in uncertain situations based on robust optimization. Measuring the efficiency of Iranian distribution companies (Sadjadi & Omrani, 2008-2011), Iranian telecommunication companies (Sadjadi & Omrani, 2010), Iranian gas companies (Sadjadi & Omrani, 2011), Iranian regional airports (Roghanian & Foroughi, 2010), are some of the applications of RDEA models. The results of these studies show that robust DEA methods are more reliable for efficiency estimating and ranking strategies.

In this paper, the proposed model by Sadjadi and Omrani (2008) has been used in ranking of Tehran hospitals. This paper is organized as follows. First we present DEA and the proposal robust DEA method. Then the RDEA and crisp DEA methods are operated using actual data, and the results are compared. Finally we summarize the contribution of the paper.

METHODS

DEA is a classic, non-parametric approach based on linear programming which is applied to measure the relative efficiency of a set of similar DMUs. Considerable advantage is that it doesn't require the determination of any parametric specification to calculate the efficiency scores (Siriopoulos & Tziogkidis, 2010). The history of DEA goes back to Rhodes PhD thesis, with supervisory of Professor Cooper in 1976. DEA methods assess the relative efficiency, and the efficiency frontier is formed by the convex combination of the most efficient units (Charnes et al., 1985).

Within this framework, models can be either constant return to scale (CRS) or variable return to scale (VRS). According to the basic principles of DEA different model has been made by many scholars and researchers in operation research. The type of models depends on the degree of control that managers have over their inputs, or outputs. Since managers have more control over their inputs, and the more emphasis in the most countries is on controlling costs rather than increasing demands (O'Neill et al., 2008), we have chosen input-oriented model in this paper. Considering that the resolution of CCR models is far greater than BCC models, we have chosen the multiplier form of CCR model to measure the technical efficiencies in this case.

The model employed in this study is developed form of basic DEA models. Consider the fractional CCR model:

$$\max \theta_0 = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i \, x_{io}}$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad j = 1, \ldots, n$$

$$u_{r,} v_i \geq 0$$

The fractional program can be converted to the linear program, known as the multiplier form of the CCR model:

$$\max \theta_0 = \sum_{r=1}^{s} u_r \, y_{ro}$$

Subject to:

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad j = 1, \ldots, n$$

$$\sum_{i=1}^{m} v_i \, x_{ij} = 1$$

$$u_{r,} v_i \geq 0$$

Traditionally we assume that input and output data are crisp, and ignore the effects of uncertainty on optimality and feasibility of the models. Ben-Tal & Nemirovski (2000) show that with small perturbation on data, several constraints may violate or the optimal solution may not remain optimal any more or even became infeasible. The classic methods dealing with uncertainty are stochastic programming (SP) and sensitivity analysis. Sensitivity analysis is only a technique to analyze well-being of the solutions and it cannot be used to produce robust results .Furthermore, sensitivity analysis in models with large number of uncertain data is not practical. And there are three main difficulties with stochastic approach:

- Knowing the exact distribution for data and therefore enumerating scenarios that capture this distribution is difficult in practice,
- Chance constraints destroy the convexity of main problem, and
- There is a dramatic increase in the size of resulting model as a function of the number of scenarios that cause substantial computational challenge (Bertsimas & Sim, 2003).

There are different approaches to deal with uncertainty in Data Envelopment Analysis; one of them is chance-constrained DEA. This method has been developed based on chance constraints. According the assumption of this method, inputs and outputs are stochastic, and the constraints of DEA are considered stochastic as well. Chance constrained DEA were introduced and developed by Sengupta (1990). It should be noted that considering different distribution for data leads to different efficiency scores, in addition, finding appropriate distribution for data is cumbersome (Land et al., 1993). Another method is imprecise DEA, in which regardless of probability distribution functions for inputs and outputs, ranges and bound are considered for data. Cooper et al. (1999) initially developed DEA models with interval, imprecise data. When the data are interval, efficiency scores obtained are interval too. Also in this case DEA models become nonlinear and it is difficult to find the optimal solution. Bootstrapped DEA was developed by Simar & Wilson (2000) is another technique to deal with uncertainty. In bootstrap techniques efficiency scores calculate by crisp DEA firstly, then standard deviation of DEA estimators can be obtained by proposed algorithm of Simar & Wilson(2000). One of the difficulties in this algorithm is finding proper value of smoothing parameter; another is the large number of iteration.

Another approach in recent years to deal with uncertainty in data is robust optimization. This approach seeks solutions that are near optimal and with high probability are feasible. In the early 1970s, Soyster presented a linear optimization model which obtains a feasible solution for all input data such that each input data can take any value from an interval (Soyster, 1973). However, this approach tends to find over conservative solutions. Ben-Tal and Nemirovski (1998, 1999, 2000), El-Ghaoui and Lebret (1997) and El-Ghaoui et al. (1998), have proposed a new idea assuming uncertain data belong to ellipsoidal uncertainty sets. Their model is less conservative than the Soyster one, but this model is a conic quadratic problem and cannot be directly applied to solve the discrete optimization models. Bertsimas and Sim (2004) expressed a different approach to control the level of conservatism. The advantage of this approach is that it leads to linear optimization model and it is suitable to solve the discrete optimization models. Sadjadi & Omrani (2008) proposed a Robust DEA model based on Bertsimas et al.(2004) approach. With uncertainty in outputs, their proposed model is expressed as follow:

$\max z$

Subject to:

$$\sum_{i=1}^{m} v_i \; x_{io} = 1$$

$$\sum_{r=1}^{s} u_r y_{ro} - \; z - \; \Gamma_o p_o - \sum_{j \in J} q_{ro} \geq 0,$$

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - \; \Gamma_j \, p_j - \sum_{j \in J} q_{rj} \geq 0, \quad j = 1, \ldots, n,$$

$$p_j + \; q_{rj} \geq e y_{rj} z_r \qquad \forall \, r, j, \; -z_r \leq \; u_r \; \leq \; z_r \; p_j, q_{rj} \geq 0, \qquad u_r, v_i, z_r \; \geq 0,$$

Where y_{rj} and x_{ij} are the *r*th output and *i*th input for DMU *j*. The efficiency of considered DMU is z, and x_{io} and y_{ro} are the *i*th input and *r*th output for the considered DMU.

In this paper we have implemented the proposed RDEA to ranking 23 hospitals of Tehran, using some actual data of year 2011.

One important aspect of DEA models is choosing input-output variables, but there is not any consensus on the best describing variables (Giannakis et al., 2005). Regard to extensive review in literature (Hollingsworth et al., 2008; Chu NG, 2011; Ramanathan, 2005) and considering the availability of data, we have chosen “number of physicians” and “number of nurses” as indicator of staffs, and “number of beds” as indicator of accumulated capital; these three implied as input variables. And output variables we have used in our model are “number of outpatient visits,” “number of inpatient visits,” “number of surgeries” and “bed occupancy”. These data are retrieved from Statistical Center of Shahid Beheshti University. Variables and summary statistics for data sets of case study are shown in table 1.

Table 1: summary statistics over input and output variables

		Max	Min	Mean
	beds	505	25	167.6
inputs	doctors	119	21	67.3
	nurses	550	43	214.6
	surgery	11228	0	4644.7
	Inpatient visit	982	25265	9519.9
	Outpatient visit	179083	20032	669891.13
outputs	Bed occupancy	42.38	90.95	70.6

RESULTS AND DISCUSSIONS

As mentioned before, 23 hospitals of Tehran have been evaluated for measuring their efficiency in 2011. At first we have solved DEA model without considering any uncertainties in data. The results are shown in the second column of the table. As we can see, nine units are technically efficient and form the efficient frontier. In terms of technical efficiency, these nine are reference set to the others. Other units obtain efficiency scores varying from minimum 0.349 to 0.927, and the average of efficiency scores is 0.79. The next three columns show the robust models results. According to Bertsimas and Sim (2004) for constraints with few numbers of uncertain data, full protection become necessary, which is similar to Soyster's method. Since in this case we have assumed output values are uncertain and the number of outputs are 4, then Γ is equal to 4 for all constraints. The perturbations e are respectively equal to 0.01, 0.05 and 0.1. The system is protected against 100% of uncertain data as the value of Γ indicates. The robust model results show that as the perturbation rate increases, the efficiency scores are decreased and the average of efficiency scores decrease from 0.77 to 0.64.

Table 2: The results from *CDEA* and *RDEA*

DMU no.	DEA	Robust Approach		
		e=0.01	e=0.05	e=0.1
1	0.635	0.622	0.574	0.519
2	1	0.98	0.905	0.818
3	0.749	0.734	0.678	0.613
4	1	0.98	0.905	0.818
5	0.492	0.482	0.445	0.403
6	0.398	0.39	0.36	0.325
7	0.736	0.722	0.666	0.602
8	0.846	0.829	0.765	0.692
9	0.349	0.342	0.316	0.283
10	0.806	0.709	0.729	0.660
11	0.593	0.581	0.537	0.485
12	1	0.98	0.905	0.818
13	1	0.98	0.905	0.818
14	0.458	0.449	0.414	0.375
15	0.669	0.655	0.605	0.547
16	0.681	0.668	0.616	0.557
17	1	0.98	0.905	0.818
18	1	0.98	0.905	0.818
19	0.804	0.788	0.728	0.658
20	1	0.98	0.905	0.818
21	0.927	0.908	0.838	0.758
22	1	0.98	0.905	0.818
23	1	0.98	0.905	0.818

CONCLUSIONS

In order to assess the comparative performance of 23 hospitals of Tehran, we have applied a new robust DEA model proposed by Sadjadi & Omrani (2008), considering output parameters with uncertainty. As long as the distribution of parameters is unknown but symmetric, the applied method can handle uncertainty on all parameters. We have compared the RDEA model results with traditional DEA, using data gathered from Shahid Beheshti university statistical center. The results represent that the robust DEA approach can be reasonably reliable method for efficiency estimation and ranking strategies. As future works the robust DEA model considering uncertainty on both input & output parameters can be developed, the model can be tested in other industries, and the model can be compared with other uncertainty models like SFA.

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AN EMPIRICAL ANALYSIS OF THE EFFICIENCIES OF TURKISH IRON AND STEEL COMPANIES DURING THE GLOBAL FINANCIAL CRISIS

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ABSTRACT

Global financial crisis that started in 2007 has been the focal point of managerial decisions taken across many different economies and industries all over the world. Effects of the crisis differ greatly from one country or industry to another. Among the globally effected industries, iron and steel companies in Turkey have had their share in terms of the challenges brought about by the crisis. The purpose of this study first, is to analyze the efficiencies of the selected Turkish iron and steel companies located in the same geographic region between the years 2005 and 2010. Data Envelopment Analysis (DEA) was employed in this stage of the study. Second, the goal is to investigate the efficiency changes over the years. Malmquist Total Factor Productivity (TFP) index was calculated using the panel data in this stage. Analysis results indicate that regardless of the company size, the global financial crisis has had impacts on the iron and steel companies' efficiencies not in the initial stages of the crisis but in the later years.

Keywords: *Technical Efficiency, Data Envelopment Analysis, Turkish Iron and Steel Industry, Malmquist Index*

INTRODUCTION

Iron and steel industry has been one of the backbone industries through the industrialization processes of countries over the years, and has kept its importance by being the predominant input material for many big industries. In the last decade Turkish economy showed a steady growth. Iron and steel industry was one of the biggest three contributing industries to this growth in terms of the employment it has created and the volume of exports shares in sales. Parallel to the increasing importance of Turkish iron and steel industry, studies generally concentrate on its weaknesses and strengths and global position (i.e. Ulgen, 2008). Research related to the performance of companies exists, but they only concentrate on the financial performance (i.e. Uygurtürk and Korkmaz, 2012). These studies are limited to a small number of iron, steel and metal related companies listed on the stock exchange. To our best of knowledge, no study has been done on the efficiency of Turkish iron and steel companies alone. In this study, we analyze the efficiencies of a sample of Turkish iron and steel companies between 2005 and 2010, covering the global Financial Crisis era, and their efficiency changes over the same period of time.

Iron and Steel industry products are predominantly used as input material within various industries such as automobile, construction and houseware. Growth level of these industries and the deficit in the flat iron supply in the Turkish market since 2011 indicate that growth trend will continue for the near future in the Turkish steel and iron industry. Evidence of this trend can also be observed by the number of newly established companies, joint ventures and expansion of production capacities of many companies in recent years. Regardless of this positive outlook in Turkey, Iron and steel industries globally are not immune to general economic fluctuations. Recent economic crisis that started in 2007 has had global impact to various degrees on most of the world economies and industries.

By the end of 2008, the effects of the 2007 global financial crisis on the iron and steel industry was beginning to show. Total world production started to slow down in 2008 and reached its lowest level in 2009 (World Steel Association (WSA), 2012). However since that year, production volume has shown a steady increase. Most of the contribution to this growth came from the increase in the following counties' production: China (46 %), India (43 %), Turkey (39 %) and South Korea (35 %) (Turkish Steel Producers Association (TSPA), 2013). In terms of production volume, Turkish Iron and Steel industry is currently in the eighth place in the world and is the second largest industry within the European countries with close to thirty six millions ton production volume (WSA, 2013).

As Turkey's production volume increased over the years, its position in the largest steel producing countries list improved as well. In 2011 Turkey moved up to the 8^{th} place from the 10^{th} in the previous years by overtaking Brazil and Ukraine. According to the Turkish Steel Producers Association figures, Turkey has the highest production increase in the top ten steel producer countries and the growth rate was 4.5 times higher than the world average. This happens especially at a time when world steel production growth drops from 17 % in 2011 to 5.2 % in 2012. (TSPA, 2013).

In terms of Turkey's pre and post crisis periods production, there was % 39 increase in the volume and it is among the five steel producing countries to carry its production to 2007 level (TSPA, 2013). Despite the production increases in recent years, Turkey is still an importer of some steel products. However the export figures have been 1.5 times higher than the import figures over the years (TSPA, 2013).

Despite of Turkey's excess production capacities in most of the steel products that can easily satisfy the national demand, import figures of some steel products are reaching considerable values. This reflects the free market structure in the Turkish iron and steel industry and the competition level in the market.

Therefore, competitiveness of Turkish companies is crucial for their long term survival and increasing presence in both domestic and global markets. Among other factors, efficiency of operations is a critical component of the creation and maintenance of competitive edge in the industry. Thus, analyzing the efficiencies of Turkish iron and steel companies during the recent years will reveal additional and insightful details and will give a better picture of the Turkish iron and steel industry.

METHODS

In this study we used standard Data Envelopment Analysis (DEA) which is a non parametric mathematical programming technique to compute the efficiencies of Turkish iron and steel companies included in the study. Efficiencies were calculated for both constant (CRS) and variable returns to scale (VRS) developed by Charnes, Cooper and Rhodes (1978) and Banker, Charnes and Cooper (1984) respectively. We consider both input and output oriented measures for the analysis. In the second stage of the study we have used DEA-Malmquist Index to calculate the total factor productivity growth of Turkish iron and steel companies. We have computed all the indices using DEAP 2.1 software developed by Coelli (1996).

Input and Output Variables: The selection of input and output variables is a crucially important step in DEA suitable to the purpose of the study. Foremost, the input and output bundle has to reflect the operations' logic or to represent the underlining input-output relationships of the decision making units included in a study. Failing to choose appropriate input and output variables such as including unrelated variables or excluding related variables in a model might have a negative impact on the discrimination power of analysis. For this study, we reviewed the literature on steel and iron industry related DEA studies and identified which input and output variables were used in analysis (Table 1). In the light of these previous studies and considering the data availability, we have chosen Paid-in Capital, Assets, Inventories, Number of Workers, Cost of Goods Sold as input variables and Net Sales, Net Profit as output variables. All data except "number of workers" were scaled by 1/100000.

Table 1: Input and Output Variables Used in DEA Analysis of Iron and Steel Industry

Study	Inputs	Outputs	Industry
Ray & Kim (1995)	Labor, capital and materials	Weighted index of shipped products	USA
Ma et.al. (2002)	Energy, Labor, Fixed Capital, Working Capital	Value of Product	China
Dwivedi & Ghosh (2011)	Cost of goods sold, Selling and administration expenses, Total assets	Sales, Profit after tax	India
Shin (2011)	Workers, Gross capital, Tangible assets	Total sales	Korea

In basic DEA models values of the numbers need to be strictly positive since analysis can not be completed with zero or negative values. Although there are various model suggestions in the literature to handle negative data, for the purpose of this study, standard DEA models were used in the analysis. In conjunction with Bowlin's (1998) suggestion, we substitute negative net profit values which represent losses in the data set with a very small positive value (for a negative value of an output variable, he suggests a substitution of a very small positive value.) Bowlin argues that using very small numbers for an output variable would not be expected to contribute to a high efficiency score. Sarkis (2002) further elaborate on this approach and state that the positive values substituted for the negative values have to be smaller than any other positive output value in the data set.

For the purpose of this study, Bowlin's translation method seems to be appropriate since we would not expect a high efficiency score for a company that has a loss in the output value. In order to assess if this transformation inappropriately affects the efficiency scores, we analyzed efficiency scores of companies who has negative net profit output values. We run a separate model which includes only net sales as output variable and compared efficiency scores of this analysis with our model that includes transformed net profit as second output variable in addition to net sales variable. As expected, comparing the two efficiency scores of the companies that have losses revealed that including the translated net profit variable as a second output did not increase the efficiency scores.

Data: Sample companies to be investigated were selected according to the general industrial classification of economic activities within the European Communities known as NACE Rev 2. 2410 code in NACE Rev 2 covers manufacture of basic iron and steel and of ferro-alloys which is classified under Division 24; basic metals manufacturing sector.

Twenty two companies with twenty or more employees were included in the analysis have relevant data available through the 2005-2010 period. The sample includes companies in different sizes, from small to very big global scale, representing the overall existing types in the Turkish iron and steel industry. Using sales data as a proxy for company size, companies in the study can be categorized into four groups. First group consists of companies whose gross sales are 1 million to 10 million (n=5). Second group involves companies with gross sales from 40 million to 90 million (n=5). Third group consists of companies with gross sales from 100 million to 350 million (n=6). Forth group includes companies whose gross sales are 490 million to 4 billion (n=6).

Data for the analysis are collected from various sources. Three of the companies are listed in the Istanbul Stock Exchange; thus they have to make their financial information publicly available. We used the Istanbul Stock Exchange database for these companies. Data for the remaining nineteen companies were obtained from corporate tax return forms, Annual Industry and Service Statistics and quarterly surveys of industrial employment from the Turkish Statistical Institute database.

RESULTS AND DISCUSSIONS

Efficiency scores of the companies were computed using CRS and VRS from both input and output orientation. From input and output oriented point of view industry efficiency averages for CRS and VRS have the same values 0.9487 and 0.9756 respectively. These same results from input and output orientation indicate that input and output variables selected for the analysis are well fitted for the industry. According to these efficiency scores only Özkul Çelik, which is a small size company, was efficient in all years.

Table 2: Efficiency Scores of Turkish Iron and Steel Companies over the Period 2005-2010

DMU	CRS						VRS						SCALE					
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
ÖZKUL ÇELİK	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
GEMSATAŞ	0.908	0.969	0.802	0.809	0.845	0.927	0.922	1.00	0.834	1.00	0.922	0.928	0.985	0.969	0.962	0.809	0.917	0.998
BİLGİNERLER	1.00	1.00	1.00	0.962	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.962	1.00	1.00
EKER	0.987	0.970	1.00	1.00	1.00	0.993	1.00	1.00	1.00	1.00	1.00	0.996	0.987	0.970	1.00	1.00	1.00	0.998
PAYSAN	1.00	0.941	1.00	0.994	0.859	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.941	1.00	0.994	0.859	1.00
PAYMETAL	0.996	1.00	0.809	1.00	1.00	0.888	1.00	1.00	0.961	1.00	1.00	0.889	0.996	1.00	0.842	1.00	1.00	1.00
KENDİRLİLER	1.00	0.976	0.933	0.908	0.948	0.969	1.00	0.976	0.940	0.914	1.00	1.00	1.00	1.00	0.993	0.994	0.948	0.969
NET	1.00	0.899	1.00	0.885	0.872	1.00	1.00	0.902	1.00	0.906	0.874	1.00	1.00	0.997	1.00	0.976	0.998	1.00
GEMCİLER	1.00	0.895	0.632	0.917	1.00	1.00	1.00	0.897	0.836	0.924	1.00	1.00	1.00	0.998	0.755	0.993	1.00	1.00
AKMET	0.957	1.00	0.860	1.00	0.886	1.00	1.00	1.00	0.897	1.00	0.889	1.00	0.957	1.00	0.959	1.00	0.997	1.00
KOÇ HADDE	0.966	0.942	0.809	0.898	0.921	0.930	1.00	0.950	0.950	0.909	1.00	0.931	0.966	0.991	0.852	0.998	0.921	1.00
İLHANLAR HADDE	0.995	1.00	1.00	0.916	0.885	0.967	1.00	1.00	1.00	0.957	0.895	1.00	0.995	1.00	1.00	0.957	0.988	0.967
TOSYALI DEMİR	0.957	1.00	1.00	0.911	0.968	1.00	1.00	1.00	1.00	0.924	0.968	1.00	0.957	1.00	1.00	0.986	1.00	1.00
BAŞTUĞ	0.966	1.00	0.967	0.888	0.773	0.944	1.00	1.00	0.990	0.893	0.790	1.00	0.966	1.00	0.976	0.994	0.979	0.944
İLHAN DEMİR	0.973	1.00	1.00	1.00	1.00	0.955	1.00	1.00	1.00	1.00	1.00	0.961	0.973	1.00	1.00	1.00	1.00	0.993
YOLBULAN	0.953	0.944	0.765	0.886	0.922	0.916	0.978	0.944	0.937	0.896	0.943	0.916	0.975	1.00	0.816	0.989	0.978	1.00
NURSAN METALURJİ	1.00	1.00	0.700	0.941	0.877	0.923	1.00	1.00	0.938	0.953	0.937	1.00	1.00	1.00	0.747	0.987	0.936	0.923
NURSAN ÇELİK	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
İSDEMİR	0.897	0.955	1.00	1.00	0.709	0.945	1.00	1.00	1.00	1.00	1.00	0.978	0.897	0.955	1.00	1.00	0.709	0.967
EREĞLİ	1.00	1.00	1.00	0.959	0.856	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.959	0.856	1.00
İZMİR	0.953	1.00	0.894	1.00	0.907	0.937	1.00	1.00	1.00	1.00	1.00	1.00	0.953	1.00	0.894	1.00	0.907	0.937
KARDEMİR	0.962	1.00	1.00	1.00	0.781	0.913	0.974	1.00	1.00	1.00	0.897	0.967	0.987	1.00	1.00	1.00	0.871	0.944
Mean (n=22)	0.976	0.977	0.917	0.949	0.910	0.964	0.994	0.985	0.967	0.967	0.960	0.980	0.982	0.992	0.945	0.982	0.948	0.984
Percent Efficient	40.9 %	59.1 %	54.5 %	40.9 %	31.8 %	40.9 %	86.4 %	77.3 %	59.1 %	59.1 %	59.1 %	63.6 %	40.9 %	68.2 %	54.5 %	40.9 %	36.4 %	54.5 %

Next, we have calculated Malmquist total factor productivity and efficiency change, technical change, pure technical efficiency and scale change component for all the companies in the sample. Total Factor Productivity (TFP) fluctuates between 2005 and 2010. Technical efficiency is the main contributor to the negative and positive TFP change. The comparison of TFP change in different companies shows that

Paysan on average has the highest growth in TFP by 17.5% during 2005-2010, followed by Gemciler that has 11% TFP. These companies are small size producers. The worst performer in terms of TFP growth is Nursan Metalurji by -25.7% followed by Kardemir (-15%). Both of these companies are big size producers.

Table 3: Malmquist Index of Yearly Means of Turkish Iron and Steel Companies.

Year	Efficiency Change	Technological Change	Pure Technical Efficiency Change	Scale Efficiency Change	Total Factor Productivity Change	Percentage change
2005-2006	0.991	1.123	0.990	1.001	1.113	11.3%
2006-2007	0.975	0.905	0.982	0.993	0.882	-11.8%
2007-2008	1.003	1.392	1.00	1.003	1.396	39.6%
2008-2009	0.967	0.555	0.991	0.975	0.536	-46.4%
2009-2010	1.052	1.205	1.023	1.029	1.267	26.7%

The comparison of productivity change before and after the financial crisis is more apparent when we investigate 2008-2009 and 2009-2010 periods. TFPs of 19 steel companies for the period 2008-2009 have values under one and these companies have experienced big decrease in productivity by 46.4%. This productivity decrease can be decomposed into 3.3% decrease of technical efficiency change and 44.5% decrease of technological change. After the global financial crisis (2009-2010), 16 Turkish iron and steel companies have values over one and mean productivity of Turkish steel companies is increased by 26.7%. This productivity increase can be decomposed into 5.2% increase of technical efficiency change and 20.5% increase of technological change. Using these results we tested if the scores differ depending on the company size. Using the previously defined four groups, a Kruskal-Wallis test was conducted on both 2008-2009 and 2009-2010 TFPs. Test indicates that there is a difference only in 2008-2009 TFP means of the groups ($X^2(3)= 11.843$, $p < .05$). Post test revealed that only group 4's (big companies) TFP mean is significantly lower than the other groups' TFP means.

Table 4: Productivity Change Before and After the Financial Crisis.

DMU	2008-2009 TFP MALMQUIST					2009-2010 TFP MALMQUIST				
	Efficiency Change	**Technological Change**	**Pure Technical Efficiency Change**	**Total Factor Productivity Change**	**TFP Ranking**	**Efficiency Change**	**Technological Change**	**Pure Technical Efficiency Change**	**Total Factor Productivity Change**	**TFP Ranking**
ÖZKUL ÇELİK	1.00	0.315	1.00	0.315	19	1.00	0.993	1.00	0.993	17
GEMSATAŞ	1.045	0.896	0.922	0.937	5	1.096	0.968	1.007	1.061	15
BİLGİNERLER	1.040	0.645	1.00	0.671	12	1.00	1.093	1.00	1.093	13
EKER	1.00	0.753	1.00	0.753	7	1.00	0.812	1.00	0.812	22
PAYSAN	0.860	0.549	1.00	0.472	17	1.162	2.775	1.00	3.226	1
PAYMETAL	1.00	0.559	1.00	0.559	14	0.890	0.957	0.890	0.851	21
KENDİRLİLER	1.070	0.941	1.094	1.007	2	1.029	1.124	1.00	1.157	11
NET	0.987	0.716	0.988	0.706	9	1.115	1.060	1.112	1.182	10
GEMCİLER	1.083	0.906	1.082	0.981	4	1.00	1.634	1.00	1.634	3
AKMET	0.915	0.768	0.919	0.703	10	1.092	0.984	1.088	1.075	14
KOÇ HADDE	1.083	0.810	1.077	0.877	6	0.942	1.046	0.943	0.985	19
İLHANLAR HADDE	0.921	0.660	0.924	0.608	13	1.073	1.371	1.082	1.470	7
TOSYALI DEMİR	1.084	0.957	1.082	1.037	1	1.00	1.007	1.00	1.007	16
BAŞTUĞ	0.768	0.935	0.770	0.718	8	1.459	1.084	1.455	1.582	5

İLHAN DEMİR	1.00	0.697	1.00	0.697	11	0.976	0.945	0.976	0.922	20
YOLBULAN	1.070	0.935	1.085	1.001	3	0.955	1.038	0.942	0.992	18
NURSAN METALURJİ	0.998	0.425	1.019	0.424	18	0.983	1.615	1.036	1.588	4
NURSAN ÇELİK	1.00	0.473	1.00	0.473	16	1.00	1.568	1.00	1.568	6
İSDEMİR	0.754	0.066	1.00	0.050	22	1.284	1.066	1.00	1.368	8
EREĞLİ	0.925	0.528	1.00	0.488	15	1.081	2.533	1.00	2.737	2
İZMİR	0.980	0.209	1.00	0.205	21	0.986	1.358	1.00	1.339	9
KARDEMİR	0.807	0.259	0.912	0.209	20	1.155	0.981	1.065	1.134	12

CONCLUSIONS

In this study, the production efficiency and productivity change of Turkish iron and steel companies were analyzed by using DEA model during the years 2005-2010. CRS efficiency scores and VRS efficiency scores fluctuates for some of the companies over the analysis period. However mean CRS and VRS scores relatively stay the same. The measurement of the Malmquist productivity indexes of Turkish iron and steel companies revealed that all companies experienced considerable decrease in productivity to different degrees due to the global financial crisis. Based on TFP Ranking before and after the crisis, big companies seem to be the ones that were affected the most. Because this study does not include all the companies in the Turkish iron and steel industry, it is not an exhaustive one. However, due to the various sizes of the companies included in the sample, it can be considered illustrative of the industry. However, for company level analysis, further studies including all the companies in the iron and steel industry would be needed.

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AN IMPROVED RANKING FOR DECISION MAKING UNITS USING OPTIMISTIC AND PESSIMISTIC APPROACHES

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ABSTRACT

The standard Data Envelopment Analysis (DEA) model usually evaluates decision making units (DMUs) using the best relative efficiency approach. This approach is known as the optimistic approach, and it is very common that this model returns many units with 100% efficiency scores, making it hard to rank these efficient DMUs. More often, decision makers are interested in reaching a complete ranking to all DMUs in the data under evaluation. Up to now, many ranking methods have been proposed in DEA literature. However, in this paper a new ranking method is proposed to achieve a better ranking by combining optimistic and pessimistic approaches with the virtual DMUs approach. Initially, two virtual DMUs are introduced to any dataset in order to adjust the efficient and inefficient frontier lines to envelop more units. Then, optimistic and pessimistic approaches are applied to that dataset and combined by using a DEA index number (AIN) and arithmetic average to compute the final score of each DMU in the data under evaluation. It is found that combining the pessimistic and optimistic approaches with the "super" and "worst" virtual DMUs returns a better ranking and higher discrimination power of the classical DEA model. Two illustration examples are provided with two-dimensional data and multiple-dimensional data.

***Keywords**: Data Envelopment Analysis DEA; ranking; discrimination power; virtual DMU; decision making units*

INTRODUCTION

Data Envelopment Analysis (DEA) is a well-known method to measure efficiency between decision-making units (known as DMU in the literature). DEA was introduced more than 40 years ago when Charnes, Cooper, and Rhodes [1] presented their model known as the CCR model, by which they were able to change the fractional linear measure of efficiency to a linear programming. DEA attracts many researchers because of its unique ability to measure the efficiency of multiple-input and multiple-output DMUs without assigning prior weight to the input and output. There is a tremendous amount of research that has been applied to DEA since its introduction, and this has resulted in heavy DEA literature.

There is a wide empirical application to DEA in many different sectors like education [2], banking [3], manufacturing [4], logistics [5], telecommunication [6], healthcare [7], and even in sports [8, 9]. The use of DEA as a decision analysis tool is limitless in literature because DEA does not focus on finding a universal relationship for all units under assessment in the sample. DEA permits every unit in the data to have its own production function and then it evaluates the efficiency of that single unit by comparing it to the efficiency of the other units in the dataset. After running the DEA model with every unit in the data, DEA classifies all units into two groups: efficient with 100% efficiency scores, and inefficient with less than 100% efficiency scores.

This characteristic of DEA is considered both a strong and a weak point of the standard DEA model because it allows DEA to be applicable to evaluate the efficiency of any dataset, but it does lack a discrimination power that brings full ranking to all units in the data. Most of the time, decision makers are not just interested in classifying the data into efficient and inefficient; more often, they are interested in reaching a complete ranking to all units in the data under evaluation. In order to overcome the discriminatory problem of DEA, another approach, method, or modification is required to reach a full ranking of all DMUs under assessment [10].

This paper suggests a new method for ranking that combines both the optimistic and pessimistic approaches with introduction of virtual units to the data. The method is discussed in detail in following section of the paper and illustrative examples will follow to show how the new model is able to reach full ranking.

DEA BASIC MODEL

The basic efficiency measure utilized in DEA is the ratio of output to input, but this measure is only applicable to cases of single input and single output. In 1957, Farrell [11] implemented this basic concept and developed the efficiency frontier analysis. The efficiency frontier analysis requires two-dimensional data where all DMUs could be plotted on a two-axis graph, and an efficiency frontier could be constructed. All units that lie on the efficiency frontier will be defined as efficient units with a 100% efficiency score, and all units that do not lie on the frontier line will be defined as inefficient units, and their locations from the efficiency line will be used to calculate their efficiency scores. The frontier line envelops the whole data (as shown in Fig.1) and this is the reason why DEA is called Data Envelopment Analysis [12].

The concept of the CCR model relies on assigning virtual weight of input and output and applies linear programming to get the maximum ratio of efficiency of the DMU under evaluation and applying this linear program to all DMUs in the data one by one.

To clarify this, let us suppose there are *n* DMUs with *s* outputs and *m* inputs, so for every DMU$_k$, there are:

Virtual input = $V_1X_{1k} + \dots\dots + V_mX_{mk}$, and

Virtual output = $U_1Y_{1k} + \dots\dots + U_sY_{sk}$

where V$_i$ (i=1,…., m) is the virtual weight for the inputs and U$_r$ (r=1,….,s) is the virtual weight of the outputs. The efficiency of any DMU will be calculated based on the basic efficiency function where virtual output is divided by the virtual input.

The CCR model aims to determine the weights for every DMU in order to maximize the efficiency ratio. Charnes et al. [1] applied the linear programming to optimize the maximum efficiency of each DMU$_k$ by solving the following fractional program:

$$\text{Max } \theta_k = \frac{u_1y_{1k} + u_2y_{2k} + \dots + u_sy_{sk}}{v_1x_{1k} + v_2x_{2k} + \dots + v_mx_{mk}} \qquad (1)$$

subject to:

$$0 \leq \frac{u_1 y_{1k} + u_2 y_{2k} + \ \dots + u_s y_{sk}}{v_1 x_{1k} + v_2 x_{2k} + \ \dots + v_m x_{mk}} \leq 1 \qquad (k = 1 \dots , n)$$

$v_1, v_2, \dots, v_m \geq 0$ & $u_1, u_2, \dots, u_s \geq 0$

OPTIMISTIC MODEL WITH SUPER VIRTUAL DMU

The standard DEA model is considered as an optimistic approach to rank all DMUs based on using the efficient frontier, so all units located on the efficiency frontier will be considered as efficient DMUs or optimistically efficient DMUs.

Based on the CCR model, the score of all efficient DMUs will be equal to 1. In order to limit the ability of achieving a full score to only very efficient DMUs and for better envelopment to the dataset under assessment we proposed to introduce a super star virtual unit noted as DMU_{super}. The super DMU is defined as a DMU that has the best output, and has the minimum input from all units in the dataset.

So if there are n units to be evaluated in the dataset with m inputs and s outputs, then the value index for the input and output of that super DMU are as follows:

$$X_{i,super} = Min\ (x_{i1}, x_{i2}, x_{i3}, \dots, x_{in})$$

$$i = (1, 2, \dots, m) \qquad (2)$$

$$Y_{r,super} = Max\ (y_{r1}, y_{r2}, y_{r3}, \dots, y_{rn})$$

$$r = (1, 2, \dots, s)$$

After the introduction of the super DMU, the optimistic model to compute the efficiency score of any DMU_k will be like model (1) except that k = 1, … , n+1. The major advantage of introducing the virtual super star DMU is that super DMU will help in eliminating more DMUs from the efficiency frontier, which means better discrimination power. According to Entani et al. [14], any approach that considers only the optimistic approach to evaluate the dataset will be considered biased. Therefore a pessimistic approach is introduced and included in our model.

PESSIMISTIC MODEL WITH WORST VIRTUAL DMU

The optimistic approach of DEA is an approach that measures the efficiency within a range of one. The CCR model is an example of the optimistic approach where all units are trying to optimize the maximum score of 1. On the other hand, the pessimistic approach is an approach that focuses on creating an inefficient frontier and ranks all DMUs according to that. A minimization program is set and the inefficient DMUs will achieve the score of 1. The fractional program of the pessimistic approach is similar to (1) except that it is a minimization problem and all constraints should be greater or equal to 1. The fractional pessimistic model will be as follows:

$$\text{Min } \theta_k^* = \frac{u_1 y_{1k} + u_2 y_{2k} + \ \dots + u_s y_{sk}}{v_1 x_{1k} + v_2 x_{2k} + \ \dots + v_m x_{mk}} \qquad (3)$$

subject to:

$$\frac{u_1 y_{1k} + u_2 y_{2k} + \ \dots + u_s y_{sk}}{v_1 x_{1k} + v_2 x_{2k} + \ \dots + v_m x_{mk}} \geq 1 \qquad (k = 1 \dots, n)$$

$$v_1, v_2, \dots, v_m \geq 0$$

$$u_1, u_2, \dots, u_s \geq 0$$

In our proposal, we suggest introducing the worst virtual $\text{DMU}_{\text{worst}}$, which is defined as a DMU that has the maximum input from all units in the dataset and has the minimum output from all units in the dataset.

So if there are n units to be evaluated in the dataset with m inputs and s outputs, then the value index for the input and output of that worst DMU are as follows:

$$X_{i,worst} = Max\ (\ x_{i1}, x_{i2}, x_{i3}, \dots, x_{in})$$

$$i = (1, 2, \dots, m) \qquad (4)$$

$$Y_{r,worst} = Min\ (\ y_{r1}, y_{r2}, y_{r3}, \dots, y_{rn})$$

$$r = (1, 2, \dots, s)$$

Thus for any DMU_k, the efficiency score with the worst DMU under the pessimistic approach can be calculated as follows:

$$\text{Min } \theta_k^* = \ u_1 y_{1k} + u_2 y_{2k} + \ \dots + u_s y_{sk}$$

subject to:

$$v_1 x_{1k} + v_2 x_{2k} + \ \dots + v_m x_{mk} = 1 \qquad (5)$$

$$u_1 y_{1k} + u_2 y_{2k} + \ \dots + u_s y_{sk} \ \geq v_1 x_{1k} + v_2 x_{2k} + \ \dots + v_m x_{mk}$$

$$(k = 1, \dots, n + 1)$$

$$v_1, v_2, \dots, v_m \geq 0$$

$$u_1, u_2, \dots, u_s \geq 0$$

As mentioned, the pessimistic approach assigns a score of 1 to all inefficient units that are located on the inefficiency line. However, it is important to note that the pessimistic approach has no restriction on the efficiency scores achieved by the efficient units, and all DMUs are ranked in a descending order from the top score to 1.

COMBINATION OF PESSIMISTIC AND OPTIMISTIC APPROACH

Both proposed models, A and B, will yield better ranking power for the DEA standard model, because the introduction of the virtual DMUs will prevent many DMUs from achieving the full efficiency score as these virtual DMUs will change the frontier lines and allow more envelopment to all units in the data under assessment. But as proved by Entani et al. [14], it is biased to use one model over the other one even though using both models brings better discrimination power.

Therefore, combining both models is an important step to reach an unbiased evaluation, and one way to combine both pessimistic and optimistic approaches is to take the geometric average of both scores. Detailed theorem and proof are provided in the work of Wang et al. [15]. Wang et al. suggested using the geometric average between the pessimistic and optimistic scores of each DMU and ranking all DMUs, accordingly. This paper critiques direct use of the pessimistic approach because the pessimistic approach could yield high scores of efficient units while their optimistic scores are limited to only 1. In this paper we suggest using the DEA index number (AIN) to rescale the scores of all efficient units under the pessimistic approach. The AIN will restrict the scores of units under the pessimistic approach to 1-2. This index was used for the same purpose in a super efficiency method by Sueyoshi [16]. The AIN index should be applied to the pessimistic approach as follows:

$$AIN = 1 + \left\{\frac{\theta_k^* - \min \theta_k^*}{\max \theta_k^* - \min \theta_k^*}\right\}, where, k = 1, \ldots, n \qquad (6)$$

So applying the optimistic approach with the super virtual DMU is considered as a first stage in our model. Then applying the pessimistic approach with the worst virtual DMU, and rescaling the results by using the AIN index is the second stage. The final score for DMU_k is calculated by using the arithmetic average of both scores, and it will range between 0.5 and 1.5. The final score can be calculated as follows:

$$\theta_k^{final} = \frac{\theta_k^* + \theta_k}{2} \qquad (7)$$

We believe that the new proposed method provides better ranking for two reasons: 1st by introducing the super and worst virtual DMUs, the model envelops more data with a distinctive score for every DMU. In other words, a limited number of DMUs will achieve equal scores under either the optimistic or the pessimistic approach. 2nd the previous models in the literature that combined the pessimistic and optimistic approaches directly, without adjusting the pessimistic scores could be biased because the optimistic approach is limited to 1 or less while there is no limitation on the pessimistic scores.

RESULTS AND DISCUSSIONS

In order to illustrate the above formulations with the new proposed model, let us consider the following example of evaluating eight graduate students according to their GPA, and their number of publications. The GPA will be considered as a 1st output and the number of publications will be considered as a 2nd output. With the assumption that all students are exactly at the same level of study and have equal capability, each student will have one input with score of 1.The raw data of the example are shown in Table I.

So after applying the three steps, all results of the CCR model, Wang et al. model, and new proposed model are shown in Table II.

It is observed from the table that the final score brought better discrimination among all DMUs in data except for student A and D. These two students are the outlier units in the data, and both are observed as efficient under optimistic approach with the score of 1, and at the same time both are considered inefficient with the score of 1 under the pessimistic approach. Figure 1 shows the location of the students on efficient and inefficient frontiers. The dashed lines show the original efficiency and inefficiency frontiers while the dotted lines show the new frontiers with virtual super and worst DMUs.

Table I. Raw data for graduate student's evaluation

Student	Input	Outputs	
	Unity*	GPA	Publications
A	1	60	6
B	1	80	3
C	1	90	4
D	1	95	1
E	1	70	2
F	1	95	3
G	1	75	1
H	1	65	2

* Unity score is given to the input to keep the data within two dimensions in order to illustrate the example graphically with efficiency frontier analysis

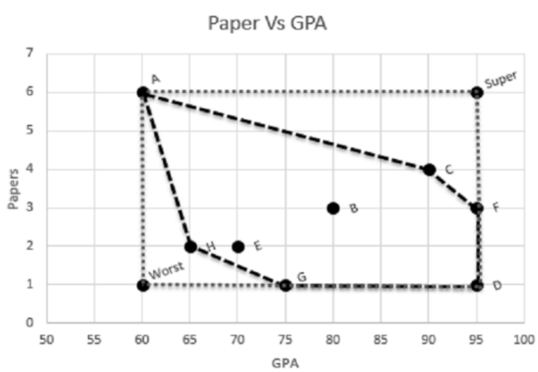

Figure 1 Efficient and inefficient frontiers of original model and with virtual DMUs models.

In the student example, more than one DMU achieved similar scores under pessimistic and optimistic approaches. This equality between DMUs was caused by using two-dimensional data. In order to show the discrimination power of the proposed model, another example of multiple inputs and multiple outputs is provided. The raw data of 12 bank branches are provided in Table III for detail clarification [17]. Table IV shows the results of the original CCR model, which has three full efficient DMUs while our proposed model provides complete full ranking to all DMUs. Moreover, this example shows that the ranking of all efficient DMUs under the geometric average method depends entirely on the ranking scheme of the pessimistic approach.

Table II. Comparison results of the proposed model with CCR and Wang et al. models (graduate student example)

	Original CCR model	Optimistic with DMU_{super}	Pessimistic with DMU_{worst}	Wang et al. approach	Proposed new approach

			(θ_k)		(θ_k^-)		(geometric Ave)		(θ_k^{final})	
Student	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
A	1	1	1	1	1	6	1.000	4	1.000	5
B	0.863636	5	0.8421	5	1.5714	3	1.0352	3	1.2068	3
C	1	1	0.9474	4	1.8571	2	1.1863	2	1.4022	2
D	1	1	1	1	1.000	6	1.000	4	1.000	5
E	0.736842	7	0.7368	7	1.2857	4	0.8833	7	1.0113	4
F	1	1	1	1	2.0000	1	1.2095	1	1.5000	1
G	0.789474	6	0.7895	6	1	6	0.8885	6	0.8947	8
H	0.684211	8	0.6842	8	1.1429	5	0.8272	8	0.9136	7

Table III. Raw data for bank branches evaluation

	Input		Output		
Branch	**Employees**	**Operating cost**	**Interest paid per saving**	**Interest paid per loan**	**Non-interest income**
1	20	829,326	4,449,202	4,786,608	1,000,188
2	7	342,554	1,020,605	1,686,859	307,375
3	7	262,008	861,443	1,516,144	426,604
4	11	301,114	4,022,446	6,491,851	1,152,494
5	9	244,918	400,783	654,434	407,243
6	6	326,759	3,056,784	1,994,946	1,055,240
7	7	269,277	1,634,220	2,291,636	1,083,105
8	6	288,521	1,232,645	1,788,427	1,001,151
9	4	165,573	445,955	904,764	462,190
10	6	218,150	536,914	1,036,494	545,877
11	3	132,788	229,635	387,528	160,227
12	23	924,037	4,879,496	8,471,185	470,160

Table IV. Comparison results of the proposed model with CCR and Wang et al. models (Bank branches example)

	Original CCR model		Optimistic with DMU_{super} (θ_k)		Pessimistic with DMU_{worst} (θ_k^-)		Wang et al. approach (geometric Ave)		Proposed new approach (θ_k^{final})	
Branch	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
1	0.512245	8	0.1460	9	1.2393	9	0.7803	9	0.6927	8
2	0.412545	11	0.1143	12	1.1334	10	0.6423	11	0.6238	11
3	0.455751	9	0.1876	8	1.3461	7	0.7902	7	0.7668	7
4	1	1	0.4410	3	1.7206	4	1.7334	4	1.0808	4
5	0.413392	10	0.1916	7	1.0822	11	0.6430	10	0.6369	10
6	1	1	0.4578	2	2.0000	1	1.9921	1	1.2289	1
7	1	1	0.4634	1	1.9819	2	1.8837	3	1.2227	2
8	0.996485	4	0.4343	4	1.8784	3	1.9296	2	1.1564	3
9	0.728561	5	0.3216	5	1.4705	5	1.0951	5	0.8961	5
10	0.622112	7	0.2883	6	1.3589	6	0.9673	6	0.8236	6
11	0.34233	12	0.1390	11	1.2396	8	0.5851	12	0.6893	9
12	0.62408	6	0.1437	10	1.000	12	0.7900	8	0.5719	12

CONCLUSIONS

The field of DEA has enjoyed a vast growth in publications and research work. Since its introduction in 1978, a tremendous amount of studies have been done on DEA, resulting in major development in its methodologies, models, and real world applications (Readers are referred to [18]). Within this development, there is a sub-field of research work that focused on developing the discrimination power of DEA by improving its differential capability to better rank all DMUs in any data under assessment. Many methods have been introduced in the literature using different criteria such as cross efficiency, super efficiency, benchmarking, etc. This paper proposed a new model that uses virtual DMUs integrated with optimistic and pessimistic approaches. The integration was achieved by rescaling the pessimistic scores using the DEA index (AIN) and combining both approaches with arithmetic average. The new method yielded better discrimination power because the added super and worst virtual DMUs adjust the frontier lines allowing them to envelop more data. This wider envelopment by itself leads to better ranking power. On the other hand, the new method equalizes the weight assigned to both optimistic and pessimistic approaches by preventing the pessimistic approach from reaching a high score in comparison to the optimistic approach by using the DEA index.

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ASSESSING THE EFFICIENCY AND THE EFFECTIVENESS OF PUBLIC EXPENDITURES ON SECURITY IN BRAZILIAN STATES

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ABSTRACT

This paper aims to present an implementation of Data Envelopment Analysis combined with econometric panel data models to evaluate the efficiency of public spending on security in Brazil. We estimated that technical efficiency is a necessary, but not sufficient, condition to bring down the high homicide rates prevailing in this country.

Keywords*: Data Envelopment Analysis, econometrics, economics of crime, Brazil.*

INTRODUCTION

Crime rates (mainly intentional homicides) have steadily grown in Brazil. We registered a rate of 26.2 homicides per 100,000 inhabitants during the year of 2011. The United Nations Organization considers as unacceptable homicide rates levels above 10 homicides per 100,000 inhabitants. The public spending in Brazil security amounted R$ 51.547.486.525,76 (approximately € 22,161,898,726.21) in 2011. The spending figures have steadily increased. Brazilian Public expenditures on security amounted 1,3% of GDP during the year of 2011 (see table 1 below).

Most economic texts about crime in Brazil are inspired in the seminal paper by Becker (1968). Our present work follows this mainstream and use Data Envelopment Analysis (DEA) to evaluate the efficiency of public spending on security in this country. We could find only three other studies using DEA applied to security in Brazil: Soares de Mello *et al.* (2005), Soares, Zabot and Ribeiro (2011) and Scalco, Amorim and Gomes (2012). The main obstacle to researchers in this field is the lack of data about criminality as well as the characteristics of the victims and their offenders. Most times we have to use homicide as a proxy to criminality, or at least, to mimic crimes against persons.

We suppose the Brazilian sates are not homogeneous by a efficiency point of view, since the spending per capita in security varies a lot across them (see table 2 below). We address specially this issue since the public spending is an important component of the public security policy. By using some statistical tests, we could not reject the hypothesis that two different efficiency frontiers prevail in our data and that high public spending states are outperformed by low public spending states in Brazil.

Beyond efficiency we also assess the effectiveness of the public spending in security in Brazil. Most econometric models which estimate the impact of public spending on homicide rates in this country found out that public spending on security is not strongly statistically significant as a crime deterrent variable. They do not take into consideration explicitly that the impact of this spending on the homicide rates might depend on its efficiency (*e.g.*: Cerqueira and Lobão (2004), Santos and Kassouf (2007), Justos (2008)). However, we show in this study that the public spending in security is statistically significant only in the states evaluated as efficient by DEA.

Table 1. Homicide figures and rates per 100,000 inhabitants; and public spending in security as a percentage of GDP in selected countries.

	2009			2010			2011		
	Homicides		% GDP	Homicides		% GDP	Homicides		% GDP
	Quantity	Rate		Quantity	Rate		Quantity	Rate	
Germany	656	0.8	1.2	690	0.8	n.a.	n.a.	n.a.	n.a.
Argentina	2,305	5.8	1.3	n.a.	n.a.	2.0	n.a.	n.a.	2.0
Brazil	42,023	21.9	1.3	43,684	22.1	1.4	42,785	22.2	1.3
Chile	630	3.7	1.7	541	3.2	1.7	636	3.7	n.a.
USA	15,399	5.0	2.3	14,722	4.8		14,612	4.7	n.a.
Mexico	19,803	17.7	0.3	25,757	22.7	0.3	27,199	23.7	0.3

n.a.: not available. Source: Brazilian Yearbook of Public Security, 2012.

METHODS

DEA evaluates the efficiency of a set with N peer entities called decision making units (DMU) which convert multiple inputs into multiple outputs. In the general case, a DMU consumes multiple inputs ($x_1,...,x_s$) and produces multiple outputs ($y_1,...,y_m$). The efficiency score is defined by the following quotient: $efficiency = (u_1 y_1 + \ldots + u_m y_m)/(v_1 x_1 + \ldots + v_s x_s) = (U \cdot Y)/(V \cdot X)$ where $V=(v_1,...,v_s)$ and $U=(u_1,...,u_m)$ denote the weights assigned to the inputs and outputs quantities respectively. Charnes, Cooper and Rhodes (1978) suggest that the vectors U and V must be determined by the linear programming problem (LPP) called DEA/CRS (constant return to scale model). Under an output orientation the measure of radial technical efficiency θ ($\theta \geq 1$) of a DMU is defined as the maximum radial expansion of the output vector Y that can be produce by using the input vector X: Efficiency=Max{θ|(X, θY)$\in$ production possibilities set T(X,Y)}. A proportional augmentation applied to all outputs of the DMU_0 being rated may not be sufficient to assure its projection on the frontier. The optimal values for the possible inputs excess s^- and for the outputs shortfalls s^+ variables that still remain after the proportional adjustment (the slacks) measure the L1 distance from the DMU_0 to its projected point on the efficiency frontier. The DMU_0 under evaluation is efficient, and lies on the efficient frontier if and only if θ=1.00 (or 100%) and all slacks are equal to zero ($s^+=0$ and $s^-=0$). Otherwise, the DMU_0 is inefficient and its score lies between 0 and 1.00 (or between 0 and 100%). The LPP must be solved for each DMU. The development of an input-oriented model is straightforward. Banker, Charnes and Cooper (1984) added the constraint $\lambda_1+\ldots+\lambda_N=1$ in the envelopment form of the CRS model. The result is a DEA model with variable return to scale called BCC or VRS (variable return to scale).

We use DEA models to assess the efficiency of public spending in security among Brazilian states. The DMUs are the Brazilian states because they are responsible by public security at local levels. A classical variable returns to scale model (BCC) is used. The model is output oriented because resources to fight the violence are scarce and shall not be reduced. The output to be augmented is only one: the inverse of the rate of homicides per 100,000 inhabitants since we want to diminish this rate. We have two inputs: (1) the public spending on security per capita; and (2) the public spending on security per homicide. We are aware that these two inputs are correlated. We keep both of them in the model since the public spending per capita is a simple measure for the general disposability of resources for security purposes. By another side, the public spending per homicide give us an idea of the effort the states exert to reduce the homicides. Each state is considered a different DMU in each year of observation because we want to perform a panel data econometric model. We have 26 states along four years (2005-2008) amounting 104 DMUs. The state of Santa Catarina was excluded because of lack of data. We have no available data on capital neither on labor inputs nor about criminals and their victims.

We executed various *Panel Data Models* (Fixed Effects, Random Effects, Pooled and Instrumental Variables) to evaluate the impact of some indicators on homicide rates in Brazil. According to Greene (2008) our panel data models are regressions of the form: $Y_{it}=a_i + b_1X_{it1} + b_2X_{it2}+...+\varepsilon_{it}$. $E[\varepsilon_{it}]=0$, $Var[\varepsilon_{it}]=\sigma^2$. There are K regressors not including the constant term a_i. The individual effect is a_i which is taken to be constant over the time t and specific to the individual cross-sectional unit i. We also use the method of *Instrumental Variables (IV)*, because the disturbance in the homicide rates can be correlated with the public spending in security per capita. We assume that the disturbance term is uncorrelated with past values of the public spending per capita in security, and that the public spending with two years lag (t-2) is a suitable instrument to be used in the model.

We follow the literature (*e.g.* Cerqueira and Lobão (2004), Santos and Kassouf (2007), Justos (2008)) and believe that public spending per capita, as a deterrent factor, should reduce the homicides rates. We also think that schooling enlarges the social opportunities and shall reduce the homicide rates. By another side, income inequality (represented by Gini Index); urbanization rate; and the prevalence of single-parent families shall increases homicide rates because all of them are factors which work against social and personal improvements. The roles of unemployment rates; average income per capita; and poverty on the homicides are still debatable in the literature. These factors could increase the quantities of potential offenders but they also may diminish the expected economic return of criminal activities.

According to Charnes, Cooper and Rhodes (1981), sometimes we must observe the differences between "*good programs which might be badly managed from worse programs that appear to be better because of management rather than program capability*". Brockett and Golany (1996), proposed a Mann-Whitney rank test to evaluate if two groups of DMUs have the same distribution of efficiency values and, consequently, if the efficiency frontier is unique. This procedure is useful here because we want to test if the high-spending Brazilian states (HS) and the low-spending (LS) Brazilian states share the same efficiency frontier.

RESULTS AND DISCUSSION

The efficiency scores vary widely among the sates. We split the sample of 104 DMUs into two groups according to the median of the spending in security per capita (€ 97.67). The average technical efficiency (TE) within the HS is 49.28% (median=47.59%) while within the LS the TE amounts 66.19% (median=55.68%). LS group appears to perform better than HS group. We extended the Brockett and Golany (*op. cit.*) approach a little further. Criminality is prone to spill over from one state to another, creating a kind of contagion between them and allowing the occurrence of an eventual statistical dependence of the scores between the states in each of the two subsamples. A Spearman test (Prob>|t|=0,099) indicated that the two subsamples are statistically independent. We adjusted the inefficient DMUS to the target levels for inputs and outputs within each of the two subgroups. This procedure aims at erasing intra-group inefficiencies and to compare only inter-groups inefficiency. Following, we merged the two adjusted subgroups into one unique adjusted and pooled group. We executed a DEA in this new group and after obtaining its new DEA scores, we split it into two new subgroups according to the median of the spending per capita. We observed that the average of the scores of efficiency in the HS is 74.22% (median=78.12%) and in the LS is 92.80% (median=96.50%). Once again, the LS frontier seems to be above the HS frontier. In order to testing the independence of the two subgroups created above, we applied again a Mann-Whitney test (p-value=0.000) in the adjusted scores of efficiency. We concluded, once more, that there exist two different and independent frontiers. The LS frontier lies statistically above the HS frontier. Some kind of inefficiency persisted and could not be eliminated by the procedures we implemented before.

Table 2. Brazilian states: public spending per capita in security (Euros-2011); public spending in security (Euros-2011); homicides rates/10^5 inhabitants (2011), average efficiency scores (2005-2008); average adjusted efficiency scores (2005-2008).

States	Public spending per capita	Public spending	Homicides Rates	Average score (%)	Average adjusted score (%)
Acre	161.73	120,713,787.04	18.5	62.52	87.10
Alagoas	97.66	306,988,928.67	74.5	35.12	87.90
Amapá	191.52	131,059,022.45	0.9	39.33	78.12
Amazonas	98.27	347,704,143.19	30	58.71	71.87
Bahia	78.29	1,103,653,602.92	31.1	52.60	98.71
Ceará	48.59	414,495,245.61	30.7	96.37	96.62
Distrito Federal	51.61	134,708,571.88	27	93.97	96.50
Espírito Santo	97.68	346,481,037.82	44.8	31.90	51.75
Goiás	92.8	564,272,459.69	16.1	48.25	75.00
Maranhão	46.21	307,132,591.28	17	96.76	97.38
Mato Grosso	149.18	458,858,724.61	30.7	42.54	57.12
Mato Grosso do Sul	152.33	377,414,103.47	17.1	39.26	65.62
Minas Gerais	144.14	2,843,735,498.93	18.4	59.51	84.37
Pará	64.79	498,107,574.93	37.5	52.60	95.44
Paraíba	72.35	274,283,103.60	43.1	55.68	98.50
Paraná	65.67	690,310,620.10	29.3	55.35	95.59
Pernambuco	95.88	849,976,151.61	36.7	42.32	89.77
Piauí	32.83	103,083,653.36	n.a.	94.23	100.00

Rio de Janeiro	121.74	1,961,503,475.75	24.9	30.34	68.75
Rio Grande do Norte	78.54	251,222,605.46	n.a.	73.17	100.00
Rio Grande do Sul	75.28	807,939,740.92	16	64.02	75.00
Rondônia	197.18	310,850,404.52	25.3	37.81	71.87
Roraima	136.02	62,592,702.03	N.A.	47.59	78.12
São Paulo	126.72	5,269,974,689.72	10.1	71.40	81.25
Sergipe	139.54	291,604,487.30	32.1	46.24	87.64
Tocantins	161.14	225,734,559.44	18.3	73.43	81.25
Federal Government	12.84	2,469,582,969.56	n.a.	n.a.	n.a.
Total	115.2	22,161,898,726.21	26.2	n.a.	n.a.

n.a.: not available. Source: research results.

Then, we stratified the sample according to the pooled adjusted DEA scores. The first subgroup is the full sample, the second is composed by the states with scores above the level of 95 % and the third subgroup comprises the states below 95% of efficiency. We ran the econometric models within each of these three groups. The only well fitted models are the Pooled Model and the Instrumental Variables Model. Our results show that the public spending is statistically significant to diminish the homicide rates only in the subsample composed just by technically efficient sates. All covariates, except unemployment rates, are significant in the sample composed only by efficient states. The Gini Index is significant in all models and always presents the expected positive signal. Inequality seems to have an important role in raising homicide rates in Brazil.

Table 3. Regression results: Pooled model and Instrumental Variables model (IV). Dependent variable: homicide rates.

Variables	All states		Inefficient sates		Efficient states	
	Pooled	IV	Pooled	IV	Pooled	IV
Const	5.2747*	8.8253*	10.3634*	15.7248*	19.7748*	19.3604*
L_school	-0.0132	-0.3195	0.2515	-0.2169	-1.9298	-3.0608*
L_unemp	0.2456	0.4030	0.9336*	0.9336*	0.8734	0.9766
L_gini	2,3075*	2.7018*	2.6718*	3,8791*	1.3011*	0.5329*
L_familiy	0.2654	0.5610	-0,0012	0,6621	1.5263*	1.2426*
L_pover	-0,4220*	-0.6960*	-0,5591*	-0.9838*	0.9714*	1.3768*
L_income	-0,5856*	-0.9622*	-0,5301*	-1.1126	0.0364*	0.0546
L_urban	0.5003	0.3588	-0.5091	-0.8690	2.1941*	1.6089*
L_spend	0,1493	0.0553	-0.0016	-0.0770	-0.6366*	-0.6635*

(*) Statistically significant at 5% level. Source: research results.

CONCLUSIONS

We applied DEA models to estimate significant differences in technical efficiency among Brazilian states according to the level of public spending on security. The low-spending states outperformed the high-spending states.

Our econometric models showed that the public spending in security appeared to be statistically significant to reduce homicide rates only in technically efficient states. Consequently, the technical efficiency in public spending on security seemed to be a necessary condition (although not sufficient) to the effectiveness in reducing the high homicide rates in Brazil. DEA should precede econometrics in this topic.

Income inequality (represented by Gini Index) also should deserve attention from researchers in this field, since it was positively correlated with homicide rates in all relevant econometric models we performed.

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ASSESSMENT OF EFFICIENCY OF GREEK AIRPORTS

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ABSTRACT

The purpose of this study is to assess the efficiency of *Greek airports. A sample of 20 airports was selected from the 45 airports of the country. The efficiency assessment was done on the basis of Data Envelopment Analysis and Stochastic Frontier Analysis. Greek airports seem to be efficient because they use and allocate their available resources so that to maximize their outputs (passengers). Specifically, their average efficiency amounts to values above 0.7 (scale [0, 1]) using both methods. This is the first time that DEA and SFA have converged towards the same goal: efficiency assessment of Greek airports. The value of the results is important as the efficiency indicators are used to identify the relatively inefficient airports and fosters best practices in the industry. The assessment of efficiency of Greek airports is based on a model with three inputs and one output. Although the relationship between inputs and outputs is not questionable according to the literature, there may be non – measurable variables that affect the selected outputs.*

Keywords*: DEA, SFA, Efficiency,* Greek airports

INTRODUCTION

Considerable attention has been focused upon the challenges facing the airport industry. Academic research has examined a variety of strategic issues, for example the tensions between private sector and national economic interests, how managerial action is constrained by an airport's mode of governance, the impact of benchmarking upon airport performance and how different forms of ownership influences an airport's economic growth (Freathy, 2004). The process of introducing private participation in the management and operation of airports brought along the need to assess the way in which airports are being operated (Perelman and Serebrisky, 2012). Airport managers are challenged worldwide to provide the best possible services in the most efficient manner. Efficiency has been the focus of much research in the recent past. Moreover, the increased competition among airlines resulting from deregulation and liberalization has placed airports in a much more competitive environment (Barros and Dieke, 2008). An efficient airport provides important economic catalysts that enable the local and regional economy to thrive and improve the quality of life in the region (Oum et al., 2008). The assessment of airports' efficiency is an issue that has been studied by many scientists internationally in many areas of the world. Most studies in the literature have used Data Envelopment Analysis and Stochastic Frontier Analysis, either individually or simultaneously. For example, Pels et al. (2003) studied the efficiency of 34 European airports using both methods. Many researchers have used the DEA method like Perelman and Serebrisky (2012), Kocak (2011), Pathomsiri et al. (2008), Barros and Dieke (2008) and others. Other researchers that have used the SFA method are Oum et al. (2008), Martin et al. (2009), Tovar and Martin

- Cejas (2010). The efficiency of Greek airports has been studied by Tsekeris and Vogiatzoglou (2010) (DEA) and Psaraki and Kalakou (2010) (DEA). Tsekeris and Vogiatzoglou (2010) studied the efficiency of all airports in Greece for 2007 by adopting the assumption of the objective of maximizing the produced outputs given a standard level of inputs. Psaraki and Kalakou (2010) studied the efficiency of 27 Greek airports using the DEA method for landside operations and airside operations for the year 2007. While the assessment of efficiency of Greek airports with non-parametric method DEA has been done at Greek airports there has been no study that incorporates the parametric method SFA. This study is an attempt to cover this gap. The purpose of this paper is the assessment of efficiency at Greek airports. The assessment of efficiency takes place using both methods, DEA and SFA.

METHODOLOGY

DATA ENVELOPMENT ANALYSIS

The DEA method was first introduced by Charnes, Cooper, and Rhodes (1978) and is called CCR model. In this study, the objective is the optimization (maximization) of outputs, taking into account that airports are trying to run their aeronautical operations given inputs of capital and labor. The selected database satisfies the constraints imposed on the statistical adequacy of the results of DEA since the number of airports (20) is greater than two times the sum of input and output variables and greater than the product of input and output variables. The efficiency of unit D can be obtained as a solution to the following linear programming problem:

Objective Function: Maximize z = $\frac{\sum_r u_r y_{rj1}}{\sum_i v_i x_{ij1}}$ (1) Under the constraints: (1) $\frac{\sum_r u_r y_{rj1}}{\sum_i v_i x_{ij1}} \leq 1$ (2) u , v ≥ 0 non negativity constraint (3) $v^*x_i = 1$ constraint preventing production of infinite solutions to the maximization problem

In 1984, since CCR model assumed DMU to be constant returns to scale for restriction of production possible set, the Banker, Charnes, and Cooper (BCC model) relaxes this restriction to be variable returns to scale (VRS) model, and evaluates technical efficiency and scale efficiency of DMU. BCC model adds the convexity restriction $\sum_{j=1}^{n} \lambda j$ =1. The DEA method can assume constant returns to scale (CRS, model CCR – overall operational efficiency) between input and output variables (Charnes et al., 1978) or alternatively variable returns to scale (VRS, model BCC – technical efficiency) (Banker et al., 1984). The fraction of overall efficiency (with CRS) to technical efficiency (with VRS) provides the scale efficiency.

STOCHASTIC FRONTIER ANALYSIS

First step in the implementation of this method is the selection of production factors, the products or services of any business unit and the determination of production function. The stochastic production function (Aigner, Lovell and Schmidt, 1977; Meeusen and Van den Broeck, 1977) is defined by the relation:

$y_i = f(x_i;\beta)\exp(e_i)$ $i = 1,\ldots,I$ with $e_i = v_i - u_i$ (2)

The term v_i is the random error that follows the normal distribution $N(0,\sigma_v^2)$). This term interprets the result of causes external to the production and errors in measurement and definition of the dependent variable. The second positive term u_i is distributed independently of the first term and follows either the half - normal distribution according to Aigner et al. (1977) or the exponential distribution according Meeusen and Van den Broeck (1977). This term determines whether the amount of product produced is above or below the production function. In the model of Batesse and Coelli (1992), which is used in the present work, the term u_{it} of production function is defined by the following equation:

$u_i^t = \eta_i^t * u_i = \{\exp[-\eta(t – T)]\}u_i$ with $i = 1,\ldots,I$ and $t = 1,\ldots,T$ (3)

The term u_i^t is distributed independently of the first term and vi^t follows the truncated - normal distribution with $N(\mu,\sigma_u^2)$. η is a parameter under estimation. According to this relationship the term u_i^t expressing technical inefficiency decreases, remains constant or increases over time if $\eta > 0$, $\eta = 0$ and $\eta < 0$ respectively. Many researchers use the Cobb - Douglas function for determining the production function. This function shows first degree correlations and does not allow interaction between the inputs. Because it significantly reduces the prospect of expressing substitutability such function can be generalized so that to provide a more appropriate and interpretable representation of the production structure. The translog production function is a more complete flexible function which is a second degree generalization of Cobb – Douglas function. The translog function is defined as following:

$lny_{it} = \beta_0 + \beta_1 lnx_{1t} + \beta_2 lnx_{2t} + \beta_3 lnx_{3t} + \beta_4(lnx_{1t})^2 + \beta_5(lnx_{2t})^2 + \beta_6(lnx_{3t})^2 + \beta_7(lnx_{1t})(lnx_{2t}) + \beta_8(lnx_{1t})(lnx_{3t}) + \beta_9(lnx_{2t})(lnx_{3t}) + v_{it} – u_{it}$ (4), y_{it} is the output of i^{th} airport in the t^{th} time period, x_{1it}, x_{2it}, x_{3it} are the inputs of i^{th} airport in the t^{th} time period, v_{it} is the random error that follows normal distribution, u_{it} is the term which was analyzed above, β_k are unknown parameters under estimation, η is a parameter under estimation. For the econometric estimation of the model, the method of maximum likelihood technique is adopted, based on two parameters: $\sigma^2 = \sigma^2 + \sigma_u^2$ and $\gamma = \sigma^2/\sigma_u^2$. γ ranges between 0 and 1. If γ is near 0 then the variances from production function are caused by random error v_{it}. If γ is near 1 then the variances are caused by technical inefficiency. Coelli et al. (2005) suggest the generalized likelihood ratio test to determine the effect of technical inefficiency under the null and alternative hypothesis. This can be expressed as follow: $LR = -2\{\ln[L(H_0)/L(H_1)]\} = -2\{\ln [L(H_0)] – \ln[L(H_1)]\}$ (5) H_0 and H_1 are the values of the likelihood function under the null hypothesis H_0: $\gamma = 0$ and the alternative hypothesis H_1: $\gamma > 0$, respectively. So comparing the LR statistic with the value $x^2 (2^{\alpha})$ (the degrees of freedom are restricted sizes of the null hypothesis), then determines to accept or reject the null hypothesis.Empirical Application to 20 Greek Airports

To be in compliance with characteristic of consistency for both DEA and SFA, this paper adopts single output and multiple inputs. The output of the selected model is the number of passengers and the selected inputs are the following: number of employees, number of flights, area of terminals. These inputs are key factors of airport operation, and are related to throughput of the airport. They are also more dynamic than other resources like runways. To confirm the correlation between inputs and output, this paper applies analysis of Pearson correlation coefficients at 0.01 significant level (two-tailed). Table 1 shows that that output variable of the model is highly correlated with the selected inputs.

Table 1: Pearson Correlation Coefficients of inputs and outputs (2012)

	Flights	Passengers	Terminals (m^2)	Employees
Passengers 2012	0.983**	-	0.890**	0.897**

RESULTS AND DISCUSSION

The assessment of efficiency of airports is based on DEAP v2.1 and Frontier v4.1. The table below shows the efficiency indicators. The determination of position in the production boundary indicates whether the scale of an airport has a significant impact on efficiency, with increasing (IRS) or decreasing (DRS) returns to scale or if there are constant returns to scale (CRS), i.e. the ratio between inputs and outputs can be expressed linearly without change in profitability.

Table 2: Efficiency Indicators and Peer Airports (2012) – DEA and SF

AIRPORT	PEER AIRPORTS				CRS	VRS	SCALE	Returns to Scale	SFA_{TR}
Thessaloniki	5	3			0,739	0,985	0,750	DRS	0,689
Rhodes	3	9			0,978	0,990	0,988	DRS	0,956
Heraklion	3				1	1	1	-	0,799
Corfu	3	9			0,964	0,970	0,994	DRS	0,858
Kos	5				1	1	1	-	0,938
Alexandroupolis	19	5	14		0,501	0,747	0,671	IRS	0,945
Mytilene	5	19	14		0,575	0,744	0,773	IRS	0,647
Limnos	18	20	14	5	0,214	0,269	0,795	IRS	0,427
Chania	9				1	1	1	-	0,856
Kefalonia	18	9	14		0,726	0,844	0,861	IRS	0,934
Zakynthos	11				0,999	1	0,999	IRS	0,624
Samos	11	9	18		0,600	0,654	0,917	IRS	0,804
Kavala	11	9	18		0,527	0,628	0,839	IRS	0,686
Kalamata	14				0,461	1	0,461	IRS	0,823
Mykonos	3	20			0,700	0,977	0,717	IRS	0,909
Santorini	5	14	19		0,842	0,940	0,896	IRS	0,901
Chios	5	19	14		0,512	0,899	0,570	IRS	0,893
Skiathos	18				0,796	1	0,796	IRS	0,964
Karpathos	19				0,721	1	0,721	IRS	0,807
Aktio	20				0,779	1	0,779	IRS	0,830
Average Efficiency	-	-	-	-	0,732	0,882	0,826	-	0,815

Regarding the results from DEA method only three airports seem to be on the production frontier and these are Heraklion, Chania and Kos. Theoretically, these airports have sufficient scale dimensions and it is not possible to deliver more output without increasing the quantity of their inputs. Most airports are characterized by relatively high efficiency, since they operate with more than 70% of the maximum efficiency of scale. Therefore the scale plays an important role in Greek airports. Many airports (Thessaloniki, Rhodes, Alexandroupolis, Zakynthos, Kalamata, Mykonos, Santorini, Chios, Skiathos, Karpathos, Aktio) display the maximum pure technical efficiency (VRS) but scale efficiency is not the greatest. These airports are likely to face problems in increasing output due to missing dimensions and inefficiency in the management of available resources. Under this model, most airports seem to operate with increasing returns to scale (IRS) and that means that the increase of an input by one unit may cause more of a unit increase in the quantity of output. On the other hand, the airports of Thessaloniki, Rhodes and Corfu exhibit decrease returns to scale. The implementation of DEA provides the airports which are out of production frontier with a set of peers. Peer airports are airports with similar characteristics in the context of use and allocation of their resources. The importance in this is that some airports can serve as benchmarking airports for their peers. That means that some airports can serve as best practice for less efficient peers. Each peer of an airport can be more or less important for an inefficient airport and this is expressed through the weights exported by the solution of the BCC model. The peer airports of the solution of BCC model are shown in table 2. Regarding the implementation of SFA, the parameters under estimation are determined through the FRONTIER v4.1. Initially, it is assumed that the parameter η is equal to 0. This is obvious as the assessment of efficiency is for one year (2012) and there is no change of efficiency over time. The first test H_0: $\beta_4=\beta_5=\beta_6=\beta_7=\beta_8=\beta_9=0$ suggests that we accept the null hypothesis that a translog function is better than a Cobb – Douglas as a representation of production technology of the 20 Greek airports. The LR value 0,36 (Cobb – Douglas MLE of the SFA model) is smaller than the critical value 11.91 of $x_{0,95}^2$ (6). We implement the translog function for APM model. We first use estimates for the truncated – normal model to test the null hypothesis that the simpler half – normal model is adequate. The relevant null and alternative hypothesis are $\mu = 0$ and $\mu \neq 0$ respectively. From the maximized log – likelihood values reported in the outputs of the two models we calculate the value of the LR statistic as LR = -2*(5,51 - 5,97)) = 0,92. The 5% critical value is $x_{0,95}^2$ (1) = 2,706 (this value is taken from table 1 in Kodde and Palm (1986)). The LR test leads us to accept the null hypothesis that the half normal model is adequate (at the 5% significance level). Regarding the null hypothesis H_0: $\gamma = \mu = 0$ the results show that LR = 3,96 > 2,706, which is the critical value of the $x^2(0.05)$ (the critical value of x^2 is adopted from Table 1 - in Kodde and Palm (1986) according to Coelli et al. (2005)). Therefore the null hypothesis H_0: $\gamma = 0$ is rejected. So the effect of technical inefficiency exists. The value of γ for the model is 0.96 and thus deviations from the limit are due to the technical inefficiency rather than random error. The average efficiency of SFA solution is 0,815. The most efficient airport according to SFA is the airport of Skiathos. This airport is almost fully efficient and for the increase of the output obtained, the available inputs should be increased. There are 15 airports with technical efficiency over 0,8. The average efficiency for the model is 0,815. This means that airports could serve 18,5% more passengers given the specific technology and inputs if the technical inefficiency didn't exist.

CONCLUSIONS

The lack of random error is the main disadvantage of DEA but has the advantage of few assumptions of production function. The opposite happens for the SFA. In this case the participation of the error term is an advantage but requires strict assumptions about the form of the function. The DEA can handle complex problems with multiple inputs and outputs. The SFA allows for measurement errors, but the technical efficiency is depended by an uncontrollable hypothesis for the distribution of the error term. The above analysis doesn't include the airport of Athens because it is too big compared to the other airports. In general the airports which serve more passengers are more efficient than airports which serve fewer. According to SFA, airports could serve 18,5% more passengers in average if the technical inefficiency didn't exist. The majority of airports have adequate infrastructure to serve future passenger demand. An important issue is that the considering of the number of flights as an input incorporates important resources such as the area of the runways and the aircraft parking area. Future work is required to address the financial performance of airports by means of financial measures and the external performance by means of the quality of services delivered to passengers and air – carriers. This study refers only to public airports. Future research should be directed to a larger sample of airports either public or private outside Greece.

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CENTRALIZED RESOURCE REDUCTION AND TARGET SETTING UNDER DEA CONTROL

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ABSTRACT

Data Envelopment Analysis (DEA) is a powerful tool for measuring the relative efficiency of decision making units (DMUs). In centralized decision-making systems, management normally imposes common resource constraints such as fixed capital, budgets for operating capital and staff count. In consequence, the profit or net value added of the units subject to resource reductions will decrease. In terms of performance evaluation combined with resource allocation, the interest of central management is to restore the general efficiency value of the DMUs. The paper makes four contributions: (1) we consider the performance evaluation of the centralized budgeting of hierarchical organizations; (2) we address the evaluation problems that the central decision maker does not desire to deteriorate the efficiency score of the DMUs after input and/or output reduction; (3) we develop a common set of weights (CSW) method; (4) we extend a new approach to optimize the inputs and/or outputs contraction such that the efficiency of all DMUs will get bigger than or equal to the efficiency of previous change.

***Keywords**: Data Envelopment Analysis; Inputs and outputs deterioration; Common set of weights.*

INTRODUCTION

Non-parametric frontier analysis was first introduced by Farrell (1957) and later developed as Data Envelopment Analysis (DEA) by Charnes et al. (1978) into a linear programming based technique for efficiency assessment and ranking of decision making units (DMUs). DEA is a rapidly growing area of operational research that deals with the performance assessment of organizations (cf. Emrouznejad et al. 2008).

Whereas the conventional analysis implicitly assumes that all DMUs enjoy complete autonomy in their actions and access to free resource and product markets, performance analysis is increasingly used within organizations under a common management. A principal difference with respect to the prior assumptions is then that the DMU are subject to common resource and market constraints, imposed by a central decision maker. Obvious examples are found in centralized budgeting of hierarchical organizations as well as sales and market allocation within manufacturing and distribution organizations. Hence, in many real-world problems we must consider significant change in input and output measures. However, the central decision maker does not desire to deteriorate the efficiency score of the DMUs after input and/or output reduction. Several researchers have applied the input and/or output deterioration to DEA models in the literature. Amirteimoori and Emrouznejad (2010) presented a DEA-based approach to determine the highest possible input reduction and lowest possible output deterioration without reducing the efficiency score for each DMU. Recently, Lozano et al. (2011) introduced a number of non-radial, output-oriented and centralized DEA models for resource allocation and target setting for inputs with integer constraints.

In this paper, we propose an alternative DEA-based method for a centrally imposed resource or output reduction across the reference set. In other words, this study addresses the following question: how much should the inputs and outputs for each DMU is reduced subject to the conditions that the efficiency scores of all DMUs increase? Consistent with the setting for a central evaluator, we use the DEA-based method in order to get better efficiency scores for all DMUs after the reduction amount of inputs and outputs.

THE TRADITIONAL DEA MODEL

Suppose that there are n DMUs to be evaluated where every DMU$_j$, $j=1,...,n$, produces s outputs $y_{rj} \in R^+$, $r=1,...,s.$, using the m inputs, $x_{ij} \in R^+$, $i=1,...,m$. The input-oriented model (CCR) for evaluating the relative efficiency of a given DMU_o is as follows (Charnes et al. 1978):

$$
\begin{aligned}
\bar{\theta}_o^* = \max \quad & \sum_{r=1}^{s} u_r y_{ro} \\
s.t. \quad & \sum_{i=1}^{m} v_i x_{io} = 1, \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j=1,...,n, \\
& u_r, v_i \ge \varepsilon, \quad r=1,..,s; \quad i=1,...,m.
\end{aligned} \tag{1}
$$

where ε is a positive non-Archimedean infinitesimal number. The model (1) is also called the multiplier model.

Definition 1: DMU_o is efficient if there exists at least one optimal (u^*, v^*) of model (1) with $u^* \ge \varepsilon$, $v^* \ge \varepsilon$ and $\sum_{r=1}^{s} u_r^* y_{ro} = 1$. Otherwise, DMU_o is inefficient.

THE COMMON-WEIGHTS DEA MODEL

The calculation of DEA scores requires a linear program (1) per DMU and obtains an individual set of endogenous weights. We recall that the differences among the individual weights may be unacceptable for management reasons, market reasons or by technical or economic necessity. To cope with these difficulties, the common set of weights (CSW) model can be used to generate a common set of weights for all DMUs which are able to produce the highest efficiency score at the same time. To pursue our aim, we can equivalently consider the following multi-objective fractional program (MOFP) for measuring the efficiency of all DMUs simultaneously:

$$\theta^* = \max \left\{ \frac{\sum_{r=1}^{s} u_r y_{r1}}{\sum_{i=1}^{m} v_i x_{i1}}, \frac{\sum_{r=1}^{s} u_r y_{r2}}{\sum_{i=1}^{m} v_i x_{i2}}, \ldots, \frac{\sum_{r=1}^{s} u_r y_{rn}}{\sum_{i=1}^{m} v_i x_{in}} \right\}$$

$$s.t. \qquad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \qquad j = 1, \ldots, n, \tag{2}$$

$$u_r, v_i \ge \varepsilon, \quad r = 1, .., s; \; i = 1, \ldots, m.$$

where the non-linear program (2) by Goal programming can be simply changed to the following linear program:

$$\min \; \sum_{j=1}^{n} s_j$$

$$s.t. \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + s_j = 0, \qquad j = 1, \ldots, n, \qquad \text{(3a)}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1, \ldots, n, \qquad \text{(3b)} \tag{3}$$

$$s_j \ge 0, \qquad j = 1, \ldots, n,$$

$$u_r, \; v_i \ge \varepsilon, \quad r = 1, .., s; \quad i = 1, \ldots, m.$$

Using the optimal solutions $(u_r^*, v_i^*, s_j^*) \; \forall r, i, j$ to (3), the efficiency scores for DMU_j, $j = 1, \ldots, n,$ are calculated as follows:

$$\theta_j^* = \frac{\sum_{r=1}^{s} u_r^* y_{rj}}{\sum_{i=1}^{m} v_i^* x_{ij}} = 1 - \frac{s_j^*}{\sum_{i=1}^{m} v_i^* x_{ij}}, \qquad j = 1, \ldots, n. \tag{4}$$

A PROPOSED METHOD

We consider a technology with m inputs, $x_{ij} \in R^+$, $i = 1, \ldots, m,$ and s outputs, $y_{rj} \in R^+$, $r = 1, \ldots, s.$ Assume that $I_1 = \{i_1, i_2, \ldots, i_k\}$, $I_2 = \{1, 2, \ldots, m\} - I_1$, $O_1 = \{r_1, r_2, \ldots, r_t\}$ and $O_2 = \{1, 2, \ldots, s\} - O_1$, where I_1 and O_1 are the subset of inputs and outputs, respectively, which the organization is willing to reduce these inputs and outputs. The total reduction of the i^{th} input and the r^{th} output, denoted by $C_i,\ \ i \in I_1,$ and $P_r,\ \ r \in O_1$, can be obtained as:

$$\sum_{j=1}^{n} \bar{c}_{ij} = C_i, \qquad\qquad i \in I_1,$$

$$\sum_{j=1}^{n} \bar{p}_{rj} = P_r, \qquad\qquad r \in O_1.$$

where $\bar{c}_{ij}$ and $\bar{p}_{rj}$ are, respectively, the i^{th} reduced input and the r^{th} reduced output with respect to j^{th} DMU. Let us θ_j^* be the efficiency score of j^{th} DMU obtained from (4) without changing the data. In order to determine the adequate assigned values to $\bar{c}_{ij}$ and $\bar{p}_{rj}$ and keep efficiency scores greater than or equal to θ_j^* for DMU_j, we require to consider the following set of constraints:

$$\begin{aligned}
&(5i) && \frac{\sum_{r \in O_2} u_r y_{rj} + \sum_{r \in O_1} u_r (y_{rj} - \bar{p}_{rj})}{\sum_{i \in I_2} v_i x_{ij} + \sum_{i \in I_1} v_i (x_{ij} - \bar{c}_{ij})} \geq \theta_j^*, \quad j = 1, \dots, n, \\
&(5ii) && \frac{\sum_{r \in O_2} u_r y_{rj} + \sum_{r \in O_1} u_r (y_{rj} - \bar{p}_{rj})}{\sum_{i \in I_2} v_i x_{ij} + \sum_{i \in I_1} v_i (x_{ij} - \bar{c}_{ij})} \leq 1, \quad j = 1, \dots, n, \\
&(5iii) && \sum_{j=1}^{n} \bar{c}_{ij} = C_i, \quad i \in I_1, \\
&(5iv) && \sum_{j=1}^{n} \bar{p}_{rj} = P_r, \quad r \in O_1, \\
&(5v) && \bar{c}_{ij} \leq x_{ij}, \quad i \in I_1, \quad j = 1, \dots, n, \\
&(5vi) && \bar{p}_{rj} \leq y_{rj}, \quad r \in O_1, \quad j = 1, \dots, n, \\
& && u_r,\ v_i \geq \varepsilon,\ \bar{c}_{ij},\ \bar{p}_{rj} \geq 0, \quad r = 1, .., s,\ i = 1, \dots, m,\ j = 1, \dots, n.
\end{aligned} \tag{5}$$

where $\bar{c}_{ij}$ and $\bar{p}_{rj}$ are decision variables. According to GP concepts, we minimize the sum of the defined negative and positive deviational variables to achieve the goals. Thereupon, we create the following model:

$$
\begin{aligned}
\min \quad & \sum_{j=1}^{n}\sum_{i\in I_1}\left(\alpha_{ij}^{-}+\alpha_{ij}^{+}\right)+\sum_{j=1}^{n}\sum_{r\in O_1}\left(\beta_{rj}^{-}+\beta_{rj}^{+}\right) \\
s.t. \quad & \left(\sum_{r=1}^{s}u_r y_{rj} - \sum_{r\in O_1} p_{rj}\right)-\theta_j^{*}\left(\sum_{i=1}^{m}v_i x_{ij} - \sum_{i\in I_1} c_{ij}\right)\ge 0, \quad j=1,\dots,n, \\
& \left(\sum_{r=1}^{s}u_r y_{rj} - \sum_{r\in O_1} p_{rj}\right)-\left(\sum_{i=1}^{m}v_i x_{ij} - \sum_{i\in I_1} c_{ij}\right)\le 0, \quad j=1,\dots,n, \\
& c_{ij}+\alpha_{ij}^{-}-\alpha_{ij}^{+}=v_i(\rho_{ij}C_i), \quad i\in I_1, \quad j=1,\dots,n, \\
& p_{rj}+\beta_{rj}^{-}-\beta_{rj}^{+}=u_r(\mu_{rj}P_r), \quad r\in O_1, \quad j=1,\dots,n, \\
& c_{ij}\le v_i x_{ij}, \quad i\in I_1, \quad j=1,\dots,n, \\
& p_{rj}\le u_r y_{rj}, \quad r\in O_1, \quad j=1,\dots,n, \\
& \sum_{j=1}^{n} c_{ij}=v_i C_i, \quad i\in I_1, \\
& \sum_{j=1}^{n} p_{rj}=u_r P_r, \quad r\in O_1, \\
& u_r, v_i\ge\varepsilon, c_{ij}, p_{rj}, \alpha_{ij}^{-}, \alpha_{ij}^{+}, \beta_{rj}^{-}, \beta_{rj}^{+}\ge 0, \quad r=1,..,s;\ i=1,\dots,m;\ j=1,\dots,n.
\end{aligned}
\tag{6}
$$

Theorem: There always exists a feasible solution to model (6).

CONCLUSIONS

In this paper, we propose a new approach to improve the efficiency of the units when some given inputs and/or outputs are reduced in the evaluation process. Our aim is to optimize the resource contraction such that the efficiency of all DMUs will get bigger than or equal to the efficiency of previous change. In this paper, we first introduce a common weights method for measuring efficiency of DMUs before and after data change. Thus, we achieve the efficiencies by solving a linear program which is computationally economical. In addition, in comparison with total weights flexibility in the traditional DEA models, the common-weights DEA model takes into account the common weights. Then, based on the goal program (GP) concept we proposed a new method to find an adequate assignment for the reduction amount of inputs and outputs in the presence of the current data effect in the evaluation system.

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COMMON SET OF WEIGHTS OF PERFORMANCE INDICES FOR A DYNAMIC NETWORK DEA PROBLEM

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ABSTRACT

This paper introduces a procedure to solve a specific dynamic network DEA problem. A decision-maker governs a set of sub-units that convert three sets of inputs, x^f, x^h and x^s, to three sets of outputs, y^f, y^h and y^s by a process that contains two parallel sub-processes, f and h. x^f and x^h are dedicated to f and h respectively to produce y^f and y^h. f and h share x^s and y^s with given upper and lower bounds. We employ the linear programming model of the Most Compromised Weights Analysis to determine the common set of weights for the inputs and outputs so that the decision-maker's performance is maximized. The proportions of each shared input and output assigned to f and h are also obtained. Base on the solutions, we compute the efficiency scores for each sub-unit in the overall process and sub-processes f and h. The decision-maker would enable to reallocate inputs and outputs to improve his/her performance.

Keywords: *Common set of Weights, Shared Resources, Network DEA, Parallel Processes, Performance measurement.*

INTRODUCTION

This research is dealing with the assessment of a private or public sector with parallel processes. For instance, a company produces and sells a set of products, *J*. We consider the situation that there are two main departments in the company: marketing and production. As depicted in Figure 1, three sets of input and three sets of output indices are used to assess the company. For a product, say *j*, (unit of assessment, UOA_j) the collected values of the six performance indices are the vectors (x_j^f, x_j^s, x_j^h, y_j^f, y_j^s and y_j^h). In the presence of input and output indices, the efficiency of products consume inputs to produce outputs could be evaluated by the legacy methods. Figure 1 depicts that there are two Process *f* and *h*. The value x_j^s and y_j^s are shared by *f* and *h* with unknown proportions (α^f and α^h) and (β^f and β^h), respectively. The manager of the production system, called as central decision-maker (CDM), desires to determine the sharing proportions and the weights of indices (V^f, V^s, V^h, U^f, U^s, U^h) have its maximum aggregate efficiency score. We developed a linear programming model to solve the problem.

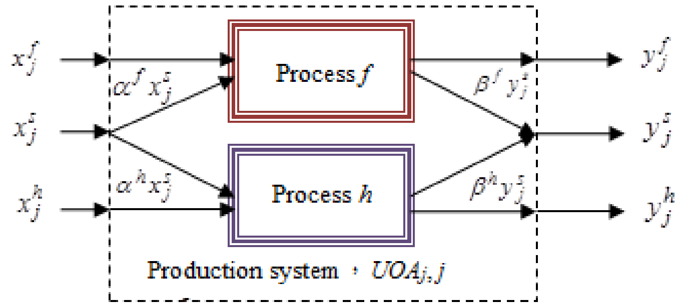

Fig. 1 Production system of parallel processes

There are many papers about the shared problems, but they mostly apply to Data Envelopment Analysis (DEA) introduced by Charnes et al. (1978). Beasley (1995) first discusses shared inputs with the simultaneous determination of the teaching and research efficiencies of university departments in England. And he supposes the weights separated into different components are the same. Molinero (1996) extends the model introduced by Beasley (1995) in shared outputs. Cook et al. (2000) think the weights divided into separated components are different. Jahanshahloo et al. (2004) share some inputs among the components and the components are involved in producing some outputs. Zha and Liang (2010) offer an approach for studying shared flow in a two-stage production process in series, where shared inputs can be freely allocated among different stages. Chen et al. (2010) think some of the inputs to the first stage are shared by both the first and second stage, but some of the shared inputs cannot be conveniently split up and allocated to the operations of the two stages.

We employ the concepts of Most Compromised Weights Analysis (MCWA) introduced by Liu et al. (2006) to develop a linear programming model to determine the common set of indices' weights and the proportions of inputs and outputs shared by the two parallel processes.

With the results of the analytical model, the CDM's efficiency is maximized and he/she could reallocate the inputs and outputs among the UOAs to improve the system overall performance. In contrasted to DEA models that an efficiency frontier is constructed for DMUs, MCWA measures the virtual gap of each UOA to the datum line that virtual input and virtual output are equal. Aggregate scores for the UOAs may be larger, equal and less one.

DETERMINE A COMMON SET OF INDICES' WEIGHTS FOR A CENTRAL DECISION MAKER

COMMON WEIGHT ANALYSIS (CWA)

Liu and Peng (2008) introduced an approach for the CDM to assess UOAs in the presence of multiple inputs and outputs indices. The goal is to obtain a common set of weights that maximizes the CDM's aggregate score.

THE MOST COMPROMISED SET OF WEIGHTS ANALYSIS (MCWA)

Liu et al. (2006) consider the CDM governs a set of UOAs. Each UOA, say j, consumes a set of inputs, I, to produce a set of outputs, R, denoted as (x_j and y_j) where $x_j = [x_{ij}, i \in I]$ and $y_j = [y_{rj}, r \in R]$. If we arbitrary assign a set of common weights $V^{\#}$ and $U^{\#}$ to the inputs and outputs, the three items virtual input, virtual output and virtual gap of $UOAj$ can be computed as $V^{\#}x_j$, $U^{\#}y_j$ and D_j, respectively.

There are three possible relationships between the three items. As shown in equations (1), (2) and (3), the virtual output $U^{\#}y_j$ minus virtual input $V^{\#}x_j$ equals to virtual gap Δ_j are larger, less and equal to zero, respectively. Figure 2 depicts the locations of the three types of UOAs on the graph of virtual input and virtual output. The diagonal datum line has slope equal 1, each point on the datum line, in set C, has the same virtual input and virtual output so that virtual gap is zero. The point A locates above the datum line so that virtual output is larger than its virtual input. It could project on the datum line by subtract a virtual gap Δ_j^{O-} from the virtual output and add a virtual gap Δ_j^{I-} to the virtual input. The point B locates below the datum line so that virtual output is less than its virtual input. It could project on the datum line by add a virtual gap Δ_j^{O+} to the virtual output and subtract a virtual gap Δ_j^{I+} from the virtual input as well.

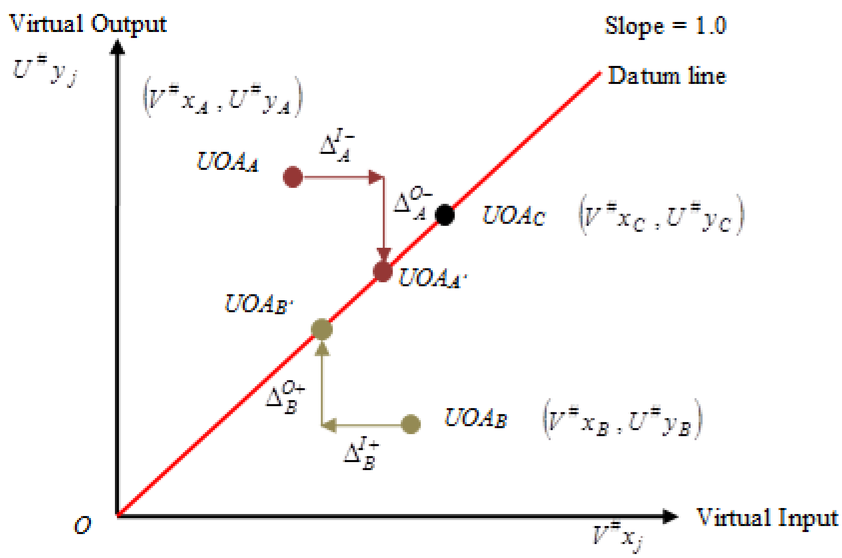

Fig. 2 The virtual gap of UOA_j in MCWA model

$$U^{\#}y_j - V^{\#}x_j - (\Delta_j^{O-} + \Delta_j^{I-}) = U^{\#}y_j - V^{\#}x_j - \Delta_j^{-} = 0, \Delta_j^{-} \geq 0,\ j \in A. \qquad (1)$$

$$U^{\#}y_j - V^{\#}x_j + (\Delta_j^{O+} + \Delta_j^{I+}) = U^{\#}y_j - V^{\#}x_j + \Delta_j^{+} = 0, \Delta_j^{+} \geq 0,\ j \in B. \qquad (2)$$

$$U^{\#}y_j - V^{\#}x_j - \Delta_j = 0, \Delta_j = 0, j \in C. \qquad (3)$$

A unique equation replaces equations (1), (2) and (3) as expressed in (4). According to equation (5), three aggregate scores are computed, h_j>1, h_j<1 and h_j=1 respectively to UOA_j in sets A, B and C. The CDM's aggregate score is computed by (6).

$$U^{\#}y_j - V^{\#}x_j + \Delta_j = 0, \Delta_j \ \textit{free in sign},\ j \in J. \qquad (4)$$

$$h_j = \left(U^{\#} y_j\right) / \left(V^{\#} x_j\right). \qquad (5)$$

$$h = \left(U^{\#} \sum_{j \in J} y_j\right) \Bigg/ \left(V^{\#} \sum_{j \in J} x_j\right). \qquad (6)$$

The MCWA model is (P1). In objective function (1.0), the summation of absolutely virtual gaps of the UOAs is minimized to obtain the optimal set of indices' weights (V^*, U^*) and the virtual gap Δ_j^* of each UOA_j. X and Y denote the vectors of the values that CDM are consumed inputs and produced outputs, respectively. In the current paper, we add (1.2) that the virtual weights of all performance indices have a positive lower bound ε.

(P1)

$$Min \quad \sum_{j \in J} \left|\Delta_j\right| \qquad (1.0)$$

$$s.t. \quad Uy_j - Vx_j + \Delta_j = 0, \quad \forall j \in J; \qquad (1.1)$$

$$UY, VX \geq \varepsilon; \qquad (1.2)$$

$$U, V \geq 0; \qquad (1.3)$$

$$\Delta_j \geq 0, \quad \textit{free in sign}. \qquad (1.4)$$

Since (P1) is a non-linear programming model, it is transferred into linear model (P2). The absolutely virtual gap $\left|\Delta_j\right|$ can be replaced with $\left(\Delta_j^+ + \Delta_j^-\right)$ as (2.0) and the virtual gaps (Δ_j^+, Δ_j^-) are nonnegative. Δ_j in (1.1) is substituted by $\left(\Delta_j^+ - \Delta_j^-\right)$. (1.2) is replaced by (2.2) and (2.3).

(P2)

$$Min \quad \sum_{j \in J} \left(\Delta_j^+ + \Delta_j^-\right) \qquad (2.0)$$

$$s.t. \quad Uy_j - Vx_j + \left(\Delta_j^+ - \Delta_j^-\right) = 0, \quad \forall j \in J; \qquad (2.1)$$

$$U \geq \varepsilon (Y)^{-1}; \qquad (2.2)$$

$$V \geq \varepsilon (X)^{-1}; \qquad (2.3)$$

$$U, V \geq 0; \qquad (2.4)$$

$$\Delta_j^+, \Delta_j^- \geq 0, \quad \forall j \in J. \qquad (2.5)$$

Transform (P2) to its dual model (P3). Assign the dual variables π, P and Q to (2.1), (2.2) and (2.3).

π is the vector of weights of UOAs, π=[π_j, j=1,2,…,|J|] in determining the optimal solution. P=[P_r, r=1,2,…,|R|] and Q=[Q_i, i=1,2,…,|I|] are slacks of outputs and inputs to improve the aggregate score, respectively. The collected values of all UOA_j in outputs and inputs are the matrices $\hat{Y}$ =[y_j, j=1,2,…,|J|] and $\hat{X}$ =[x_j, j=1,2,…,|J|]. The unit vector e is used for summation. The value ε is assigned to 1. In objective function (3.0), the terms $P(Y)^{-1}$ and $Q(X)^{-1}$ respectively are the ratios of outputs and inputs to improve the aggregate score, respectively. Therefore, model (P3) possesses unit-invariant property.

(P3)

$$Max \quad \varepsilon[P(Y)^{-1} + Q(X)^{-1}]e \tag{3.0}$$

$$s.t. \quad \hat{Y}\pi + P = 0; \tag{3.1}$$

$$-\hat{X}\pi + Q = 0; \tag{3.2}$$

$$-\pi \le e; \tag{3.3}$$

$$\pi \le e; \tag{3.4}$$

$$P, Q \ge 0. \tag{3.5}$$

METHODOLOGY

Consider the case as shown in Figure 1, UOA_j has two sets of inputs, x_j^f and $\alpha^f x_j^s$ are send to Process f. Multiply inputs values by weights V^f and V^{sf}, its virtual weights of inputs indices in f is the appended vector T_j^{If} , see equation (7). Similarly, its other three virtual weights vectors are T_j^{Ih} , T_j^{Of} and T_j^{Oh} shown in (8), (9) and (10).

$$T_j^{If} = [V^f x_j^f, V^{sf}(\alpha^f x_j^s)], \quad \forall j \in J \tag{7}$$

$$T_j^{Ih} = [V^h x_j^h, V^{sh}(\alpha^h x_j^s)], \quad \forall j \in J \tag{8}$$

$$T_j^{Of} = [U^f y_j^f, U^{sf}(\beta^f y_j^s)], \quad \forall j \in J \tag{9}$$

$$T_j^{Oh} = [U^h y_j^h, U^{sh}(\beta^h y_j^s)], \quad \forall j \in J \tag{10}$$

The set of weights V^{sf}, V^{sh}, U^{sf} and U^{sh} are assigned to the shared values $\alpha^f x_j^s$, $\alpha^h x_j^s$, $\beta^f y_j^s$ and $\beta^h y_j^s$, respectively. X^g and Y^g denote the overall consumed inputs and produced outputs of g of the company, respectively. For instance, $X^g = \sum_{j \in J} x_j^g$ and $Y^g = \sum_{j \in J} y_j^g$ where g could be f, s and h. We employ the concept of (P1) to solve the current problem, as shown in (P4). The objective function (4.0) minimizes the total of virtual gaps of the set J. For UOA_j in Process f, the sum of *virtual output* $T_j^{Of} e$, *virtual input* $T_j^{If} e$ and *virtual gap* Δ_j^f is zero, as shown in (4.1). Δ_j^f could be positive, zero and negative. For UOA_j in Process h is shown in (4.2). Constraints (4.3) and (4.4) ensure the summations of the unknown proportions equals to 1. Constraints (4.5) and (4.6) fulfill the practical requirement that the CDM specifies the upper bound and lower bound to the unknown proportions. The additional inequality (4.7) and (4.8) ensure the virtual weights of performance indices have a positive bound ε.

(P4)

$$Min \quad \sum_{j \in J} \left(\left| \Delta_j^f \right| + \left| \Delta_j^h \right| \right) \tag{4.0}$$

$$s.t. \quad T_j^{Of} e - T_j^{If} e + \Delta_j^f = 0, \quad \forall j \in J; \tag{4.1}$$

$$T_j^{Oh} e - T_j^{Ih} e + \Delta_j^h = 0, \quad \forall j \in J; \tag{4.2}$$

$$\alpha^f + \alpha^h = 1; \tag{4.3}$$

$$\beta^f + \beta^h = 1; \tag{4.4}$$

$$\underline{b} \le \alpha^f \le \overline{b}; \tag{4.5}$$

$$\underline{B} \le \beta^f \le \overline{B}; \tag{4.6}$$

$$U^g Y^g, V^g X^g \ge \varepsilon, \quad g = f \ \& \ h; \tag{4.7}$$

$$U^{sg} Y^s, V^{sg} X^s \ge \varepsilon, \quad g = f \ \& \ h; \tag{4.8}$$

$$U^g, V^g \ge 0, \quad g = f \ \& \ h; \tag{4.9}$$

$$\Delta_j^f, \Delta_j^h \quad \textit{free in sign.} \tag{4.10}$$

(P4) is a non-linear program since there are multiplication of two decision variables such as $V^{sf}\alpha^f$, $V^{sh}\alpha^h$, $U^{sf}\beta^f$ and $U^{sh}\beta^h$. They are substituted by $\hat{V}^{sf}$, $\hat{V}^{sh}$, $\hat{U}^{sf}$ and $\hat{U}^{sh}$, respectively. $\hat{T}_j^{If}$, $\hat{T}_j^{Of}$, $\hat{T}_j^{Ih}$ and $\hat{T}_j^{Oh}$ are defined by (11), (12), (13) and (14), respectively. The CDM's aggregate score (ζ^*) is computed by equation (15). Equations (16), (17) and (18) are the aggregate score of UOA_j in overall Process, *f* and *h*.

$$\hat{T}_j^{If} = [V^f x_j^f, \hat{V}^{sf} x_j^s], \quad \forall j \in J \tag{11}$$

$$\hat{T}_j^{Ih} = [V^h x_j^h, \hat{V}^{sh} x_j^s], \quad \forall j \in J \tag{12}$$

$$\hat{T}_j^{Of} = [U^f y_j^f, \hat{U}^{sf} y_j^s], \quad \forall j \in J \tag{13}$$

$$\hat{T}_j^{Oh} = [U^h y_j^h, \hat{U}^{sh} y_j^s], \quad \forall j \in J \tag{14}$$

$$\zeta^* = \left(\sum_{j \in J} \hat{T}_j^{Of*} e + \sum_{j \in J} \hat{T}_j^{Oh*} e \right) \Bigg/ \left(\sum_{j \in J} \hat{T}_j^{If*} e + \sum_{j \in J} \hat{T}_j^{Ih*} e \right) \tag{15}$$

$$\zeta_j^* = \left(\hat{T}_j^{Of*} e + \hat{T}_j^{Oh*} e \right) \Big/ \left(\hat{T}_j^{If*} e + \hat{T}_j^{Ih*} e \right) \tag{16}$$

$$\zeta_j^{f*} = \left(\hat{T}_j^{Of*} e \right) \Big/ \left(\hat{T}_j^{If*} e \right) \tag{17}$$

$$\zeta_j^{h*} = \left(\hat{T}_j^{Oh*} e \right) \Big/ \left(\hat{T}_j^{Ih*} e \right) \tag{18}$$

(P4) is transformed into linear model (P5). The concept of (P5) is similar to (P2).

(P5)

$$Min \quad \sum_{j\in J}\left[\left(\Delta_j^{f-}+\Delta_j^{f+}\right)+\left(\Delta_j^{h-}+\Delta_j^{h+}\right)\right] \tag{5.0}$$

$$s.t. \quad \hat{T}_j^{Of}e-\hat{T}_j^{If}e+\left(\Delta_j^{f+}-\Delta_j^{f-}\right)=0, \quad \forall j\in J; \tag{5.1}$$

$$\hat{T}_j^{Oh}e-\hat{T}_j^{Ih}e+\left(\Delta_j^{h+}-\Delta_j^{h-}\right)=0, \quad \forall j\in J; \tag{5.2}$$

$$\alpha^f+\alpha^h=1; \tag{5.3}$$

$$\beta^f+\beta^h=1; \tag{5.4}$$

$$\underline{b}\le\alpha^f\le\bar{b}; \tag{5.5}$$

$$\underline{B}\le\beta^f\le\bar{B}; \tag{5.6}$$

$$\hat{V}^{sg}X^s-\alpha^g\varepsilon\ge 0, \quad g=f\ \&\ h; \tag{5.7}$$

$$\hat{U}^{sg}Y^s-\beta^g\varepsilon\ge 0, \quad g=f\ \&\ h; \tag{5.8}$$

$$V^gX^g, U^gY^g\ge\varepsilon, \quad g=f\ \&\ h; \tag{5.9}$$

$$U^g, V^g\ge 0, \quad g=f\ \&\ h; \tag{5.10}$$

$$\Delta_j^{f-},\Delta_j^{f+},\Delta_j^{h-},\Delta_j^{h+}\ge 0, \quad j\in J. \tag{5.11}$$

Assign the vectors of dual variables π^f, π^h, d^I and d^O to (5.1), (5.2), (5.3) and (5.4), respectively. The dual variables ($\underline{\delta}^I$, $\bar{\delta}^I$) and ($\underline{\delta}^O$, $\bar{\delta}^O$) are assigned to (5.5) and (5.6). Constraints (5.7) to (5.9) ensure the virtual weights of shared indices have a lower bound ε. Actually, constraint (5.9) is rewrote as $U^g\ge\varepsilon\left(Y^g\right)^{-1}, V^g\ge\varepsilon\left(X^g\right)^{-1}, g=f\ \&\ h.$ Assign the dual variables (Q^{sf}, Q^{sh}), (P^{sf}, P^{sh}) and (Q^f, Q^h, P^f, P^h) to (5.7), (5.8) and (5.9), respectively. The dual model of (P5) is (P6). In (P6), the dual variables of (5.7), (5.8) and (5.9) will be inserted in the objective function, the model becomes unit-invariant that any units used to measure the input and output values would not affect the final results.

See model (P6) for the detail discussions. The collected values of all UOA_j in outputs and inputs are the matrixes of $\hat{Y}^g$ =[y_j^g, j=1,2,…,|J|] and $\hat{X}^g$ =[x_j^g, j=1,2,…,|J|], where g could be f, s and h. In the objection function, assign the value ε to 1 would not affect the final solution. In determining the optimal solution, π^f and π^h are the vectors of weights of UOAs respectively to Process f and h. On the right-hand part of the objective function, the model (P6) has the property unit-invariant.

(P6)

$$Max \quad \left\{\delta^I e + \underline{b}\underline{\delta}^I - \overline{b}\overline{\delta}^I + \delta^O e + \underline{B}\underline{\delta}^O - \overline{B}\overline{\delta}^O + \varepsilon[P^f (Y^f)^{-1} + P^h (Y^h)^{-1} + Q^f (X^f)^{-1} + Q^h (X^h)^{-1}]e\right\} \quad (6.0)$$

$$s.t. \quad \hat{Y}^g \pi^g + P^g = 0, \quad g = f \,\&\, h; \quad (6.1)$$

$$\hat{Y}^s \pi^g + P^{sg} = 0, \quad g = f \,\&\, h; \quad (6.2)$$

$$\hat{X}^g \pi^g - Q^g = 0, \quad g = f \,\&\, h; \quad (6.3)$$

$$\hat{X}^s \pi^g - Q^{sg} = 0, \quad g = f \,\&\, h; \quad (6.4)$$

$$\delta^I + \underline{\delta}^I - \overline{\delta}^I - \varepsilon Q^{sf} \left(X^s\right)^{-1} e = 0; \quad (6.5)$$

$$\delta^I - \varepsilon Q^{sh} \left(X^s\right)^{-1} e = 0; \quad (6.6)$$

$$\delta^O + \underline{\delta}^O - \overline{\delta}^O - \varepsilon P^{sf} \left(Y^s\right)^{-1} e = 0; \quad (6.7)$$

$$\delta^O - \varepsilon P^{sh} \left(Y^s\right)^{-1} e = 0; \quad (6.8)$$

$$-e \le \pi^g \le e, \quad g = f \,\&\, h; \quad (6.9)$$

$$Q^g, Q^{sg}, P^g, P^{sg} \ge 0, \quad g = f \,\&\, h; \quad (6.10)$$

$$\overline{\delta}^I, \underline{\delta}^I, \underline{\delta}^O, \overline{\delta}^O \ge 0; \quad (6.11)$$

$$\delta^I, \delta^O \quad f.i.s; \quad (6.12)$$

$$\pi^g \ f.i.s, \quad g = f \,\&\, h. \quad (6.13)$$

NUMERICAL EXAMPLES

Consider a CDM desires to assess a set of its 18 products. Marketing (Process *f*) and production (Process *h*) departments are the two main departments. These two departments share the resource of computer system x_j^s and share the profit y_j^s. Selling expenses x_j^f and operating costs x_j^h are inputs dedicated to Process *f* and *h*, respectively. The outputs, inventory turnover ratio y_j^f and production volume y_j^h are dedicated to Process *f* and *h*, respectively. The hypothetical data is depicted in Table 1. We set $\underline{b} = 0.3$, $\overline{b} = 0.7$, $\underline{B} = 0.2$ and $\overline{B} = 0.8$. At the bottom line of Table 1 lists the values of X^g and Y^g where *g* could be *f*, *s* and *h*. Employ (P5) or (P6) to solve the problem. The solutions are listed in Tables 2~5.

Table 1. The data of the 18 UOAs

UOA_j	Inputs				Outputs		
	Selling expenses (x_j^f)	Computer systems (x_j^s)	Operating costs (x_j^h)		Inventory turnover ratio (y_j^f)	profit (y_j^s)	Products (y_j^h)
1	1146	59	3631		40	17988	68
2	4897	23	5701		42	38987	151
3	6500	69	3706		32	92031	160
4	6131	24	3375		50	19720	147

5	4108	29	7662		14	80487	82
6	2275	54	6609		49	31523	14
7	7874	27	4699		48	35403	39
8	2301	152	5257		11	71954	75
9	1801	113	4402		2	33837	101
10	4521	116	1866		3	54765	75
11	3067	89	4693		11	52290	42
12	919	103	9555		37	8179	67
13	2032	99	786		3	17963	57
14	7184	95	9789		18	85016	34
15	5518	116	3409		22	14860	70
16	1831	165	8964		7	13597	131
17	3399	122	7585		20	32139	14
18	6213	185	4385		8	21180	15
X^g&Y^g	71717	1640	96074		417	721919	1342

The optimal weights and virtual weights of inputs and outputs are listed in Table 2. We can know the dedicated input *f* has more influent than the other indices. Use (15) could obtain CDM's aggregate score ζ^*=0.9752. Use (16), (17) and (18), each UOA_j's aggregate scores ζ_j^* , ζ_j^{f*} and ζ_j^{h*} are listed in Table 3. The optimal values π_j^{f*} , Δ_j^* , π_j^{f*} , Δ_j^{f*} , π_j^{h*} and Δ_j^{h*} for each UOA_j are also listed in Table 3. We rank the 18 UOAs by aggregate scores. For an UOA_j, its virtual gap to the datum line: $\Delta_j^* < 0$ and $\pi_j^* = -1$, $\Delta_j^* > 0$ and $\pi_j^* = 1$, and $\Delta_j^* = 0$ or $-1 < \pi_j^* < 1$ indicate it locates above, below, and on the datum line. Certain decision variables in (P6) are listed in Tables 4 and 5.

At the bottom line of Table 4, list the normalized improvement ratios of inputs and outputs. The total improvement ratio of output *f* (P^{f*}/Y^f) takes 35.66% and the input *f* (Q^{f*}/X^f) takes24% indicate the focus of improvement. The objective function value (6.0) ($\delta^I e + \underline{b}\underline{\delta}^I - \bar{b}\bar{\delta}^I$)+($\delta^O e + \underline{B}\underline{\delta}^O - \bar{B}\bar{\delta}^O$)+ [$P^f (Y^f)^{-1}$ +[$P^h (Y^h)^{-1}$]+[$Q^f (X^f)^{-1}$]+[$Q^h (X^h)^{-1}$]=1.52. Q^{sf*}/X^s is 0.365 ($= \delta^I + \underline{\delta}^I - \bar{\delta}^I$), Q^{sh*}/X^s is 0.27 ($= \delta^I$), P^{sf*}/Y^s is 0.072 ($= \delta^O + \underline{\delta}^O - \bar{\delta}^O$) and P^{sh*}/Y^s is 0.072 ($= \delta^O$). V^{s*} X^s=α^{f*} X^s V^{sf*}+α^{h*} X^s V^{sh*} =0.5822, so V^s=3.55*10^{-4} and U^{s*} Y^s=β^{f*} Y^s U^{sf*}+β^{h*} Y^s U^{sh*}=0.5848, so V^s=8*10^{-7}.

Table 2. Weights, virtual weights of inputs and outputs, and shared proportions

Notations	V^{f*}	V^{s*}		V^{h*}	U^{f*}	U^{s*}		U^{h*}
		α^{f*}	α^{h*}			β^{f*}	β^{h*}	
		V^{sf*}	V^{sh*}			U^{sf*}	U^{sh*}	
		$\hat{V}^{sf*}$	$\hat{V}^{sh*}$			$\hat{U}^{sf*}$	$\hat{U}^{sh*}$	
	$V^{f*}X^f$	$\hat{V}^{sf*}X^s$	$\hat{V}^{sh*}X^s$	$V^{h*}X^h$	$U^{f*}Y^f$	$\hat{U}^{sf*}Y^s$	$\hat{U}^{sh*}Y^s$	$U^{h*}Y^h$
Values	1.5*10^{-5}	3.55*10^{-4}		10^{-5}	2.4*10^{-3}	8*10^{-7}		7.5*10^{-4}
		0.3	0.7			0.36	0.64	
		1.8*10^{-4}	4.3*10^{-4}			5*10^{-7}	9*10^{-7}	
		5*10^{-5}	3*10^{-4}			1.8*10^{-7}	5.7*10^{-7}	
	1.076	0.09	0.49	1	1	0.13	0.41	1

Table 3. The results of the 18 UOAs

UOA_j	Overall			Process							
				f				*h*			
	ζ_j^*	Δ_j^*	Ranking	ζ_j^{f*}	Δ_j^{f*}	π_j^{f*}	Ranking	ζ_j^{h*}	Δ_j^{h*}	π_j^{h*}	Ranking
1	1.8854	-0.0805	1	3.7479	-0.0769	-1	1	1.0575	-0.0036	-1	8
2	1.8197	-0.1204	2	1.5469	-0.0425	-1	4	2.1262	-0.0779	-1	3
3	1.8150	-0.1452	3	1.1140	-0.0126	-1	6	2.9505	-0.1327	-1	1
4	1.8109	-0.1150	4	1.3459	-0.0334	-1	5	2.7990	-0.0816	-1	2
5	1.2959	-0.0471	5	1.1021	-0.0068	-1	7	1.4368	-0.0402	-1	5
6	1.2631	-0.0357	6	3.0271	-0.0892	-1	2	0.4175	0.0535	1	15
7	1.0526	-0.0097	7	1.0787	-0.0097	-1	8	0.9996	0	1	10
8	1	0	8	1	0	-0.7458	9	1	0	0.1287	9
9	0.8954	0.0148	9	0.4551	0.0260	1	14	1.1188	-0.0112	-1	7
10	0.8793	0.0191	10	0.3880	0.0545	1	16	1.5141	-0.0354	-1	4
11	0.8723	0.0190	11	0.8427	0.0098	1	11	0.8936	0.0092	1	11
12	0.8519	0.0261	12	2.8441	-0.0602	-1	3	0.3986	0.0863	1	16
13	0.7527	0.0245	13	0.3327	0.0324	1	17	1.1575	-0.0079	-1	6
14	0.6960	0.0814	14	0.6841	0.0395	1	12	0.7063	0.0418	1	13
15	0.6639	0.0635	15	0.5785	0.0439	1	13	0.7685	0.0197	1	12
16	0.6018	0.0882	16	0.4090	0.0341	1	15	0.6697	0.0541	1	14
17	0.5036	0.1014	17	0.8731	0.0093	1	10	0.2968	0.0921	1	17
18	0.2372	0.1920	18	0.2342	0.0973	1	18	0.2402	0.0947	1	18

Table 4. The input *f*, *h* and shared and output *f*, *h* and shared percentage

Notations	δ^{I*}	$\underline{\delta}^{I*}$	$\bar{\delta}^{I*}$	δ^{O*}	$\underline{\delta}^{O*}$	$\bar{\delta}^{O*}$	Q^{f*}	Q^{h*}	P^{f*}	P^{h*}	
	$\delta^I + \underline{b}\underline{\delta}^I - \bar{b}\bar{\delta}^I$			$\delta^O + \underline{B}\underline{\delta}^O - \bar{B}\bar{\delta}^O$			Q^{f*}/X^f	Q^{h*}/X^h	P^{f*}/Y^f	P^{h*}/Y^h	
Values	0.2715	0.0946	0	0.0725	0	0	598.6	29235.5	226.2	405.3	Sum
		0.2995			0.0725		0.365	0.304	0.542	0.302	1.52
%		19.7%			4.77%		24%	2%	35.66%	13.87%	100%

Table 5. The value of shared slacks in input and output

Slacks	Q^{sf*}	Q^{sh*}	P^{sf*}	P^{sh*}
Value	598.6	443.6	52331.6	52331.6
Ratio	Q^{sf*}/X^s	Q^{sh*}/X^s	P^{sf*}/Y^s	P^{sh*}/Y^s
Value	0.365	0.270	0.072	0.072
Percentage	57.4%	42.6%	50%	50%

CONCLUSIONS

This paper introduced the model for shared inputs and outputs under two parallel processes. The common set of weights and the unknown proportions shared by inputs and outputs are computed by a linear programming model based on minimizing total virtual gaps to maximize the CDM's aggregate score. The CDM is able to modify the total virtual gaps to improve its aggregate and reallocated the inputs and outputs. The model also can rank all UOAs.

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COMPARISON OF FREE ZONES IN TURKEY BY MEANS OF DEA

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ABSTRACT

Turkey adopts export led growth model after 1980 and has currently 19 free zones. Free trade zones are attraction centers for foreign investors and for domestic investors who want to direct their vast majority of production to export. The purpose of government incentives given to these regions is to increase encouraging exports and foreign direct investments. The effectiveness of free trade zones plays a great role on the decision of the number and structure of potential free zones in future. Relative performances of 12 free zones which have most employment ratio are compared with Data Envelopment Analysis and the results are examined.

Keywords*: Free zones, Data Envelopment Analysis, performance comparison*

INTRODUCTION

In today's world, no economy can be self-sufficient. The economy that is not integrated with global world lags behind change and can develop. Whichever are aware of this change of global world launches to join in the world not only goods, labour and capital movements do not have any borders but also to increase their competitiveness and regional economic co-operation have begun to give weight to the mergers(Duzenli,2006).

In the global economic system, the countries which aim to get a bigger share from the circulation of goods and capital develop new strategies. Free zone applications also takes place an important alternative among these strategies. Today, free zones in developed countries as effective trade centers have taken very important role of logistic functions. In terms of developing countries free zones stand out as a tool for new opportunities to make additional employment and benefit much more effective from international trade and investment facilities.

In general, free zones are the places that legal and administrative regulations not applied related to valid commercial, financial and economic fields in a country or partially applied, more given incentives for industrial and commercial activities and separated from the rest of the physical locations of the country. Free zones were established in 1985. Founding places of free zones are ports and high volume trade regions. They are known as the most commonly tax benefit applied regions. They are strong economic eco systems with their about 55.000 employment and over 20 billion trade volume. In accordance with the data from the economy ministry there are 19 free trade zones.

Establishment Purposes of Free Zones; To promote export-oriented investment and production, to accelerate the entry of foreign direct investment and technology, to direct business for exporting, to develop international trade.

Functions of FZ; To create an appropriate basis for getting foreign capital and technology into country, to ease reaching some of raw materials and intermediate goods on desired amount and time without any time loss needed by industrialists, with the aim of low-cost production and export of goods by provided incentives and benefits, the sale of goods from outside of Turkey transit to other countries, the creation of new employment opportunities, to facilitate and accelerate the export of Turkish exports.

Employment rates (Figure 2): (i)The highest employment is in Aegean free zone, (ii)Aegean, Bursa and Mersin free ones constitute about 60% of total employment, (iii)Employment is under 500 in Adana-Yumurtalık, Samsun, Gaziantep, Trabzon, Denizli, Mardin and Rize free zones.

Table 1. Employment rates of free zones(%)

Aegean : 35,28	Antalya :6,16	TÜBİTAK: 4,97	İzmir :2,76
Bursa : 15,04	Istanbul Ind.Trade:5,42	Europe :3,99	IstThrace:2,56
Mersin : 12,10	Kocaeli : 5,41	Kayseri :2,93	Others: 3,39

Structure of the companies operating in free zones is categorized in Table 2 (Ministry of Economy, 2011). The legal advantages of free trade zones set out in Table 3.

Table 2. Structures of Firms in Free Zones

USER'S ACTIVITIES	LOCAL	FOREIGN	TOTAL
PRODUCTION	669	183	852
PURCHASING-SELLING	1402	338	1740
OTHER	519	94	613
TOTAL	2590	615	3205
Production/Total			0,27

Table 3. Tax Benefits Provided to Free Zones

Tax Exemptions	Producers	Other Licenses
Income and Corporation Tax	Privileged (Up To EU Membership)	-
Income Tax (withholding tax)	% 85 Subject to Export %85 Rate (Up To EU Membership)	-
Stamp T. Duties, Charges	Privileged (Up To EU Membership)	Privileged (Up To EU Membership)
Customs Duty	Privileged	Privileged
Value Added Tax	Privileged	Privileged

Free zones, which are established For the purpose of promoting investment and production oriented export, accelerating the entry of foreign direct investment and technology, directing enterprises to export and developing international trade are important for an country in terms of effecting on its foreign, are important for an country in terms of effecting on its foreign. Free zone experiences in the Far East showed that it could play a great role on macro-economic development in many countries when the free zones were constituted in the phase of countries' developing periods under appropriate conditions (Öztürk, 1998).

The measurement of effectiveness of free trade zones to determine how much provide benefits to their purposes, taking decision on establishing new zones and changing structure of incitements in the future will play a great role on . Productivity measurement is often carried out in the free zones by surveys (Chiu and others, 2011, Ozdemir, 2007). In this study relative performance of free zones compared by means of Data Envelopment Analysis (DEA) and results are analyzed.

METHODS

The DEA is used as analysis method. DEA is a nonparametric linear programming technique which aims to measure the relative performances' of the decision making units (DMUs), in circumstances that where inputs and outputs having different unit of measures or measured at different scales make it difficult to comparison. The relative effectiveness of a decision unit in DEA, is defined as the ratio of the weighted sum of the outputs to weighted sum of the inputs and is also referred to as "technical efficiency" (Bulbul ve Akhisar, 2007).

DEA is a linear programming (LP) method that is developed firstly by Charnes, Cooper and Rhodes (1978) and aims to analyze relative efficiencies of decision making units (DMUs) which produce similar products or services (Banker, 1992:74). The model that is used in DEA is solved for every DMU and according to analysis, the DMUs, whose objective function equals "1" is determined as "efficient". On the other hand, the DMUs, whose objective function is not equal to "1", are compared and simulated to other appropriate DMU. So, every non-efficient DMU is made to efficient. Since DEA can be used in every research area, there are many applications at different sectors. For example, Pakdil et. al. (2010), compare university hospitals with DEA. According to their analysis, both for output oriented and input oriented model results, the same two hospitals are observed as efficient. The inputs that are used in the article are patient bed number, specialist doctor number, doctor number. Outputs are, polyclinic number, discharged patient number, death number, time (day) that is spend at hospital and surgical number. Another study at service sector is carried by Oliveira and Tabak in 2005 for 41 countries' bank sectors. They compared the banks for 8 years (1995-2002) by DEA then review the changes by years and they observe that Asia banks are more efficient than Ibero-America banks. In production sector on the other hand, Mousavi-Avval et. al.(2011) have a study related to energy consumption optimization on soybean and Aras and Gencer (2011) have DEA studies on marble enterprises. Furthermore, there are various studies on many different areas like coal mine security efficiency (Lei ve Ri-jia, 2008) and management strategy determination on fisheries (Griffin ve Woodward, 2011).

The DEA studies until 2010 are analyzed by Liu et. al. in 2013 in terms of cite number. Besides, current researches on DEA have a growing trend on the use with fuzzy logic and AHP (Wu ve Olson, 2010, Lee ve diğerleri, 2011, Veni ve diğerleri, 2012, Lee, Mogi ve Hui, 2013).

DEA STAGES

1. Determining Decision Making Units (DMUs): If the input number is m and the output number is p, then at least m+p+1 DMUs should be chosen. Also, DMU number should be at least 2x (m+p) (Boussofiance, 1991).

2. Determining Inputs and Outputs: The inputs and outputs should be chosen carefully because they form the base of comparison. They should be reasonable and causatively belongs to the process.

3. Determining Efficiency Values: Simply efficiency is defined as (Karacabey, 2001):

$$Efficiency = \frac{\text{Weighted sum of outputs}}{\text{Weighted sum of inputs}} = \frac{u^{'} y_i}{v^{'} x_i} \qquad u^{'} = output\ weight \quad y_i = output\ amount \quad v^{'} = input\ weight \quad x_i = input\ amount$$

There are two mathematical models used in DEA for efficiency calculation which are "input oriented" and "output oriented". Although these two models are in similar basis, input oriented DEA models search for optimum input composition to obtain a certain output, while output oriented DEA models search for maximum output with on hand input (Charnes ve d., 1981). These models are:

- CCR Model
- BCC Model
- Proportional DEA Model
- Weighted DEA Model
- Envelopment DEA model

4. **Potential improvement values for non-efficient DMUs**

The most benefit of DEA is, setting achievable goals for inefficient DMUs in order to help to improve their performances. By applying these goals, it is assumed that those inefficient DMUs would be efficient.

RESULTS AND DISCUSSIONS

The research is carried on 5 steps. The studies in each step are:

Step1 (Data Collection): The majority of data are statistics which are obtained from the web site of the ministry of economy. The rest of the data are obtained from the web sites of free zones or by e-mail and telephone interview.

Step2 (Input and Output Determination): According to the establishment objectives and functions, performance measures/desired outputs are trade volume and employment rate. These outputs are desired to be high. The inputs that support the outputs are area, foreign and total firm numbers, because the outputs increase while firm number increases. Besides, as the area that the free zone is located expands the more firm can be established. However, the correlation of area seems too low at the Table4.

Table 4. The correlation between inputs and outputs

Correlation	Employment	Trade volume
Foreign firms	0.59	0.83
Total firms	0.22	0.70
Area	0.04	-0.08

Step3 (DMU Selection): 12 free zones are chosen as DMUs which have employment number over 500. As input number, m=3 and p=2 the chosen DMU number satisfies the least DMU number constraint:

The DMUs=12 > m+p+1= 3 + 2 + 1 =6

> 2x (m+p) = 2x (3+ 2) = 10

Step4 (Model Determination): In this study, output oriented Envelopment DEA Model is used and its general formulation is:

$$E_k = Maks\beta + (\varepsilon \sum_{i=1}^{m} S_i^-) + (\varepsilon \sum_{r=1}^{t} S_r^+) \quad (1)$$

$$\sum_{j=0}^{n} (x_{ij}\lambda_j) + S_i^- - x_{ik} = 0 \quad (2)$$

$$\sum_{j=1}^{n} (y_{rj}\lambda_j) + S_j^+ - (\beta y_{rk}) = 0 \quad (3)$$

$$\lambda_j, S_i^-, S_j^+ \geq 0 \qquad i = 1,\dots\dots,m \quad ; \quad r = 1,\dots\dots,t$$

E_k : The effectiveness of DMU k

β : Coefficient of expansion of output

ε : Sufficiently small positive number

S_i^- : Obs value of DMU k belongs to its i. input

S_r^+ : Obs value of DMU k belongs to its r. output

x_{ij} : i input amount used by DMU j

λ_j: The density value of DMU j

y_{rj} : r output amount produced by DMU j

n : DMUs number

t : Output number

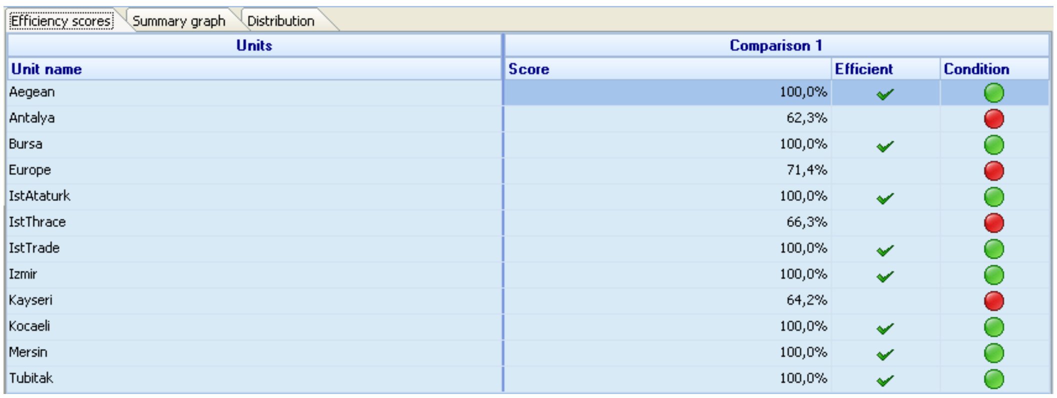
m : Input number

Step 5 (Model Solving): Output Oriented Envelopment DEA Model is solved on Banxia Frontier Analyst 4 software by using the data in Table4. As a result, the efficiency percentages are shown in Figure 4. According to this result, the free zones that have the ratio %100 which are Ege, Bursa, İstanbul Atatürk, İstanbul Ticaret, İzmir, Kocaeli, Mersin, Tubitak are efficient while Antalya, Avrupa, İstanbul Trakya, Kayseri are inefficient.

Table 5. Data used in DEA

Free Zones	**INPUTS**			**OUTPUTS**	
	area	firms	frgnfirms	emplymnt	Tradevolume($)
Aegean	2200000	225	77	19962	5221937

Bursa	825000	102	23	8041	1532317
Mersin	836000	605	48	7883	3832246
Antalya	625490	113	37	3797	749707
Kocaeli	798000	21	6	1636	738265
Tubitak	360000	55	7	3000	208007
Europe	2000000	142	42	2153	2364905
Kayseri	6905000	87	9	1791	696971
Izmir	1620473	20	3	1447	326535
IstThrace	387500	268	36	1307	1443596
IstAtaturk	180000	194	64	1270	2103566
IstTrade	500000	511	34	2820	3220084



Units	Comparison 1		
Unit name	Score	Efficient	Condition
Aegean	100,0%	✓	
Antalya	62,3%		
Bursa	100,0%	✓	
Europe	71,4%		
IstAtaturk	100,0%	✓	
IstThrace	66,3%		
IstTrade	100,0%	✓	
Izmir	100,0%	✓	
Kayseri	64,2%		
Kocaeli	100,0%	✓	
Mersin	100,0%	✓	
Tubitak	100,0%	✓	

Figure 4. Efficiency percentages

Table 6. Current and Objective Values

	CURRENT VALUES					OBJECTIVE VALUES				
Free Zone	Area	Firms	Foreign firms	Employ-ment	Trade volume	Area	Firms	Foreign firms	Employ-ment	Trade volume
Antalya	625490	113	37	3797	749707	625490	86,36	17,88	6091,67	1202783
Europe	2000000	142	42	2153	2364905	2000000	142	42	10778,53	3313106,58
Istthrace	387500	268	36	1307	1443596	387500	268	36	2744,45	2178891,04
Kayseri	6905000	87	9	1791	696971	1844850,69	36,54	9	2787,61	1084804,43

The Table 6 shows the current and objective values of inputs and outputs for inefficient free zones while Figure5 shows the potential improvement values. With the help of these values, an evaluation to an accrual amount for making these DMUs to efficient can be made. For instance, Antalya region would be efficient if total firm number is decreased by -23,6 %, foreign firm number decreases by -51,7 %, and employment increases by 60,4 % and trade volume increases by 60,4 %.

Unit name	Compariso	Score	Percent area	Percent firms	Percent frgnfirms	Percent emplymnt	Percent trdvlm
Antalya	0	62,33	0,0	-23,6	-51,7	60,4	60,4
Europe	0	71,38	0,0	0,0	0,0	400,6	40,1
IstThrace	0	66,25	0,0	0,0	0,0	110,0	50,9
Kayseri	0	64,25	-73,3	-58,0	0,0	55,6	55,6

Figure 5. Potential Improvement Values

CONCLUSIONS AND FUTURE WORKS

Efficiency measurement of free zones that are established to direct the firms to export and improving the international trade plays a significant role to on changing the encouragement structure and in the decision of establishing more free zones. For this purpose, in this study 12 free zones in Turkey are compared and their relative performances' are analyzed via DEA. Most of them (8) are observed as efficient while for in efficient ones, potential improvement percentages are calculated.

The aim of future research is sorting the efficient free zones. This is not possible with DEA. For this purpose, the Balanced Score Card (BSC) method would be used. The performance criterions are determined by BSC, and then the linguistic evaluation would be requested from every free zone's expert. Then this evaluation is turned to numeric values by fuzzy logic. So free zones are sorted in terms of BSC dimensions.

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COMPUTING THE BIENNIAL MALMQUIST INDEX USING MODIFIED VARIABLE RETURNS TO SCALE DEA MODEL

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ABSTRACT

In this paper,the Malmquist productivity index is introduced which is used for comparing two group's performance at the same period of time or measuring the productivity change of decision making units between two different periods of time. The biennial Malmquist index and its decomposition into technical, efficiency and scale changes is illustrated. Then modification on production possibility set of BCC model is proposed by using facet analysis. This modification contains some changes in BCC model. Finally, the biennial Malmquist index will be computed using modified BCC model and advantages of this approch will be illustrated by an example.

Keywords: *Data Envelopment Analysis, Malmquist Index, ModifiedVariable Returns to Scale Model*

1 INTRODUACTION

Certainly, the exact evaluation is the basic aim of many evaluation systems. So Data Envelopment Analysis (DEA) as the one of most important element of these systems must take care of this aim. In DEA the evaluation has done by mathematical models and in special cases, these models do not achieve exact result. Many papers have suggested the methods for modification of these mathematical models and removing the difficulties of them [1,2,3], but these methods themselves have problems.

One of the major problems of BCC and CCR models is that evaluate DMUs on weak frontier as efficient DMUs. Because the weights as inputs or outputs of the DMUs on the weak frontier in evaluation of this DMU by BCC model are zero, and this lead to evaluation of such DMU is unhelpful. For removing this difficulty Charnes, Cooper and Rohdes use the non-archimedean number ε. As a theoretical construct, ε provide a lower bound for multipliers, to keep them away from zero. Some difficulties arise in representing as infinitesimal, because of finite tolerances in computer calculation. Ali and Seiford[3] based on Ali[1,2] have proposed on upper bound on ε for feasibility of the multiplier side and boundless of the envelopment side of the CCR and BCC models. But Mehrabian, Jahanshahloo and Alirezaei by an example, showed that the bound which proposed in [3] for ε, is invalid. They suggested a procedure for determining the assurance interval of ε. The assurance interval for ε is the interval that for each value of ε from this interval the basic models of DEA feasible in multiple side and bounded in envelopment side. Also they provided a single linear programming for determining the assurance interval for ε. Daneshvar[1] introduced the facet analysis on basic mathematical models of DEA and modified them and showed that, facet analysis can be applied in sensitivity analysis on DEA models.

2 MALMQUIST PRODUCTIVITY INDEX

In this study, we apply the methods of Färe et al. (1994) to estimate total factor productivity indices without a priori specification of the underlying technology and producer behavior. The productivity change is calculated as the geometric mean of two Malmquist productivity indices. The Malmquist index, introduced by Caves et al. (1982), is constructed from the distance functions, allowing explicit isolation of changes in efficiency. In contrast to the Tornqvist index, the Malmquist index does not require price or share data to aggregate inputs and outputs.

Let P be the production possibility set of the industry that produces the output vector yt with the input vector xt in year t. The output distance function is defined as:

$$D^t(x^t, y^t) = \min\{\theta \mid (x^t, y^t/\theta) \in p^t\} \quad (1)$$

Where è is the proportional increase of all outputs that would bring the industry to the production frontier. To define the Malmquist index requires definition of distance functions with respect to two different time periods such as:

$$\begin{aligned} D^t(x^{t+1}, y^{t+1}) &= \inf\{\theta \mid (x^{t+1}, y^{t+1}/\theta) \in p^t\} \\ D^{t+1}(x^{t+1}, y^{t+1}) &= \inf\{\theta \mid (x^{t+1}, y^{t+1}/\theta) \in p^{t+1}\} \end{aligned} \quad (2)$$

The first distance function in Eq. (2), measures the maximum proportional change in outputs required to make *(x^{t+1}, y^{t+1})* feasible in relation to the technology at time *t*. Similarly, the second distance function measures the maximum proportional change in the output, required to make *(x^t, y^t)* feasible under the technology at time *t*+1.

Caves et al. (1982) defined an output-based Malmquist productivity index relative to technology at time t as:

$$M^t = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \quad (3)$$

And for t+1 as:

$$M^{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \quad (4)$$

Färe et al. (1994) employed the geometric mean of two output-based Malmquist indices, defined above, to yield the Malmquist-type measure of productivity under the assumption of constant-return-to-scale technology:

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \quad (5)$$

M(.)>1 means productivity increases; M(.)=1 means productivity do not change; M(.)<1 indicates that productivity decreases.

Following Färe et al. (1994), an equivalent expression of Eq. (5) is:

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times [\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}]^{\frac{1}{2}} \quad (6)$$

Where the geometric mean of the two rations inside the bracket captures the shift in technology between the two periods evaluated at x^t and x^{t+1} . That is, it measures the technical change (TC). TC>1 stands for technical progress; TC<1 shows technical regress. While, the ratio outside the bracket of Eq. (6) measures efficiency change (EC), i.e. the change in how far the observed production is from maximum potential production. EC>1 means efficiency has improved; EC<1 means efficiency has deteriorated.

Assume that, at each time period $t=1,\ldots,T$, there are j=1,…,J observations using inputs $x_n^{j,t}$, $n=1,\ldots,N$, to produce outputs $y_m^{j,t}$, m=1,…,M. The frontier technology in period t is constructed from the data as:

$$S^t = \{(x^t, y^t) : y_m^t \le \sum_{j=1}^{J} \lambda^{j,t} y_m^{j,t}, \quad m = 1,\ldots, M, \ \sum_{j=1}^{J} \lambda^{j,t} x_n^{j,t} \le x_n^{j,t}, \quad n = 1,\ldots, N, \ \lambda^{j,t} \ge 0, \quad j = 1,\ldots, J\} \quad (7)$$

Where $\ddot{e}^{j,t}$ is an intensity variable indicating the intensity at which a particular activity (or observation) may be employed in production. The four distance function used to construct the Malmquist index, $D^t(x^t,y^t)$, $D^{t+1}(x^{t+1},y^{t+1})$, $D^t(x^{t+1},y^{t+1})$ and $D^{t+1}(x^t,y^t)$ can be solved by using Data Envelopment Analysis (DEA). The linear programming problem to be solved for $D^t(x^t,y^t)$ is:

$$\begin{aligned} &[D^t(x^t, y^t)]^{-1} = \max_{\theta\lambda} \ \theta && (8) \\ &s.t \quad \theta y_m^{j,t} - \sum\nolimits_{j=1}^{J} \lambda^{j,t} y_m^{j,t} \le 0, \quad m = 1,\ldots, M \\ &\sum\nolimits_{j=1}^{J} \lambda^{j,t} x_n^{j,t} \le x_n^{j,t}, \quad n = 1,\ldots, N \\ &\lambda^{j,t} \ge 0, \quad j = 1,\ldots, J \end{aligned}$$

The computation of $D^{t+1}(x^{t+1},y^{t+1})$ is exactly like Eq. (8), where t+1 is substituted for t.

The other two distance functions require information from two periods. The linear programming problem for $D^t(x^{t+1},y^{t+1})$ is:

$$\begin{aligned} &[D^t(x^{t+1}, y^{t+1})]^{-1} = \max_{\theta\lambda} \ \theta && (9) \\ &s.t \quad \theta y_m^{j,t+1} - \sum\nolimits_{j=1}^{J} \lambda^{j,t} y_m^{j,t} \le 0, \quad m = 1,\ldots, M \\ &\sum\nolimits_{j=1}^{J} \lambda^{j,t} x_n^{j,t} \le x_n^{j,t+1}, \quad n = 1,\ldots, N \\ &\lambda^{j,t} \ge 0, \quad j = 1,\ldots, J \end{aligned}$$

The last linear programming problem we need to solve for $D^{t+1}(x^t,y^t)$ is also a mixed-period problem. It is is specified as in Eq. (9), but the t and t+1 superscripts are reversed.

Thought we calculate the Malmquist index relative to the constant-return-to-scale (CRS) technology, Färe et al. (1994) indicate that we can calculate distance function under variable return to scale (VRS) by adding $\sum_{j=1}^{J}\lambda^{j,t}=1$ constraint. Then $[\frac{D^{t+1}(x^{t+1},y^{t+1})}{D^{t}(x^{t},y^{t})}]$ term, EC, in Eq. (6) can be further decomposed into pure efficiency change (PEC),

$$[\frac{D^{t+1}(x^{t+1},y^{t+1}"|VRS)}{D^{t}(x^{t},y^{t}|VRS)}], \quad (10)$$

And scale efficiency change (SEC),

$$[\frac{D^{t+1}(x^{t+1},y^{t+1}"|CRS)}{D^{t+1}(x^{t+1},y^{t+1}|VRS)}\times\frac{D^{t}(x^{t},y^{t}|VRS)}{D^{t}(x^{t},y^{t}|CRS)}]. \quad (11)$$

So, the further decomposition of $M(x^{t+1},y^{t+1},x^{t},y^{t})=TC\times EC$ leads to $M(x^{t+1},y^{t+1},x^{t},y^{t})=TC\times PEC\times SEC$. PEC is calculated relative to the variable-return technology, while the residual scale component, SEC, captures the changes in the deviation between the variable-return and constant-return-to-scale technology. SEC>1 shows that the industry is relatively approaching the long-term optimal scale at t+1; SEC<1 indicates that the industry is deviating from the long-term optimal scale.

3 MODIFICATION OF WEAK FRONTIER USING FACET ANALYSIS

Facet analysis focuses on hyperplanes of PPS frontier. The efficient frontier estimates production function in inputs-outputs space. For basic DEA models, the efficient frontier is constructed by hyperplanes, which support the PPS in efficient DMUs. Facet Analysis helps us to get more information about these hyperplannes. In the next subsection the hyperplanes, which construct the weak frontier, will be moved. This movement should ensure the retainment of the properties of the PPS. In facet ε perturbs the normal vector and do not let the hyperplanes of weak frontier to be formed. Then the efficiency score of weak efficient DMUs and also the DMUs, that are compared with them, will change depending on the value of ε. To choose on the value of ε will have impact on the efficiency score of the DMUs. So the correct scores may not be obtained.

4 FINDING UPPER BOUND FOR V_O AND MODIFICATION OF BCC MODEL

Suppose that there are n DMUs. Each DMU consumes m inputs to produce s outputs. Now for the efficient DMUs, for example DMU $_0$, solve the following problems:

$$v_o^+ = Max\ v_o$$
$$subject\ to\ \sum_{i=1}^{m} v_i x_{io} + v_o = 1$$
$$\sum_{r=1}^{s} u_r y_{ro} = 1$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - v_o \le 0, \quad j = 1,2,...,n$$
$$v_i \ge 0,\ u_r \ge 0, \quad r = 1,2,...,s \quad i = 1,2,...,m$$
$$v_o \quad free\ in\ sign$$

(12)

$$v_o^- = Min\ v_o$$
$$subject\ to\ \sum_{i=1}^{m} v_i x_{io} + v_o = 1$$
$$\sum_{r=1}^{s} u_r y_{ro} = 1$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - v_o \le 0, \quad j = 1,2,...,n$$
$$v_i \ge 0,\ u_r \ge 0, \quad r = 1,2,...,s \quad i = 1,2,...,m$$
$$v_o \quad free\ in\ sign$$

(13)

Suppose that the optimal value of models (1), (2) are v_o^+ and v_o^- , respectively. Note that weak frontier in classical BCC model correspond to the hyperplanes with $v_0^+ = 1$ and $v_0^- < 1$. Now, consider that: ε = Max { $v_0^- \mid v_0^+ = 1$, $v_0^- < 1$}. By placing ε as upper bound for free variable of classical BCC model This model is modifie .

5 NUMERICAL EXAMPLES

Suppose we have two time periods. Table 1 shows information about each of these time periods. As can be seen each of these periods involves 21 DMUs and each of these DMUs involves 3 input and 3 output. Now we first obtain VRS frontier for above time periods, then evaluate DMUs of above time periods using BCC model, then we calculate Malmquist index and its components: technical change, efficiency change and scale change, that the results of these calculations are given in table 2. Then The models (12) and (13) are used on efficient DMUs and then from above, value of ε is obtained 7083. By placing ε as upper bound for free variable of BCC model This model is modified. Then we evaluate efficiency scares of DMUs using modified BCC model and recalculate Malmquist index and its components, that results of these calculations are showen in Table3.

Table 1: Data of numerical example

	Period 1						Period 2					
DMUs	Input1	Input2	Input2	Output1	Output2	Output3	Input1	Input2	Input3	Output1	Output2	Output3
1	350	4	75	433	5	88	45	0	40	56	1	45
2	202	1	50	242	1	55	27	1	9	35	2	10
3	190	1	31	233	2	38	35	4	42	46	6	40
4	305	1	60	406	1	65	45	3	1	51	6	0
5	802	7	120	989	10	140	65	2	55	75	2	60
6	1004	8	130	1276	9	145	130	2	62	148	2	60
7	1800	6	140	2190	6	165	170	1	21	189	2	20
8	502	5	73	634	6	82	55	5	38	68	4	40
9	659	4	70	757	4	78	80	2	9	103	2	10
10	352	10	50	650	12	64	17	3	135	25	2	130
11	456	5	80	525	6	90	36	9	118	43	8	120
12	899	2	91	1020	2	100	97	2	2	116	1	0

13	1602	8	120	1718	11	140	96	3	48	111	4	50
14	901	5	105	1025	6	120	71	4	92	80	3	90
15	600	10	75	655	11	88	22	8	45	30	10	50
16	852	3	85	924	5	92	28	0	22	39	1	20
17	301	4	62	360	6	72	25	1	18	31	1	20
18	701	7	90	779	8	102	130	0	8	146	1	10
19	491	4	82	589	5	92	97	2	1	115	1	0
20	351	4	67	441	4	80	27	0	18	35	1	20
21	175	7	40	258	5	50	7	1	20	11	1	20

DMU	$D_0^t(t)$	$D_0^{t+1}(t+1)$	$D_O^t(t+1)$	$D_0^{t+1}(t)$	$D_0^t(t\|VRS)$	$D_0^{t+1}(t+1\|VRS)$	PEC	SEC	TC	MI
1	0.686	0.655	0.6863	0.6605	0.8028	0.8272	1.0304	0.92660	1.043186	0.9960018
2	0.749	0.996	0.8856	0.8635	0.7491	1.000	1.3349	0.99610	0.878211	1.160000
3	1.00	1.00	1.2237	2.1000	1.000	1.000	1.000	1.0000	0.763357	0.763357
4	1.00	1.00	1.5000	1.0914	1.000	1.000	1.000	1.0000	1.1723401	1.1723401
5	0.447	0.437	0.4381	0.4455	0.6759	0.7114	1.05251	0.925461	1.002942	0.976934
6	0.763	0.778	0.7663	0.7695	1.000	1.000	1.0000	1.019659	0.98825	1.007678
7	1.00	0.927	0.9807	0.9567	1.000	1.000	1.0000	0.92700	1.0515751	0.9748101
8	0.638	0.648	0.6567	0.6010	0.8974	0.8062	0.89835	1.130596	1.0372158	1.053469
9	0.876	1.00	1.0429	0.8562	0.8925	1.000	1.12045	1.018834	1.032965	1.179181
10	1.00	1.00	0.8224	1.7668	1.000	1.000	1.0000	1.0000	0.682257	0.682257
11	1.00	1.00	0.8648	1.1800	1.000	1.000	1.0000	1.0000	0.856084	0.856084
12	1.00	1.00	1.1959	0.9298	1.000	1.000	1.0000	1.0000	1.134103	1.134103
13	0.6134	0.602	0.6013	0.6138	0.8026	0.8692	1.08296	0.906829	0.998767	0.980845
14	0.619	0.750	0.5820	0.9200	1.000	0.9688	0.96880	1.250652	0.722574	0.875494
15	0.8267	0.720	0.8807	0.6755	0.9423	1.000	1.06120	0.820697	1.223514	1.065598
16	0.285	0.334	0.3304	0.3822	0.4130	0.4033	0.97579	1.200117	0.859088	1.006041
17	0.439	0.436	0.4527	0.4207	0.4652	0.4822	1.03654	0.958550	1.040898	1.0342106
18	1.00	1.00	1.0101	1.0110	1.000	1.000	1.0000	1.0000	0.999555	0.999555
19	1.00	1.00	1.0091	1.0274	1.000	1.000	1.0000	1.0000	0.991054	0.991054
20	0.405	0.402	0.4155	0.3896	0.4450	0.4791	1.07649	0.92210	1.036551	1.028868
21	0.380	0.366	0.2912	0.5000	1.000	0.4269	0.42690	2.25620	0.777610	0.748961

Table 2: The productivity indices of the DMUs before modifying weak frontier

Table 3: The productivity indices of the DMUs after modifying weak frontier

DMUs	$D_0^t(t)$	$D_0^{t+1}(t+1)$	$D_O^t(t+1)$	$D_0^{t+1}(t)$	$D_0^t(t\|VRS)$	$D_0^{t+1}(t+1\|VRS)$	PEC	SEC	TC	MI
1	0.686	0.655	0.6863	0.6605	0.7434	3.3434	4.49744	0.212301	1.043186	0.9960460
2	0.749	0.996	0.8856	0.8635	0.7491	0.9961	1.3297	1.00040	0.878211	1.1677957
3	1.00	1.00	1.2237	2.1000	1.000	1.000	1.000	1.0000	0.763357	0.763357
4	1.00	1.00	1.5000	1.0914	1.000	1.000	1.000	1.0000	1.172340	1.172340
5	0.447	0.437	0.4381	0.4455	0.5552	0.62583	1.12721	0.86734	1.002942	0.9805385
6	0.763	0.778	0.7663	0.7695	1.000	1.000	1.000	1.01966	0.988252	1.0076801
7	1.00	0.927	0.9807	0.9567	1.000	1.000	1.000	0.92700	1.0515751	0.9748101
8	0.638	0.648	0.6567	0.6010	0.7423	0.7469	1.0062	1.69476	1.0372158	1.78732
9	0.876	1.00	1.0429	0.8562	0.8838	1.000	1.1315	1.00891	1.032965	1.179207
10	1.00	1.00	0.8224	1.7668	1.000	10000	1.000	1.0000	0.682257	0.682257
11	1.00	1.00	0.8648	1.1800	1.000	1.000	1.000	1.0000	0.856084	0.856084
12	1.00	1.00	1.1959	0.9298	1.000	1.000	1.000	1.0000	1.134103	1.134103
13	0.6134	0.602	0.6013	0.6138	0.7396	0.7838	1.0598	0.92668	0.998767	0.980880

14	0.619	0.750	0.5820	0.9200	0.8627	0.9663	1.1201	0.839591	0.722574	0.6795272
15	0.8267	0.720	0.8807	0.6755	0.9423	1.000	1.0612	0.820680	1.223514	1.065565
16	0.285	0.334	0.3304	0.3822	0.3023	0.3656	1.2094	0.969022	0.859088	1.006796
17	0.439	0.436	0.4527	0.4207	0.4468	0.4552	1.0188	0.974840	1.040898	1.033786
18	1.00	1.00	1.0101	1.0110	1.000	1.000	1.000	1.0000	0.9995555	0.999555
19	1.00	1.00	1.0091	1.0274	1.000	1.000	1.000	1.0000	0.991054	0.991054
20	0.405	0.402	0.4155	0.3896	0.4172	0.4290	1.0283	0.97004	1.036551	1.033951
21	0.380	0.366	0.2912	0.5000	0.3789	0.3664	0.9670	0.99602	0.777610	0.748956

6 CONCLUSIONS

The DEA models used in the Malmquist productivity index can either be input or output oriented. Consequently, the Malmquist productivity index can be input-oriented when the outputs are fixed at their current levels or output-oriented when the inputs are fixed at their current levels. In this paper we use output-oriented BCC and CCR models, to calculate Malmquist productivity index. So MI >1 indicates progress in the total factor productivity of the DMU from period1 to 2, while MI=1 and MI <1 respectively indicate the status quo and deterioration in the total factor productivity. As mentioned earlier after modifying the weak frontier, there is no DMUs on this frontier, so efficiency score of this DMUs will changed. The comparison of the column 11 of table 2 and table 3 shows that value of Malmquist index has been better ofter modifying VRS frontier

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CUSTOMER EFFIEINCY VERSUS FIRM EFFIEINCY: A BANKING EXAMPLE

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ABSTRACT

Customer focus is a key issue in firm management for success and the most important pillar of customer focus is to ensure customer satisfaction. However there are many firms in market and all of them are trying to attract customer for being efficient. In the same manner demand side of the market also wants to be efficient. It is evident that one side is efficient whereas the other side is inefficient under this circumstance. In this study the interaction between customer and firm efficiencies will be examined by the means of DEA. Therefore, banking sector data will be used to demonstrate the importance and interaction between two efficiency measures.

Keywords: *Customer Focus; Customer Satisfaction; Efficiency; DEA; Banking*

INTRODUCTION

Efficiency has been an important issue from the beginning of history to today. Due to the technological and economic developments, efficiency has become more important. Efficiency could simply be defined as spending less input and/or getting more output. As a result, everybody needs and wants efficiency in their work. Tradesmen want less costs and more income for being efficient; conversely, customers want less prices but more service from the firms and so on. Modern technology gives the chance of selecting better service for a lesser cost to customers from the global market, but the same modern technology makes firms difficult to get more profit and be more efficient. This could be defined as two sided sharp knife. The firms that are selling their products for higher prices gets more profits, but they could sell less, and the firms that want to sell more product accept to get less profit for product. Less customer or less profit, or is there a mix of the both, if so what is this mix? These are the questions of firms and researchers from many disciplines had tried and still been trying to find the answer.

Pre-millennium, the global market faced with economical and political crisis mainly caused from developing countries which have great potential but financial problems. Furthermore, current global economic crisis influencing primarily developed countries has also financial base. Especially, in the previous two decade Turkish economy has faced with crises which are affecting Turkish banking system directly and mainly caused from the financial system. As a result of the policies implemented to resolve the crisis, Turkey's economy less affected by the current global economic crisis. As an idea; Uygur (2001), Zaim (1995), Ekinci & Ertürk (2007), Ercan et al. (2010) the working paper of Turkish Banking Regulation and Supervision Agency (2010) reveals the fact.

Especially under cruel conditions and ruthless competition of the global market the importance of efficiency increases day by day. Efficiency has become more important due to the technological and economic developments, because it is an undeniable fact that any social, political or economic crisis affects firstly the inefficient entities. It is also obvious in today’s global crisis conditions that efficiency is a must for overcoming the crisis.

However, the themes of this work will be efficiency from the customer and firm point of wiev. Hence, banks which are the main branches of financial system could be demonstrative for our purposes. In literature, Avkiran (1999), gave an application reference in bank branching to novice researcher, Cook & Hababou (2001) measures the sales performance of bank branches, Mercan *et al.* (2003) studied the financial performance of Turkish banking sector, Berger & Humprey (1997), Fethi & Pasiouras (2010), Paradi & Zhu (2013) made surveys about efficiency of banking sector from different point of wiev. Paradi *et al.* (2011) summerized the performance assessment of banks and bank branches and also discussed the relations of banks with customer under the title of service quality. However, none of these studies subjected directly to the customer's point of view. In other world, the customer was not the analyst, instead the analyser were the banks which consider attracting or manages customers. Thus, double side of the efficiency measurement would be made to a sample of Turkish Bank. For our purpose, DEA a well-known efficiency measurement technique proposed by Charnes et al. (1978) was used for the analyze and in this paper, the idea of Gölcükcü and Bal (2001), about customer based efficiency measurement was tested and expanded to double sided efficiency measure. Hence, for a double sided efficiency measurement the variables were selected specially. Cleary, for our analysis inputs of a bank had to be the outputs of a customer at the same time and outputs of a bank had to be the inputs of customer at the same time. Also, it was considered that the data had to be taken by customers by any means.

Under these circumstances two DEA analysis were made by using additive model of Charnes et al,(1985). It was expected that the two analyses results would be different from each other. The used model was given in the second section, the variables and the data was introduced in the third section. The results are tabulated and explained under two sub title in the fourth section. Lastly comparisons and conclusions and post-crisis status of the banks in the data set would be given in the final section.

THE METHOD

While the bank managers trying to increase the relative efficiency of their bank in the financial market, in the same manner the customers desire to determine the bank that they want to work with. In this paper, it is thought that DEA would be a useful tool for both the customer and the management sides of efficiency measurement. Therefore, DEA would be a useful tool for both sides of efficiency measurement. Since the pioneer work of Charnes *et al.*,(1978), many models and extensions of DEA had been evaluated. In this paper, the additive model of Charnes et al. (1985) which focuses on Pareto-Koopmans efficient empirical production function would be used to depict both costumer and firm efficiency. This model is also remarked as profit efficiency by Cooper et al. (2011) which we are focused on. The primal and dual form of Additive model could be given as in model (1) and (2). Our purpose is not the comparison of theoretical models but depicting and comparing the difference of customer and firm efficiency. So as, the original additive model would be used instead of extensions like Seiford and Zhu,(1998) or Sueyoshi, (1999).

Additive Primal Model (1)	Additive Dual Model (2)

$$\min_{\lambda, s^+, s^-} \quad z_0 = -\sum_r s_r^+ - \sum_i s_i^-$$
$$st.$$
$$\sum_j \lambda_j y_{rj} - s_r^+ = y_{r0}$$
$$\sum_j \lambda_j x_{ij} + s_i^- = x_{i0}$$
$$\sum_j \lambda_j = 1$$
$$\lambda, s_r^+, s_i^- \geq 0$$
$$r = 1,..., p,\ i = 1,...,k,\ j = 1,...,n$$

$$\max_{\mu, \nu, u_0} \quad w_0 = \sum_r \mu_r y_{r0} - \sum_i \nu_i x_{i0} + u_0$$
$$st.$$
$$\sum_r \mu_r y_{rj} - \sum_i \nu_i x_{ij} + u_0 \leq 0$$
$$-\mu_r \leq -\varepsilon$$
$$-\nu_r \leq -\varepsilon$$
$$r = 1,..., p,\ i = 1,...,k,\ j = 1,...,n$$

VARIABLES AND THE DATA

The variable selection is important in all kinds of analysis. In some cases, the variables that are used in an analysis could be output for one but input for another. Therefore, while the bank managers trying to increase the relative efficiency of their bank in the financial market; the customers desire to determine the bank that they want to work with. Thus, for our purposes the variables would be selected specially. Inputs of banks would be the outputs of the customers and also outputs of the banks would be the inputs of customers. Namely, for our analysis, inputs of a bank assumed to be the outputs of a customer and also at the same time outputs of a bank assumed to be the inputs of customer. Clearly, for the same data set, the input and output variables interchanged

It is considered that the data under the selected variables should be obtainable by customer in any way and it was thought that the easiest way of collecting the data is the economy pages of daily newspapers. Consequently, the newspapers that are sold in Turkey searched and the data taken from the newspaper Hürriyet dated to Feb, 18, 2001 was used in the analysis. Secondly, it was also considered that, for comparison and a double sided efficiency measurement, interchangeable variables selected. Thus, six variables presented in Table 1. were selected. The first three of those variables (TL, USD, DM) desired as inputs for banks and outputs for customers for the reason that it is paid by banks to customer and they provide income to customers. And the last three of those variables (KON, TST, TKT) desired as outputs for banks and inputs for customers for the reason that it is paid by customer to banks and they are the sources of incomes for banks. The raw banking data collected under the title of selected variables was given in Table 2.

Table 1. Variables

Variables	Definition
TL	Interest rates for Turkish Liras given by the bank to deposits per year
USD	Interest rates for United States Dollars given by the bank to deposits per year
DM	Interest rates for German Mark given by the bank to deposits per year
TKT	Interest rates for consumer credits taken by the bank from the customer per month
TST	Interest rates for automobile credits taken by the bank from the customer per month

KON	Interest rates for dwelling credits taken by the bank from the customer per month

Table 2. The Banking Data

DMU NO	BANKS	INPUTS(%)			OUTPUTS(%)		
		TKT	TST	KON	TL	USD	DM
1	AKBANK	5,25	4,95	5,25	25,89	12,00	12,00
2	ANADOLUBANK	8,50	7,50	7,50	20,04	10,00	10,00
3	DEMİRBANK	6,50	5,75	5,75	20,88	9,50	7,00
4	DENİZBANK	6,50	5,50	7,00	29,33	6,75	4,50
5	DIŞBANK	9,50	7,50	7,50	39,25	8,00	7,50
6	EMLAKBANK	6,00	5,50	6,00	26,00	9,00	7,00
7	ESBANK	6,25	6,00	6,00	34,24	7,50	6,50
8	FİNANSBANK	6,50	5,00	5,00	28,39	10,00	7,50
9	GARANTİ BANKASI	5,75	5,25	5,25	35,91	9,00	8,00
10	İŞ BANKASI	5,75	5,25	5,25	34,24	7,00	6,00
11	KENTBANK	7,75	7,25	8,00	26,72	8,50	7,50
12	KOÇBANK	6,95	5,65	5,65	36,74	8,25	6,75
13	OSMANLI BANKASI	8,50	5,95	5,95	33,40	7,50	5,25
14	OYAKBANK	5,95	5,45	5,45	37,58	11,00	9,25
15	PAMUKBANK	6,50	5,75	5,75	29,23	10,00	9,00
16	SİTEBANK	9,50	8,00	8,00	29,23	12,00	12,00
17	ŞEKERBANK	5,90	5,75	6,00	30,06	8,50	8,50
18	TEB	7,50	6,50	6,75	32,57	8,50	7,50
19	TOPRAKBANK	5,50	5,00	5,00	32,57	9,00	9,00
20	TÜRK TİCARET BANKASI	5,75	5,25	5,25	28,39	7,50	6,50
21	YAPI KREDİ BANKASI	5,25	5,00	5,25	26,72	9,50	7,50

ANALYZE RESULTS

MANAGEMENT SIDED EFFICIENCY

The interest rates, given for the money in deposits accounts and taken from the selected credits by banks are the decisions of bank management. As could be said by considering the interest rates of deposit accounts as the inputs of banks, and the interest rates of the credits as the outputs of banks, the relative efficiency of management of a bank among the others in the market could be measured. Therefore, additive model of DEA (1) was applied to measure the management efficiency of sample Turkish Banks and efficiency results was calculated by the formula (3) of Charnes (1985) and the results given in Table 3. According to these results

Table 3. Management based results of DEA Additive Model

KVB(Banks)	DEA Score	S^-_{TL}	S^-_{USD}	S^-_{DM}	S^+_{TKT}	S^+_{TST}	S^+_{KON}
AKBANK	0,646	3,25	2,55	2,25	5,85	2	2
ANADOLUBANK	1,000	0	0	0	0	0	0
DEMİRBANK	1,000	0	0	0	0	0	0
DENİZBANK	1,000	0	0	0	0	0	0
DIŞBANK	1,000	0	0	0	0	0	0
EMLAKBANK	0,878	1,409091	0,909091	1,277273	0,892727	0,772727	0

ESBANK	0,760	0	1,157143	6,917143	0	0,728571	0
FİNANSBANK	0,794	1,090909	1,590909	2,272727	4,127273	1,477273	0
GARANTİ BANKASI	0,766	2,022727	1,522727	2,068182	12,49182	0,181818	0
İŞ BANKASI	0,847	0,903846	0,403846	1,788462	5,624615	0	1,076923
KENTBANK	1,000	0	0	0	0	0	0
KOÇBANK	0,871	0,368182	0,668182	1,554545	11,21045	0,170455	0
OSMANLI BANKASI	1,000	0	0	0	0	0	0
OYAKBANK	0,727	2,277273	1,777273	1,981818	16,27318	1,443182	0
PAMUKBANK	0,817	1,636364	1,386364	1,659091	7,500909	0,590909	0
SİTEBANK	1,000	0	0	0	0	0	0
ŞEKERBANK	0,841	1,676923	0,826923	1,269231	5,732308	0	1,038462
TEB	0,940	0,076923	0,076931	0,519231	8,242308	0	0,038462
TOPRAKBANK	0,724	2,384615	1,884615	2,346154	9,671538	0	0,692308
TÜRK TİCARET BANKASI	0,857	1,211538	0,711539	1,865385	1,203846	0	0,730769
YAPI KREDİ BANKASI	0,776	2,340909	1,590909	2,022727	2,457273	0,977273	0

There are seven banks named Anadolubank, Denizbank, Dışbank, Kentbank, Osmanlı Banksı and lastly Sitebank takes the DEA score of 1 and determined as %100 efficient. As the results the other banks operates and inefficiently on the subjects we examine. The slack variables show the source and the amount of inefficiency.

CUSTOMER SIDED EFFICIENCY

In this section of the work in the sense that the interest of deposit accounts are the incomes of a customer, the three interest rates (TL, USD and DM) are taken as output and besides that, with the same sense that the interest of credits given by banks to customers are the expenses of a customer the three interest rates (TKT, TST and KON) are taken as inputs. Hence, the inputs of previous section were taken as output and also outputs were taken as inputs. For a brief comparison the same additive DEA model (1) was used and the results were presented in Table 4.

Table 4. Customer based results of DEA Additive Model

KVB(Banks)	DEA Score	S^+_{TL}	S^+_{USD}	S^+_{DM}	S^-_{TKT}	S^-_{TST}	S^-_{KON}
AKBANK	1,000	0	0	0	0	0	0
ANADOLUBANK	0,710	14,35182	1,272727	0	2,740909	2,186364	2,104545
DEMİRBANK	0,755	16,7	1,5	2,25	0,55	0,3	0,3
DENİZBANK	0,620	8,25	4,25	4,75	0,55	0,05	1,55
DIŞBANK	1,000	0	0	0	0	0	0
EMLAKBANK	0,817	11,58	2	2,25	0,05	0,05	0,55
ESBANK	0,797	3,34	3,5	2,75	0,3	0,55	0,55
FİNANSBANK	1,000	0	0	0	0	0	0
GARANTİ BANKASI	1,000	0	0	0	0	0	0
İŞ BANKASI	0,833	1,113333	3,111111	3,138889	0	0	0
KENTBANK	0,711	10,86	2,5	1,75	1,8	1,8	2,55
KOÇBANK	0,843	0,84	2,75	2,5	1	0,2	0,2
OSMANLI BANKASI	0,696	4,18	3,5	4	2,55	0,5	0,5

OYAKBANK	1,000	0	0	0	0	0	0
PAMUKBANK	0,900	8,35	1	0,25	0,55	0,3	0,3
SİTEBANK	1,000	0	0	0	0	0	0
ŞEKERBANK	0,869	6,685	2,571429	0,946429	0	0,335714	0,564286
TEB	0,793	5,01	2,5	1,75	1,55	1,05	1,3
TOPRAKBANK	1,000	0	0	0	0	0	0
TÜRK TİCARET BANKASI	0,833	6,9633	2,611111	2,638889	0	0	0
YAPI KREDİ BANKASI	1,000	0	0	0	0	0	0

It was seen that in customer based analyze, as could be expected the efficient and inefficient banks and the source and the amount of inefficiency had changed. At this time, eight banks named Akbank, Dışbank, Finasbank, Garanti Bankası, Oyakbank, Sitebank, Toprakbank and Yapı Kredi Banksı are efficient and on the frontier. The other banks are inefficient and the slack variables again show the source and the amount of inefficiency.

COMPARISON AND CONCLUSIONS

In this paper, the importance of efficiency was emphasized for both the entities and customer. Therefore, customer based approach and management based approach of efficiency was compared with each other by using additive DEA model. It is expected that the result of two approaches would be different from the other. The expectations confirmed by the results. It was seen that in management based approach seven banks were efficient (Anadolubank, Denizbank, Dışbank, Kentbank, Osmanlı Banksı and Sitebank), besides that in customer based approach we have eight efficient banks (Akbank, Dışbank, Finasbank, Garanti Bankası, Oyakbank, Sitebank, Toprakbank and Yapı Kredi Banksı). Despite of these result and the expectations it wass also seen that there was two banks named Sitebank and Dışbank was efficient in both situations but also there was eight inefficient bank in both approach (Emlakbank, Esbank, İş Bankası, Koçbank, Pamukbank, Şekerbank, TEB, Türk Ticaret Bankası). Inefficient banks had to be more careful in both sides. Efficient banks in management based DEA had to find ways to attract customers because their interest rates for credits were higher than the others but their profit rates are lower than the other banks. As a consequence it is undesirable for customers. On the other hand efficient banks in customer based analysis were the dreams of customers but they had to find ways to increase income.

Overall, the data was taken a few days before an economic crisis in Turkey. The last column of Table 5, shows the current situation of the banks in our anlaysis.

Table 5. Comparision of two model and current status of banks

KVB(Banks)	Customer based results of DEA	Management based results of DEA	Current status
AKBANK	1	0,646	active
ANADOLUBANK	0,71	1	active
DEMİRBANK	0,755	1	inactive
DENİZBANK	0,62	1	active
DIŞBANK	1	1	inactive
EMLAKBANK	0,817	0,878	inactive
ESBANK	0,797	0,76	inactive

FİNANSBANK	1	0,794	active
GARANTİ BANKASI	1	0,766	active
İŞ BANKASI	0,833	0,847	active
KENTBANK	0,711	1	inactive
KOÇBANK	0,843	0,871	active
OSMANLI BANKASI	0,696	1	inactive
OYAKBANK	1	0,727	active
PAMUKBANK	0,9	0,817	inactive
SİTEBANK	1	1	inactive
ŞEKERBANK	0,869	0,841	active
TEB	0,793	0,94	active
TOPRAKBANK	1	0,724	inactive
TÜRK TİCARET BANKASI	0,833	0,857	inactive
YAPI KREDİ BANKASI	1	0,776	active

Anyone who wants to know the recent situation of the banks has to repeat this analysis. Besides, all these efficiency rankings and results are valid for the used variables and data. DEA analysis shows the situation of DMUs according to the used variables and data set. This analysis will be repeated by accountancy variables to get more accurate results. It cannot be said that inefficient banks are bad but they were losing their potential. These results could be guide for both banks and customers for identifying their positions in market.

ACKNOWLEDGEMENT

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DATA ENVELOPMENT ANALYSİS APPLİCATİON ON İNDİCES OF SERVİCE, CONSTRUCTION AND MANUFACTURİNG SECTORS BY USİNG THE İNPUTS OF UNEMPLOYMENT AND İNFLATİON

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ABSTRACT

Countries must have solid economic fundamentals to have a say in economic respect in the world. Economic crises in recent years have adversely effected especially on developed and developing countries. In this study, inflation and unemployment, which are important economical indicators, are used as inputs. Service, construction and manufacturing sectors, which have important parts in Gross Domestic Product (GDP), are used as outputs. These are analyzed by CCR and BCC models for 25 European Countries. The results of the analysis obtained for the years 2005-2012 are evaluated within the frame of economical developments.

Keywords*: DEA, CCR, BCC, Inflation and Unemployment, Service, Construction, Manufacturing sectors*

INTRODUCTION

In globalized world economy, various concepts are used to evaluate the outputs obtained from the inputs of all small and large businesses. Efficiency and productivity, being used more frequently in recent, are the most important ones. In literature, Data Envelopment Analysis (DEA) based on the logic of linear programming comes at the beginning of efficiency measurement methods. CCR single input-single output efficiency measurement is suggested by Charnes, Cooper and Rhodes (1978) as a non-parametric method that can be used for multiple input-multiple output systems. In later years, BCC multiple input-multiple output efficiency measurement method that is based on variable return assumption instead of constant returns assumption in CCR is developed by Banker, Charnes and Cooper (1984). DEA making relatively comparisons in a whole separates the Decision Making Units (DMU) the two sets as effective and ineffective. This method gives an idea about how to make ineffective DMU more effective by changing their inputs and outputs. Inflation and unemployment are used as important parameters to compare economical and social structures of developing countries. Inflation and unemployment, which are directly related to the quality of life of the people, come at the beginning of Turkey's problems to solve. Inflation and unemployment values are monitored on a monthly basis by TUİK and regularly sent to EUROSTAT'S. These values are periodically published with other European Countries values.

There are various criterias for comparing development levels of countries. Gross Domestic Product (GDP) can be defined as money equivalent of all final goods and services produced of a country's for a specific period. GDP values are used by international assessment bodies (IMF, WB, UN,…) to evaluate the development levels of countries. Service, construction and manufacturing industries have an important part in GDP. International Economic Indicators is a publication compiled from data of WB and published by the Ministry of Development in 2012. Sector share in GDP of countries are given in this publication (Table 1). These important three sectors are followed by TÜİK and data are shared with EUROSTAT'S.

Table 1. Sector share in GDP of countries, Ministry of Development 2012

Countries	GDP,billions of dolars		Rate of GDP							
			Agriculture		Industry				Services (Construction, Trade,Transportation)	
					Total		Manufacturing Industry			
	1998	2011	1998	2011	1998	2011	1998	2011	1998	2011
Belguim	255,94	472,54	1,46	0,70	27,77	21,77	19,95	...	70,78	77,54
Bulgaria	13,16	53,55	18,39	5,36	27,30	31,39	18,97	16,24	54,32	63,26
The Czech Repuclic	63,86	197,67	...	...	...	...	...	...	...	...
Germany	2.181,16	3.312,19	1,24	0,09	31,02	28,17	22,80	20,92	67,73	70,96
Esthonia	5,60	18,95	...	...	...	...	...	...	...	...
Ireland	88,26	207,64	4,47	...	41,31	...	33,30	...	54,22	...
Greece	133,87	301,63	...	...	...	...	...	...	...	...
Spain	601,29	1.391,76	4,86	2,71	29,10	25,96	18,99	...	66,03	71,33
France	1.470,89	2.570,59	3,21	23,43	...	...	...	...	73,35	...
South Cyprus	9,43	23,00	4,17		20,59		10,65	...	75,24	...
Lithuanian	11,25	42,72	8,67	3,51	31,11	28,16	18,31		60,22	68,34
Latvia	6,73	28,25	4,00	4,14	27,58	21,81	16,36	12,18	68,43	74,05
Luxemburg	19,38	53,43	0,88	0,29	20,92	12,82	13,04	6,06	78,20	86,88
Hungary	171,20	514,50	5,95	3,54	32,86	31,63	19,32	18,49	61,19	64,83
Malta	3,87	8,17	2,87	1,92	47,58	32,70	20,47	13,41	49,55	65,38
Netherland	403,20	781,20	2,97	1,96	25,26	23,89	16,15	13,27	71,77	74,15
Austria	213,62	380,02	2,18	1,53	30,65	29,08	19,70	19,12	67,17	69,39
Poland	171,20	514,50	5,95	3,54	32,86	31,63	19,32	18,49	61,19	64,83
Slovenia	21,77	47,25	3,97	2,46	36,09	31,60	25,84	21,08	59,94	65,94
Slovakia	22,39	87,24	5,37	3,86	34,60	34,94	23,01	20,72	50,02	61,20
Finland	129,94	237,24	3,47	2,89	34,43	29,04	25,96	18,86	62,10	68,06
Sweden	257,84	469,32	2,45	1,83	29,29	26,39	21,96	16,27	68,26	71,77
England	1.462,14	2.267,48	1,18	0,72	28,51	21,67	19,44	11,43	70,31	77,61
Croatia	21,63	59,42	6,90	5,51	30,04	27,28	19,88	17,99	63,06	67,20
Turkey	269,13	731,29	13,58	9,60	35,54	26,65	26,04	17,70	50,87	63,75

For example; In 2011, The total share of the three sectors in GDP for Germany %91.88, Netherland %87.42, England %89.04, Turkey %81.45.

Economic crises experienced in recent years and are still going on some countiries affect unemployment, inflation and service-construction-manufacturing sectors used in our research. Within the this frame, data of 25 European countries are analyzed with DEA and score values are evaluated for the years 2005-2012.

METHODS

CCR and BCC output oriented models from classical DEA models are used in our research.

THE CCR MODEL:

Suppose that there are n DMUs to be evaluated in terms of m inputs and s outputs. Let xij (i= 1, …, m) and yrj (r =1, …, s) be the input and output values of DMUj (j= 1, …, n). Then the efficiency of DMUj can be defined as:

$$\theta j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x'_j}; j = 1, \ldots, n,$$

Where vi (i= 1, …, m) and ur (r =1, …, s) are respectively the input and output weights assigned to the m inputs and s outputs. To determine the input and output weights, Charnes et al. established the following well-known CCR model, which is named by their acronym:

$$
\begin{aligned}
&Maximize\,\theta_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{r=1}^{m} v_i x_{i0}} \\
&Subject \quad to\,\theta_i = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{r=1}^{m} v_i x_{ij}} \le 1,\ j = 1,\ldots n, \\
&\qquad u_r \ge 0,\ r = 1,\ldots,s, \\
&\qquad v_i \ge 0,\ i = 1,\ldots,m.
\end{aligned}
$$

THE BCC MODEL

Throughout this study we confine attention to technical aspects of efficiency so that no price or cost data are required. Suppose, therefore, that we have n DMUs where each DMUj , j= 1,…,n, produces the same s outputs in (possibly) different amounts, yrj (r=1,…s), using the same m inputs, xij (i=1,…,m), also in (possibly) different amounts. The efficiency of a specific DMU0 can be evaluated by the “BCC model” of DEA as introduced in Banker et al.(1984) which present in “envelopment from” as follows:

$$
\begin{aligned}
&\text{minmize } \theta_0 - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
&subject \quad to \quad \theta_0 x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^-, \quad i = 1,\ldots,m \\
&\qquad y_{r0} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+, \quad r = 1,\ldots,s \\
&\qquad 1 = \sum_{j=1}^{n} \lambda_j, \\
&\qquad 0 \le \lambda_j, s_i^-, s_r^+ \quad \forall_i, r, j.
\end{aligned}
$$

Data used our research is obtained from the website of EUROSTAT’S (http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/search_database). DEA is applied with the help of EMS programming (1.3 version) by using CCR and BCC output oriented models. Inverse of data of inflation and unemployment are taken to annihilate their negative effects in the model.

Inputs:

X1: Rate of unemployment-annual average

X2: Rate of inflation-annual average

Outputs:

Y1: Industry Sector Production Index-annual data (on 2010 basis)

Y2: Construction Sector Production Index-annual data (on 2010 basis)

Y3: Service Sector Endorsement Index-annual data (on 2010 basis)

RESULTS AND DISCUSSIONS

For the classification of the study it’s used classification of the World Bank. CCR-Output Oriented Model Score Values for 25 European Countries given in Table 2. In graphs 1, 2, 3, we can not observe the effect of the economic crisis experienced in 2009 on 25 European countries. However, we can see it for average score in graph 4.

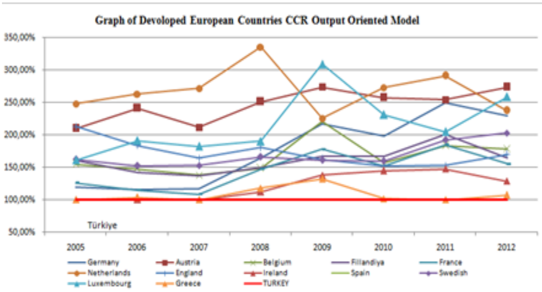
While the average score value of developed european economies was 171.96% in 2008, it became 190.42% in 2009. In other developed european economies the avarage score value was 186.83% in 2009, while it was 158.5% in 2008. The avarage score value of emerging and developing economies and european union candidate countries was 120.04% in 2008, it became %113.20 in 2009. Developed european economies decreased to 174.51% in 2010, in other developed european economies, score value decreased to 161.58% in 2010.

In graphs 5, 6, 7, we can see the effect of the economic crisis experienced in 2009 on 25 European Countries. Also, we can see it for average score in graph 8.

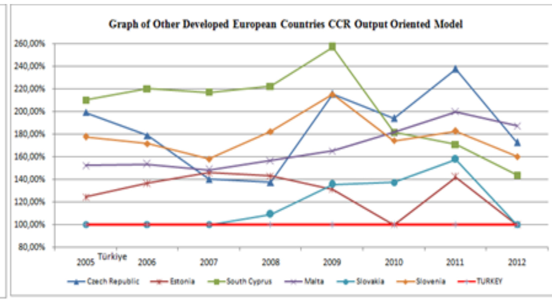
While the average score values of Developed European Economies was 107.7% in 2008, it became 110.42% in 2009.These values were 105.96% in 2008, 110.92% in 2009 for Other Developed European Economies. In Emerging and Developed Economies and European Union Candidate Countries, it can be said that they have an improvement with the decrease of the average score value from %104.84 in 2008 to%100.73.

Table 2. CCR- Output Oriented Model Score Values

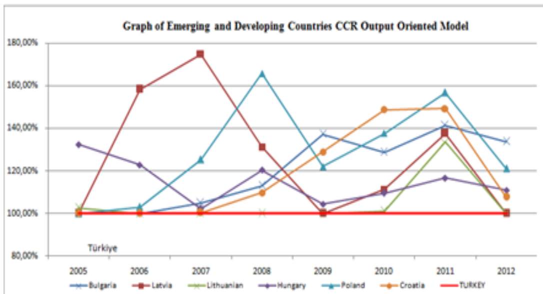
	Ülke	2005	2006	2007	2008	2009	2010	2011	2012	Average Score
Developed European Economies	Germany	120,04%	115,38%	116,89%	164,50%	217,55%	198,70%	250,16%	229,23%	176,56%
	Austria	209,58%	241,08%	211,45%	251,04%	273,95%	257,38%	254,24%	273,79%	246,56%
	Belgium	154,56%	147,00%	138,11%	148,31%	220,37%	156,88%	183,58%	178,83%	165,96%
	Fillandiya	160,15%	142,43%	136,76%	148,93%	167,54%	166,58%	201,20%	164,91%	161,06%
	France	125,70%	114,87%	108,25%	147,47%	177,82%	152,05%	185,08%	155,20%	145,81%
	Netherlands	247,81%	262,98%	271,87%	335,96%	225,76%	273,27%	290,96%	237,30%	268,24%
	England	212,87%	183,56%	164,01%	180,55%	162,01%	151,97%	153,09%	169,74%	172,23%
	Ireland	100,00%	100,00%	100,00%	112,16%	138,11%	144,50%	147,52%	128,75%	121,38%
	Spain	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%
	Swedish	162,16%	152,47%	152,70%	166,17%	160,83%	159,94%	192,22%	202,69%	168,65%
	Luxembourg	161,22%	191,38%	182,60%	190,26%	309,14%	231,35%	204,90%	258,88%	216,22%
	Greece	100,00%	103,52%	100,00%	118,18%	131,97%	101,47%	100,00%	107,37%	107,81%
Other Developed European Economies	Czech Republic	199,35%	178,89%	140,27%	137,27%	215,57%	194,25%	237,77%	172,81%	184,52%
	Estonia	124,44%	136,48%	146,04%	142,93%	131,14%	100,00%	142,04%	100,00%	127,88%
	South Cyprus	210,17%	220,34%	217,16%	222,53%	257,02%	181,78%	171,10%	143,72%	202,98%
	Malta	152,24%	153,40%	148,45%	156,82%	165,27%	181,79%	200,01%	187,48%	168,18%
	Slovakia	100,00%	100,00%	100,00%	109,19%	135,58%	137,38%	157,73%	100,00%	117,49%
	Slovenia	177,77%	171,77%	157,91%	182,28%	215,22%	174,30%	182,75%	160,11%	177,76%
Emerging and Developing Economies	Bulgaria	100,00%	100,00%	104,91%	113,06%	137,18%	128,69%	141,44%	133,68%	119,87%
	Latvia	100,00%	158,25%	174,84%	131,21%	100,01%	111,30%	137,49%	100,00%	126,64%
	Lithuanian	102,65%	100,00%	100,00%	100,00%	100,00%	101,17%	133,50%	100,00%	104,67%
	Hungary	132,39%	122,77%	102,29%	120,37%	104,29%	109,59%	116,70%	110,86%	114,91%
	Poland	100,00%	103,00%	125,30%	165,80%	122,04%	137,63%	156,74%	121,05%	128,95%
EU Candidate Countries	Croatia	100,00%	100,00%	100,29%	109,83%	128,89%	148,76%	149,30%	107,63%	118,09%
	TURKEY	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%



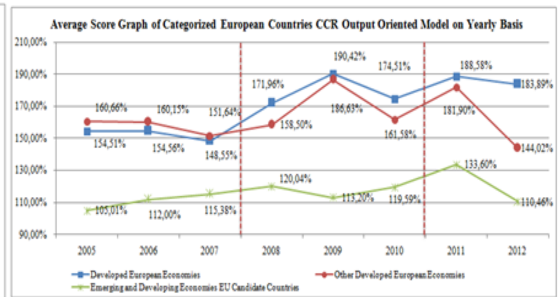
Graph 1. Graph of Devoloped European Countries CCR Output Oriented Model



Graph 2. Graph of of Other Developed European Countries CCR Output Oriented Model



Graph 3. Graph of Emerging and Developing Countries CCR Output Oriented Model



Graph 4. Average Score Graph of Categorized European Countries Output Oriented Model on Yearly Basis

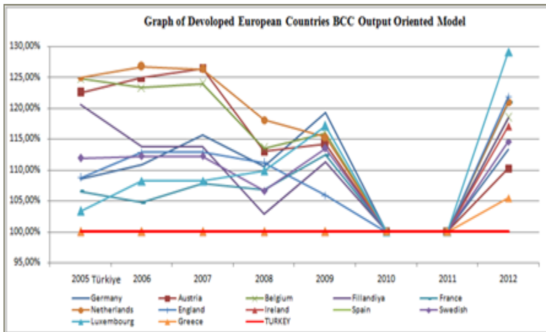
BCC-Output Oriented Model Score Values for 25 European Countries given in Table 3.

Table 3. BCC- Output Oriented Model Score Values

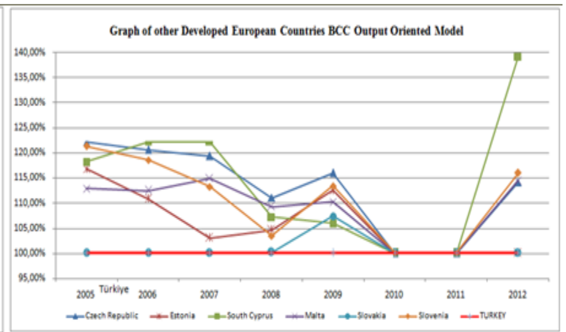
	Ülke	2005	2006	2007	2008	2009	2010	2011	2012	Average Score
Developed European Economies	Germany	108,51%	110,81%	115,71%	110,62%	119,34%	100,05%	100,05%	113,32%	109,80%
	Austria	122,51%	124,88%	126,44%	112,96%	114,21%	100,06%	100,06%	110,24%	113,92%
	Belgium	124,76%	123,30%	123,94%	113,49%	115,98%	100,10%	100,10%	118,40%	115,01%
	Fillandiya	120,57%	113,69%	113,69%	102,82%	111,26%	100,05%	100,05%	118,44%	110,07%
	France	106,51%	104,75%	107,82%	106,80%	112,42%	100,05%	100,05%	120,92%	107,42%
	Netherlands	124,99%	126,71%	126,27%	118,05%	115,34%	100,09%	100,09%	120,96%	116,56%
	England	108,70%	112,86%	112,86%	111,20%	105,85%	100,04%	100,04%	121,83%	109,17%
	Ireland	100,00%	100,00%	100,00%	100,00%	100,00%	100,09%	100,08%	117,02%	102,15%
	Spain	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%
	Swedish	111,91%	112,23%	112,23%	106,59%	113,48%	100,07%	100,07%	114,56%	108,89%
	Luxembourg	103,37%	108,23%	108,23%	109,84%	117,12%	100,05%	100,05%	129,13%	109,50%
	Greece	100,00%	100,00%	100,00%	100,00%	100,00%	100,10%	100,00%	105,43%	100,69%
Other Developed European Economies	Czech Republic	122,14%	120,59%	119,33%	111,07%	116,02%	100,04%	100,04%	114,15%	112,92%
	Estonia	116,76%	110,82%	103,07%	104,60%	112,50%	100,00%	100,00%	100,00%	105,97%
	South Cyprus	118,25%	122,24%	122,24%	107,17%	105,94%	100,05%	100,05%	139,13%	114,38%
	Malta	112,92%	112,44%	114,97%	109,22%	110,22%	100,06%	100,06%	114,51%	109,30%
	Slovakia	100,00%	100,00%	100,00%	100,17%	107,43%	100,00%	100,00%	100,00%	100,95%
	Slovenia	121,28%	118,59%	113,27%	103,52%	113,41%	100,14%	100,14%	116,00%	110,79%
Emerging and Developing Economies	Bulgaria	100,00%	100,00%	100,00%	100,00%	102,80%	100,00%	100,00%	111,18%	101,75%
	Latvia	100,00%	116,19%	106,20%	100,00%	100,00%	100,00%	100,00%	100,00%	102,80%
	Lithuanian	102,07%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,26%
	Hungary	121,81%	111,39%	100,82%	107,30%	100,00%	100,03%	100,01%	109,42%	106,35%
	Poland	100,00%	100,00%	116,54%	126,32%	102,31%	100,02%	100,02%	109,38%	106,82%
EU Candidate Countries	Croatia	100,00%	100,00%	100,00%	100,27%	100,00%	100,00%	100,00%	100,00%	100,03%
	TURKEY	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%	100,00%

CONCLUSIONS

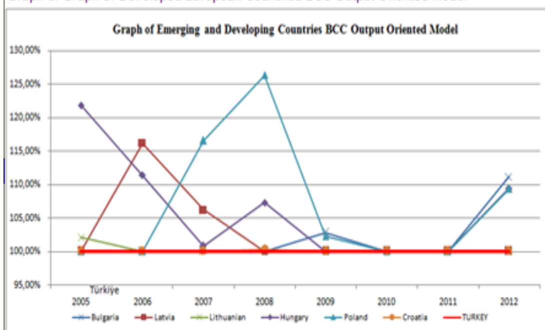
Countries, which is efficient in the CCR model, is also efficient in the BCC model. In the CCR and BCC models, measures taken by countries and international economic organizations for the economic crisis experienced are seen to be useful. However, the effects of the economic crisis in some European countries have continued in recent years. It would be more accurate to evaluate the crisis experienced by data obtained in the following years.



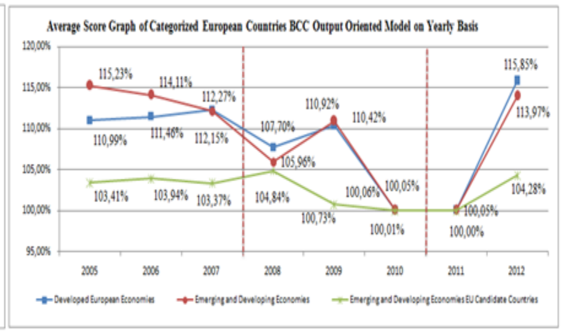
Graph 5. Graph of Devoloped European Countries BCC Output Oriented Model



Graph 6. Graph of Other Developed European Countries BCC Output Oriented Model



Graph 7. Graph of Emerging and Developing Countries BCC Output Oriented Model



Graph 8. Average Score Graph of Categorized European Countries Output Oriented Model on Yearly Basis

Remark: The score values DEA of Turkey and Croatia are idicated in the graphics of Emerging and Developing Economics.

The reflection to our model of the developments experienced in economic indicators and sectors of countries with small economies are more evident, but it is less for large economies.

When the study is evaluated for Turkey, Turkey seems as an efficient country in CCR and BCC models. In particular for the economic crisis experienced in 2009 is seen to be useful in the measures taken. Unemployment, inflation and industry-specific measures provide a solid foundation for the our country's economy. These measures taken are tax reduction, investment allocation, incentive law, employment package and loan guarantee fund. The application results show that measures taken in Turkey are the more successful than in European countries.

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DEA SCORES AS A DEBIASING TOOL TO PREVENT THE "DECOY EFFECT"

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ABSTRACT

Choice has been shown to be usually made in relative terms, i.e., by comparing easily comparable alternatives and avoiding those that are not easily comparable. Introducing an alternative (A^{-}) which is worse than another one (A) but very similar to it facilitates the comparison among these two alternatives. As a consequence, the non-dominated alternative (A) appears to be not only better than the dominated one (A^{-}), but also better than any other alternative. This effect is known as the decoy effect. In a performance evaluation context, the choice of the best performing decision making unit (DMU) may be susceptible to the decoy bias. We experimentally evaluate the occurrence of this bias for an evaluation case in which Data Envelopment Analysis (DEA) scores are provided/not provided. The results show that the decoy effect occurs in the treatment without DEA scores, but it is neutralized in the treatment including DEA scores, thus suggesting that the presence of DEA scores may serve as an appropriate debiasing tool. This has significant managerial implications, since DEA scores may help evaluators to concentrate their attention on all efficient DMUs, avoiding that some DMUs profit from their similarity to any dominated DMU.

***Keywords**: performance evaluation; decoy effect; debiasing procedure; DEA*

INTRODUCTION

There is overwhelming evidence that performance ratings and evaluations are context dependent. Evaluators' preferences are influenced not only by the past performance of a DMU, but also by the performance of other DMUs under analysis (Woehr & Roch, 1996). A special case of such context effects is the decoy effect, which implies that the inclusion of a dominated alternative can influence the choice of the best performing DMU. Adding a decoy to the choice set alters the preferences of the decision maker, increasing the attractiveness of the dominating alternative (Wedell & Pettibone, 1996). Ariely (2009) suggests that the decoy effect occurs because the decision maker cannot easily elaborate the trade-offs necessary to choose between the two superior alternatives. The introduction of a dominated alternative permits the decision maker to reduce the cognitive load by creating a simple relative comparison between the decoy and the target. If this effect occurs, the question arises whether the incorporation of DEA scores can act as a debiasing tool.

To shed a light on these questions, we conducted a vignette-based experiment with bachelor students taking different management control and business accounting courses. The traditional experimental setting from the area of consumer behavior was adapted to the performance context since performance evaluators were expected to behave similarly to consumers in a choice task. This means that managers will favor the targeted subsidiary when a decoy is included in the choice set. Replicating previous experimental research, we present a case describing the performance of two superior subsidiaries and an asymmetrically dominated one by means of four attributes.

Supposed that the decoy effect is originated on focusing attention on the decoy and the target option, redirecting decision maker's attention towards all superior alternatives could act as a debiasing procedure. One possible method to do this is incorporating an attribute that is easily comparable among alternatives and that could serve as a performance marker. Thus, reporting an overall performance measure, e.g., using DEA, might serve as a debiasing mechanism. The superior alternatives will be identified by DEA as efficient DMUs, while dominated decoys will be characterized as inefficient DMUs. DEA scores are expected to serve as relevant clues for decision makers, who will eliminate inefficient DMUs from further analysis, thus reducing the choice set just to the two superior alternatives.

The results show that adding a dominated DMU to the choice set augments the attractiveness of the target DMU. Therefore, a decoy effect can be observed when DMUs are compared with one another with the aim of determining the best performing one. The role of reporting DEA results as a debiasing procedure for the identified decoy effect is considered. Participants in the corresponding treatments were provided with additional information about DEA scores. The results indicate that DEA scores discriminating between efficient and inefficient DMUs can significantly reduce the decoy effect in a relative performance evaluation context.

METHODS

Participants and design

Bachelor students (N = 327) taking introductory management control and business accounting courses at a German university received during a lecture a vignette presenting a performance report. The majority of the students were male (77%). Two different control conditions were considered, one containing DEA scores and one without any kind of performance aggregation measure. A total of six treatments were analyzed. Students were randomly assigned to each of the different conditions.

Case materials and procedure

A short vignette presenting the case of a delivery chain with two/three subsidiaries was presented. The participants were required to assume the role of the central management and to decide within five minutes which of these subsidiaries deserves a bonus based on the available performance criteria. All participants received a table containing the data of two criteria to be minimized and two criteria to be maximized for each of the subsidiaries. The DEA conditions also included a brief description of the method and the corresponding DEA efficiency scores. The participants were informed that the aim of the study was to capture the different responses to a performance assessment case from a descriptive point of view, implying that there was no "right" or "wrong" answer. If fact, choosing the decoy as the best performing DMU would be an irrational choice but the instructor preferred to reduce the stress of the participants by avoiding this information.

The attribute values of the superior DMUs were selected so that both alternatives appear approximately equally attractive and each of them is selected by about half the participants (Connolly et al., 2013). The decoys were created by changing the original values in less than 10%. The purpose of this small variation in each of the performance criteria was to create almost efficient decoys with the same DEA scores. Table

1 presents the values corresponding to each of the performance criteria for the two superior DMUs and each of the decoys.

Table 3: Performance criteria

Performance criteria	**A**	**B**	**A⁻**	**B⁻**
To be minimized				
Number of call-center employees (monthly average)	43	25	45	27
Number of complains (daily average)	34	56	37	59
To be maximized				
Processed purchase orders of clothing articles (hourly average)	190	120	186	119
Processed purchase orders of household articles (hourly average)	134	202	127	198
Efficiency score (θ)	100%	100%	96%	96%

RESULTS AND DISCUSSIONS

The decoy effect in a performance evaluation context

The principle of regularity states that the probability of choosing an element *x* from a set A cannot be inferior to the probability of choosing this element from a set B, when A is a subset of B. In this case, B = {*a*, *b*, *c*}, where *a* corresponds to the subsidiary A, *b* to the subsidiary B, and *c* to the decoy, and A = {*a*, *b*} represents the control condition. The experimental results indicate that this axiom is violated in the context of performance evaluation (see Table 2). As shown in Fig. 1, the percentage of participants choosing subsidiary A as the best performing DMU increases when a decoy dominated by this alternative (A^-) is included in the choice set. The same occurs for the case of subsidiary B, when the corresponding decoy (B^-) is presented.

Table 4: Choice preferences in the treatments without DEA scores

		Choice proportions		
Choice set	**N**	**A**	**B**	**Decoy**
A, B	57	0.614	0.386	–
A, B, A^-	53	0.755	0.208	0.038
A, B, B^-	55	0.481	0.463	0.056

Analyzing the results for the different choice sets, an individual choice reversal due to the incorporation of decoys can be identified. The probability of evaluating DMU A as the best performer is superior when A^- is added to the choice set (75.5%) than when a B^- is included (48.1%). For the case of DMU B, the probability of choosing it as the best performer increases from 20.8% to 46.3% when B^- is added instead of A^-. The addition of A^- and B^- significantly altered the choice made by the evaluators (P(A): z = 2.915, *p*-value = 0.004; P(B): z = 2.802, *p*-value = 0.005). Fig. 1 graphically shows the results for the case that no DEA scores are provided.

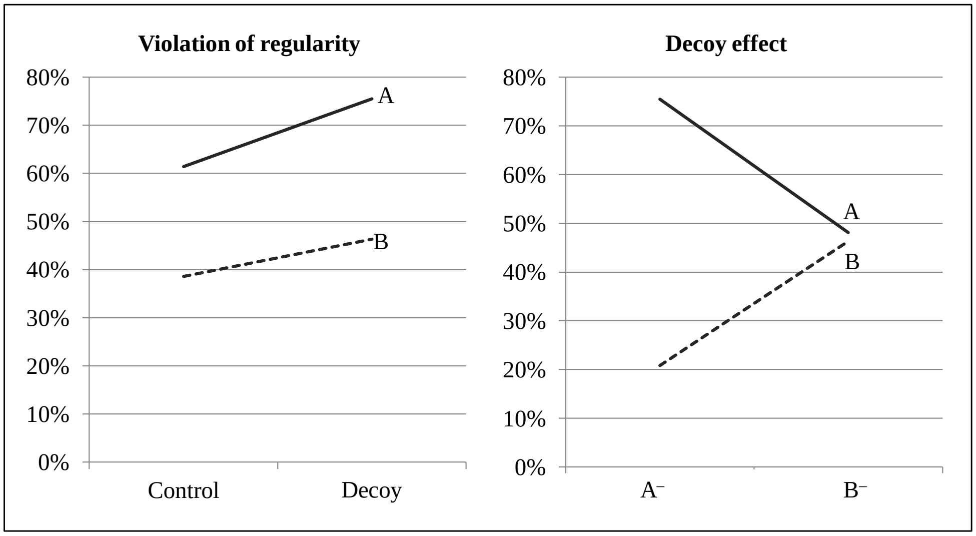

Fig. 1: Visualization of the choice preferences for the treatments without DEA scores

These experimental results suggest that performance evaluation is likely to be affected by the decoy effect, at least when a few subsidiaries have to be compared based on a manageable number of performance criteria.

Using DEA as a debiasing mechanism

The decoy effect in performance evaluation is problematic not only regarding the fairness of the appraisal, but also with respect to strategic consequences. When two DMUs are attaining a superior performance, but they are not easily comparable, the inclusion of a third DMU with a lower performance appears to be critical for the decision of which DMU should be presented as a benchmark for all others. This problem may be avoided by incorporating an overall performance measure that highlights the difference among efficient and inefficient DMUs. This debiasing procedure is expected to focus decision maker's attention on the two efficient DMUs, thus avoiding the effect of the decoy alternative on the choice.

Table 5: Choice preferences in the treatments with DEA scores

		Choice proportions		
Choice set	**N**	**A**	**B**	**Decoy**
A, B	55	0.585	0.415	–
A, B, A^{-}	56	0.661	0.286	0.054
A, B, B^{-}	51	0.490	0.471	0.039

Reporting DEA scores that differentiate among efficient and inefficient DMUs seems to act as a debiasing procedure for reducing the decoy effect (see Table 3). The proportion choosing subsidiary A as the best performing when A^{-} is added to the choice set does not significantly differ from the corresponding proportion when B^- is included (P(A): z = 1.791, *p*-value = 0.073). However, this result is not concluding for the proportion choosing subsidiary B (P(B): z = 1.976, *p*-value = 0.048).

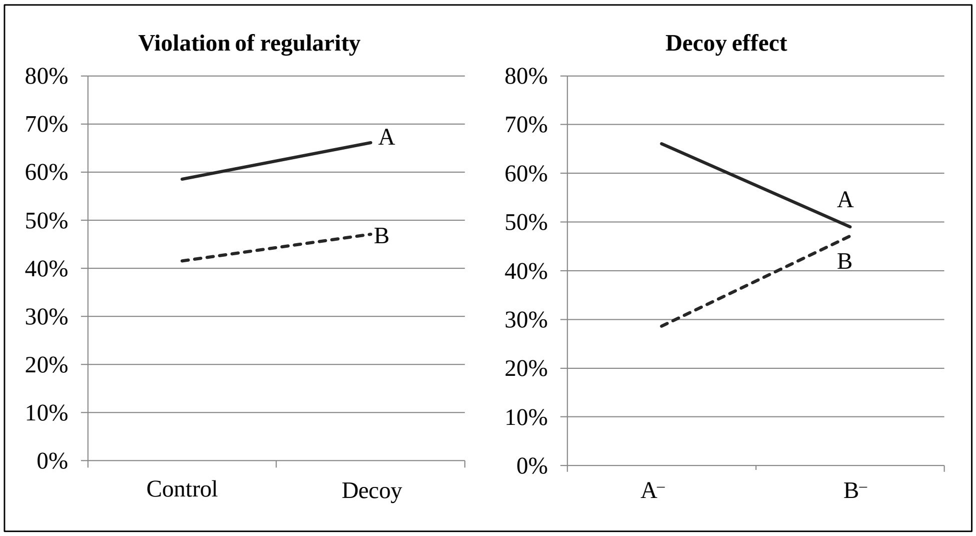

Fig. 2: Visualization of the choice preferences for the treatments with DEA scores

In general, reporting DEA scores contributes to a reduction of the decoy effect, but directional effects are still observable: the regularity condition is violated (see Fig. 2, left part) and the tendency to prefer the target alternative can still be recognized (see Fig. 2, right part). A possible explanation may be that inefficient decoys with high DEA scores are not immediately dismissed from the analysis, thus still influencing decision maker's choice.

CONCLUSIONS

The present study offers an analysis of the decoy effect in a performance evaluation context, focusing on the debiasing characteristics of DEA scores. The traditional experimental setting commonly used in consumer behavior was slightly modified with the aim of adapting it to a relative performance evaluation case. To the best of our knowledge, it constitutes the first attempt to evaluate the consequences of the DEA approach on the occurrence of this kind of context effect. The results of the experiments indicate that the relative performance evaluation at least of a small number of DMUs is susceptible to decoy effects and that DEA scores may help to eliminate this bias.

As expected, the addition of the decoys significantly altered the decision made by evaluators. When the decoys were added to the choice set, the proportion of participants choosing the target DMU as the best performing DMU significantly increased. This can raise managerial issues not only regarding the fairness of the appraisal, but also about its strategic consequences, especially due to its influence on the selection of benchmarks (Page & Page, 2010). This effect is expected to be even stronger in real performance evaluations than in the experimental conditions, as the central management will usually need to justify its judgments when providing feedback to the DMU managers (Simonson, 1989).

Our second main result indicates that reporting DEA scores that differentiate among efficient and inefficient DMUs seems to act as a partial debiasing procedure for the decoy effect. Adding a decoy accompanied by the corresponding DEA scores did not cause significant differences in the proportion of participants choosing the target DMU as the best performing subsidiary. Nevertheless, a directional effect is still observable, thus suggesting that inefficient decoys with a high DEA score may not be immediately dismissed from further search for the best DMU.

Our findings need to be interpreted in light of various limitations. A main critic to our design may be that the results were obtained from a bachelor students' sample. Therefore, it is advisable to be cautious with the generalizations being drawn from our experiments. Additionally, the participants did not have previous experience with DEA and their knowledge of this approach was limited to the brief explanation included in the vignette. Nevertheless, our experience with implementing DEA in companies suggests us that managers using DEA results for performance evaluations will also not have a much more comprehensive understanding of the approach. Finally, the number of DMUs included in the report was lower than the recommended one for reaching a reasonable level of discrimination in DEA performance evaluations. Since the purpose of the experiment was to study the debiasing role of DEA scores on the decoy effect and not to deal with methodological aspects of the DEA approach, a standard decoy experimental with only two/three alternatives setting was chosen. Incorporating more alternatives to the choice set could have created noise, hindering hypothesis testing.

Further research needs to be conducted towards achieving an exhaustive understanding of behavioral performance evaluation and the possible debiasing role of DEA. For example, the addition of other kinds of decoys and the occurrence of the other kinds of effects should be analyzed.

ACKNOWLEDGEMENT

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DEA-EFFICIENCY OF TRADITIONAL FARMING WITH CONSIDERATION OF GRASSLAND BIODIVERSITY: THE CASE OF THE UKRAINIAN CARPATHIANS

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ABSTRACT

Land abandonment and/or agricultural intensification are the most probable scenarios which could be expected for remote mountainous areas in Eastern Europe. Both of them can be a threat to the situation existing in the rural areas of the Ukrainian Carpathians where a high degree of connectivity between farming activities and the ecosystem still exists. In this area certain agricultural practices are more conducive to biodiversity than others. In the paper we aim at building an economic-ecological model to evaluate the efficiency of farming performance in this area with special consideration of such positive environmental externality as grassland biodiversity. DEA (Data Envelopment Analysis) is considered as a suitable method for this evaluation and for identification of the farming management patterns which are most efficient from economic and environmental perspectives. The data from socioeconomic and geo-botanic surveys conducted in the Ukrainian Carpathians were used to show how the method can be applied to evaluate the farming efficiency at the research sites.

This paper is a contribution to the development of the DEA method for the purposes of evaluation of environmental aspects in agricultural production and a trial to analyse economic and environmental performance of farming practices which produce such positive externality as biodiversity.

***Keywords**: efficiency; traditional agriculture; positive environmental externalities; biodiversity; DEA method.*

INTRODUCTION

Trends of land use change connected to land abandonment have been observed in many areas of Europe. This phenomenon appears more frequently in the less favourable areas (LFA) which have difficult geographical and climate conditions, in particular mountain regions (MacDonald et al. 2000, Dullinger et al. 2003). A common alternative scenario examined in literature is agricultural intensification or modernisation which can be observed in some relatively prosperous mountainous landscapes as a finalised process of land use change (Tasser & Tappeiner 2002). As opposed to this situation, the rural areas of the Carpathian Mountains are currently representing the state of the development where these processes have not been yet finalised but have already started (Nuppenau et al. 2011); to find indicators for this development and its direction is an important and exciting research topic.

The Ukrainian part of the Carpathians is still characterised to a certain and large extent by low-intensity traditional farming as well as still exhibits high biodiversity and has partly intact landscapes. Since the level of biodiversity is closely connected to the type and intensity of farming (Kleijn et al., 2009), we can argue that various farming practices have a certain impact on species diversity. Therefore, if we assume that there is a certain variation in farming intensity and in agricultural practices (even within the homogenous group of low-intensity farmers), the environmental performance might also vary. To measure these variations, it is important to include analysis of environmental performance (the level of grassland biodiversity in our case) into the evaluation of the farming efficiency. Although the concept of environmental (or ecological) efficiency is quite ambiguous and there are various approaches to its definition (Kuosmanen and Kortelainen, 2004; Reinhard et al., 1999), this kind of analysis is a suitable approach within the context of the current research.

The aim of this paper is to develop further the environmental efficiency approach which would allow to consider ecological and economic parameters simultaneously and to examine the question of possibilities to measure economic performance in agriculture with the consideration of positive environmental externalities. The implementation of such analyses in the area with traditional farming implies certain peculiarities in specification of inputs and outputs for the efficiency analysis.

METHODS

Data Envelopment Analysis (DEA) has been used in some studies to evaluate the performance efficiency of decision making units with consideration of environmental parameters (e.g. De Koeijer et al., 2002, Reinhard et al., 2000, Sipiläinen et al., 2008, etc.). Due to some of its characteristics it is regarded as a suitable method for our research. For instance, the fact that minimal prior assumptions are made with respect to the functional form or weights is especially beneficial for the case of environmental evaluation since subjective assessment is this case is quite a difficult task (Kuosmanen and Kortelainen, 2004, p.7, Kuosmanen and Kortelainen, 2005, p.64).

Following the approach of Sipiläinen et al. (2008), positive environmental externality (in our case grassland biodiversity) is introduced as a desirable output into the modified formula of output-oriented technical efficiency. For this the output distance function is used in which efficiency is obtained by increasing the outputs with the constant inputs (Sipilainen et al., 2008, Färe et al., 1994, Mulwa, 2006):

$$(D_o(x,y))^{-1} = Max\,\theta_k = Max\{\theta > 0 : \theta y_k \in S\}$$

s.t.

$$\theta Y_{kj} \leq \sum_{i=1}^{N} Y_{ij}\lambda_i\, , j = 1, \ldots M \qquad (1)$$

$$X_{kr} \geq \sum_{i=1}^{N} X_{ir}\lambda_i\, , r = 1, \ldots L$$

$$\lambda_i \geq 0$$

$$\sum_{i=1}^{N} \lambda_i = 1$$

where: $\boldsymbol{D_o(x, y)}$ is an output-distance function which refers to N DMUs (Decision Making Units) $(i = 1, \ldots, N)$;

$\boldsymbol{\theta}$ is the efficiency measure which estimates the maximum possible expansion of output y of farm k. In this formulation for the linear programming problem θ is a degree with which the outputs y can be expanded, while remaining producible by input vector x. This measure is reciprocal to the output-distance function and is acquiring a value between 0 and 1;

x is the set of inputs $x = (x_1, \ldots, x_l)$;

y is the set of outputs $y = (y_1, \ldots, y_m)$;

$\boldsymbol{\lambda}$ are intensity variables or weights attached to each DMU;

S is the boundary of production possibilities or the reference technology constructed from the data. The reference technology forming the frontier is represented by the set of the constraints.

For our efficiency analysis of farms performance we use the formula 1 to analyze, first of all, the regular efficiency of the farmers without consideration of the environmental output (Eff1). Secondly the same formulation of the LP problem will be used to consider both: conventional and environmental outputs (EnvEff1). Thus, we check possibility to optimize the production of both outputs (Sipilainen et al., 2008, pp. 10-11).

We use two main sources of data for this article. First of all there is a socioeconomic survey conducted in the Ukrainian Carpathians with the aim to analyze the farming and grassland management system prevailing in the Ukrainian Carpathians, in particular with consideration of production itself and the influence on the environment (Solovyeva et al. 2011). Altogether 33 households were interviewed. The main prerequisite for choosing households for the survey was ownership of high altitude grasslands (hay meadows or pastures). We also tried to consider different access options to machinery, income sources, different status, etc. to present possibly full picture of management types in the study regions.

Beside economic data, botanic data on plant biodiversity of the mountain grasslands were collected with the help of a geo-botanic survey related to every questioned household. The Braun-Blanquet methodology was used for this survey (Poore, 1955). The distinct data on the following aspects was gathered for 60 sites related to the interviewed households: environmental features of the plot, land use history, height and percentage cover of vegetation, list of the plant species presented on the plot, how those species are represented.

After the preliminary statistical analysis of the data the specification of inputs and outputs is made for the model. Labour, fertilizers, capital and land are chosen as conventional inputs. The conventional output is represented in the form of volume index which includes all the agricultural products produced by the households. The environmental output was represented as a specially introduced biodiversity indicator (aggregated biodiversity index calculated on the basis of the available data).

RESULTS AND DISCUSSIONS

General Algebraic Modelling Systems (GAMS) has been used to evaluate the efficiency of environmental and economic performance of the farms. The average efficiency scores for each evaluation case are summarized in Table 1 of the Appendix. The mean efficiency of the production in case when environmental performance is not considered (Eff1) shows the lowest value in comparison to anther evaluation option (mean efficiency score=0,57). Only about one third of farmers are efficient within this type of analysis and about half of them have really low efficiency scores (below 0,5). These results are partially reflecting the character of semi-subsistence type of farming which is spread in the study area. However we can see that in case when the environmental output (grassland biodiversity indicator) is considered, the mean efficiency of the farmers is significantly higher (=0,90). In case we consider the proportionate increase of both outputs (EnvEff1), the amount of efficient farmers increases up to 54% and there are no farmers with the efficiency below 0,50 (see table 1 of the appendix).

We see that the efficiency scores differ quite a lot between the evaluation options however their comparison does not give us much valuable information since we cannot directly compare these values coming from different production sets. Therefore we check how the efficiency rankings of the farms are changing with different evaluation options (Areal et al., 2012) (see Table 2 of the appendix). This gives us two groups of farms: one group represents the households whose efficiency scores in case of consideration of environmental component are improved in comparison to the regular production efficiency analysis, the second group includes farmers whose efficiency scores for EnvEff1 decrease in comparison to Eff1. Distinguishing of these two groups provides the basis for the following analysis of the sources of inefficiencies which have an impact on the farming activities.

CONCLUSIONS

The results of this research present the efficiency evaluation of the farming in the Ukrainian Carpathians. The paper further elaborates the DEA efficiency method in order to approach the analysis of environmental efficiency with consideration of positive externalities such as grassland biodiversity.

Taking into consideration the described peculiarities of traditional farming with respect to the regions in Ukrainian Carpathians and the special features of the considered DEA-method, the application of the environmental and economic efficiency evaluation method can contribute to the agri-environment policy in few ways:

- It gives possibilities for farmers' performance evaluation which might be used for policy decisions, justification and design of the suitable support measures;
- It can contribute to the targeting of the policy support: in case of traditional farming this method would allow to identify the farmers which are less efficient with respect to economic and environmental performance;

- Depending on the outcomes of the efficiency analysis (and efficiency in this case is identified as environmental efficiency) the groups of farmers can be identified which need support.

This paper is a contribution to the research on the influence of traditional farming on the biodiversity and at the same time a trial to develop the environmental efficiency approach for the evaluation of economic and environmental performance of farms with consideration of positive environmental externality.

APPENDIX

Table 1. Efficiency scores

Parameter	Definition	Mean	Std. Deviation	% of farms where efficiency score =1	% of farms where efficiency score is below 0,50
Eff1	Efficiency of production without consideration of environmental output (one output-four inputs model)	0,57	0,33	30,10%	48,50%
EnvEff1	Efficiency of production with consideration of environmental output: both outputs are maximized (two outputs-four inputs model)	0,90	0,15	54,50%	0,00%

Table 2. Comparison of efficiency rankings

Farm	Rank of Eff1	Rank of EnvEff1	Change in rankings	Farm	Rank of Eff1	Rank of EnvEff1	Change in rankings
8	30,5	9,5	21	23	15	30	-15
20	30,5	9,5	21	24	18,5	33	-14,5
1	28,5	9,5	19	27	13	27,5	-14,5
16	26	9,5	16,5	11	12	26	-14
6	24	9,5	14,5	25	16	27,5	-11,5
33	23	9,5	13,5	5	20	31	-11
17	21	9,5	11,5	15	18,5	29	-10,5
22	32	21	11	29	10	20	-10
21	28,5	19	9,5	26	17	25	-8
10	33	24	9	28	27	32	-5
7	14	9,5	4,5				
2	25	23	2				
31	11	9,5	1,5				

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DECISION MAKING UNITS WITH INTEGER VALUES IN DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Usually in many applications some of inputs or outputs data may characteristically be integer values such as the number of students, hospitals and vehicles. However, the traditional Data Envelopment Analysis (DEA) models would project a Decision Making Unit (DMU) onto targets that generally do not respect such type of integrality constraints. There are some methods in DEA to assess the performance of DMUs inclusive integer-valued data. This study surveys the previous Mixed Integer Linear Programming (MILP) and illustrates the flaw of them with some counter examples. The study improves the previous MILP models and characterizes its capabilities with a numerical example. The simulations have been also performed with Lingo11/win64 software.

***Keywords**: Data Envelopment Analysis, Arash method, Mixed integer linear programming, Benchmarking, ranking.*

INTRODUCTION

Lozano and Villa [1] addressed the shortcomings of conventional Data Envelopment Analysis (DEA) models in rounding down/up the target values of Decision Making Units (DMUs) which are restricted to the set of integer numbers. They proposed an integer Production Possibility Set (PPS) with a Mixed Integer Linear Programming (MILP) DEA model to guarantee the required integrality of the computed targets. Soon later, Kuosmanen and Kazemi Matin [2, 3] argued that the theoretical foundation of the Lozano and Villa’s Model (LVM) is ambiguous, because it is not consistent with the minimum extrapolation principle [4]. They also claimed that LVM overestimates the efficiency results and tried to propose an integer axiomatic foundation in DEA with a suggested improved MILP. However, Khezrimotlagh et al. [5] commented on those papers, and claimed that the mentioned shortcomings are not valid. They also identified the flaws in the proposed axioms of Kuosmanen and Kazemi Matin [2, 3] and improved them. Khezrimotlagh et al. [6] also proved that the proposed input target of the Kuosmanen and Kazemi Matin Model (KKM) in input-oriented case may not be less than that of LVM. There are also some non-redial models suggested by Lozano and Villa [7], Wu and Zhou [8], and Du et al. [9], however, Khezrimotlagh et al. [10] identified that none of these models are simultaneously able to arrange and benchmark technically efficient and inefficient DMUs discussed in [11]. Khezrimotlagh et al. [10] also illustrated that the proposed super-efficiency model by Du et al. [9] is not a harmless model to rank DMUs. Therefore, they proposed a novel robust MILP based on the Linear Kourosh and Arash Model (L.KAM) [11] called Integer-KAM (IKAM) in order to remove all the previous mentioned shortcomings.

This paper introduces Linear Integer Arash Method (IAM) and depicts the shortcomings in the current MILPs. The paper also reviews on the discussions in [5, 6, 10].

The shortcomings in the current MILPs

The work of Kuosmanen and Kazemi Matin's papers [2, 3] can be classified into three different parts. The first part is "the proposed axioms for integer-valued DEA", the second part is "the proposed mixed integer linear redial model" and the third part is "the presented results of LVM and KKM in the numerical example".

For the first part, Khezrimotlagh et al. [5] illustrated that the conventional DEA axioms are enough to operate with integer and real values. Because as data are restricted to the set of integer numbers set, the axioms can also be restricted to the set of integer numbers set. Besides if we would interest to have a direct axiomatic foundation to operate integer values, the axioms should not include the real values. However, Kuosmanen and Kazemi Matin [2, 3] used the variable 'λ' in their proposed axioms with the conditions such as $0 \leq \lambda \leq 1$. *If it is supposed that λ is integer, therefore, $\lambda = 0$ or $\lambda = 1$, and the axioms are not valid to make the right PPS. Therefore, Khezrimotlagh et al. [5] supposed to replace two integer numbers u and v with λ, and proposed the following improved axioms:*

a) Natural disposability: $(x, y) \in T$ and $(u, v) \in \mathbb{Z}_+^{m+s}$, $y \geq v \Longrightarrow (x + u, y - v) \in T$,

b) *Integer convexity*: $(x', y'), (x'', y'') \in T$, $\exists u, v \in \mathbb{Z}_+$, $u \leq v, (x, y) \in \mathbb{Z}_+^{m+s}$, and $(x, y) = \frac{u}{v}(x', y') + \left(1 - \frac{u}{v}\right)(x'', y'') \Longrightarrow (x, y) \in T$,

c) *Integer divisibility*: $(x, y) \in T, \exists u, v \in \mathbb{Z}_+ : u \leq v, \left(\frac{u}{v}x, \frac{u}{v}y\right) \in \mathbb{Z}_+^{m+s} \Rightarrow (\frac{u}{v}x, \frac{u}{v}y) \in T$,

d) *Integer augment-ability*:$(x, y) \in T, \exists u, v \in \mathbb{Z}_+ : u \geq v, \left(\frac{u}{v}x, \frac{u}{v}y\right) \in \mathbb{Z}_+^{m+s} \Rightarrow (\frac{u}{v}x, \frac{u}{v}y) \in T$,

   where $\frac{a}{b}c \in \mathbb{N}$, for $a, b, c \in \mathbb{N}$, if $b|c$, i.e., b divides c, that is, there is an integer t such that $c = bt$, and $\mathbb{Z}_+ = \mathbb{N} \cup \{0\} = \{0,1,2, \dots\}$.

For the second part, Khezrimotlagh et al. [6] gave a counter example which depicts that the proposed input target of KKM may not be less than that of LVM in input-oriented case. The input target of LVM in input-oriented case may even be less than the input target of KKM in input-oriented case even if the generated space by the KKM constraints is greater than that of LVM constraints. This phenomenon firstly recognized the shortages of redial approach to benchmark DMUs and secondly illustrates that, although, in input-oriented case the less value of inputs are interested, the values of outputs should also be considered. Because, the models in input-oriented case have input and output constraints and the optimum targets are selected within the points with less input and more output values. Therefore, it is not reasonable that in input-oriented case, the input values are only considered. By this reason, LVM and KKM are equivalent in their proposed targets, because KKM (LVM) may suggest less input with less output, and LVM (KKM) may propose greater input with greater output. Therefore, the overestimated efficiency score of LVM is not its shortages. Khezrimotlagh et al. [10] proved that a DMU is LVM-efficient if and only if it is KKM-efficient. They also improved KKM called Enhanced KKM (EKKM) to compute the results easier.

For the third part, Khezrimotlagh et al. [5] identified that the generated PPSs by KKM and LVM are the same, and every target of KKM (LVM) belongs to the LVM (KKM) generated PPS. However, Kuosmanen and Kazemi Matin [2] claimed that it is impossible to find intensity weights λ for DMU 13 in LVM which satisfy both $\sum_{i=1}^{42} x_i\lambda_i = (0,872,0)$ and constraints $\sum_{i=1}^{42} y_i\lambda_i \in \mathbb{Z}_+^4$, $\sum_{j=1}^{42} y_j\lambda_j \geq (812, 8, 10, 2)$ simultaneously. Moreover, the presented results in tables of the Kuosmanen and Kazemi Matins papers identify that the inputs and outputs of DMUs are restricted in the set of integer numbers, although, KKM is written for DMUs inclusive integer inputs and real outputs.

Moreover, the proposed super-efficiency MILP by Du et al. [9] is based on the Andersen and Petersen technique [12] which is not a harmless technique to arrange DMUs as discussed in [11]. This shortcoming clearly demonstrates that their finding by the super-efficiency MILP is not valid. Furthermore, Khezrimotlagh et al. [10] depicted the weak outcomes of this super-efficiency MILP with a clear numerical example. They also proposed the Integer Slack Based Measure Model (ISBM) and proved its relationship with LVM and EKKM in input-oriented case similar to the relationship between Slack Based Measure (SBM) [13] and Charnes, Cooper and Rhodes (CCR) [14]. Indeed, a DMU is input-oriented ISBM-efficient if and only if it is LVM-efficient (or EKKM-efficient) [10]. Moreover, the efficiency score of ISBM or input-oriented ISBM is not greater than the efficiency score of LVM and EKKM.

INTEGER ARASH METHOD (IAM)

Recently, Arash Method (AM) was proposed to remove some shortcomings in the base of DEA [16]. In order to explain its advantages, let us suppose the six DMUs in Table 1 labelled A to F with two inputs and a single constant output. Figure 1 depicts the integer and real inputs spaces with the real Farrell frontier [15]. It identifies that the DMUs are technically efficient in the integer inputs space, because for each DMU none of the integer inputs can be improved without worsening the other. However, they are inefficient in the real inputs space except A and F.

Table 1: The example of six DMUs.

DMU	A	B	C	D	E	F
Input 1	2	4	5	7	8	9
Input 2	8	7	6	5	4	3
Output	1	1	1	1	1	1

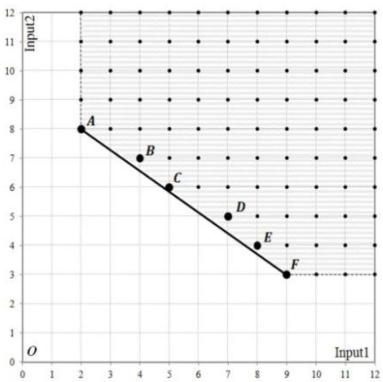


Figure 1: The integer and real inputs space.

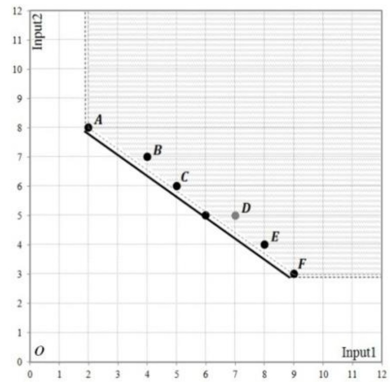


Figure 2: Two hundredth errors by the scale of *D*'s inputs.

Now, let us suppose that two hundredth errors are introduced in the Farrell frontier by the scale of D's inputs [10]. Figure 2 depicts the affected on the Farrell frontier, and showed the technically efficient integer DMUs with the blacker small circles. The outcomes demonstrates that D is an inefficient integer DMU when 2% errors are introduced in the Farrell frontier by the scale of D's inputs. However, the other technically efficient integer DMUs are stable even 2% errors are introduced in the Farrell frontier by the scale of their inputs. From Figure 1, although, the AF line segment is quite close to the point $(6, 5)$, this point is infeasible due to the conventional DEA axioms. As it is supposed that two hundredth errors can be introduced in the Farrell frontier by AM, it is strongly suggested that the point $(6, 5)$ is more acceptable than the point $(7, 5)$ within the available DMUs. Indeed, the current integer DEA methods only propose the value of 3 for an input of an evaluated DMU, even if the suggested value for the input is 2.00001 or 2×10^{-10} by the real Farrell frontier, whereas from our expectations the value of 2 should be considered.

Figure 7 also depicts the suggested technically efficient integer DMUs when eight hundredth errors are introduced in the Farrell frontier by the scale of A's inputs. From the figures, A is a stable technically efficient integer DMU even if 8% errors are introduced in the Farrell frontier by the scale of all technically efficient integer DMUs. These results clearly characterize that the performance of A is better than other technically efficient integer DMUs. Therefore, the rank of DMUs can be suggested as follows: $A > F > C > E > B > D$, where $\varepsilon_j^- = \varepsilon / w_j^-$, $w_j^- = 1/x_{lj}$, for $j = 1,2, \dots, m$ and $\varepsilon > 0$, $w_k^+ = 1/y_{lk}$, for $k = 1,2, \dots, p$. In these cases, when a DMU has large input/output values, the effects on the Farrell frontier is greater than when it has small input/output values [10]. However, ε_j^- and ε_k^+ can be defined as $\varepsilon \times \min\{x_{ij}: x_{ij} \neq 0, i = 1,2, \dots, n\}$ and $\varepsilon \times \min\{y_{ik}: y_{ik} \neq 0, i = 1,2, \dots, n\}$, where $\varepsilon \in \mathbb{R}_+$, to have the same commensurate effects in the Farrell frontier for evaluating each DMU. For instance, $\varepsilon = 0.1$, $w_j^- = 1/x_{lj}$, for $j = 1,2, \dots, m$ and $w_k^+ = 1/y_{lk}$, for $k = 1,2, \dots, p$, in Figure 8, and $\varepsilon_1^- = 0.2$ (horizontal decreasing) and $\varepsilon_2^- = 0.3$ (vertical decreasing). As can be seen, technically efficient

DMUs A, F and C have the better performance in comparison with other DMUs and other technically efficient DMUs should try to decrease their inputs for improving their performances.

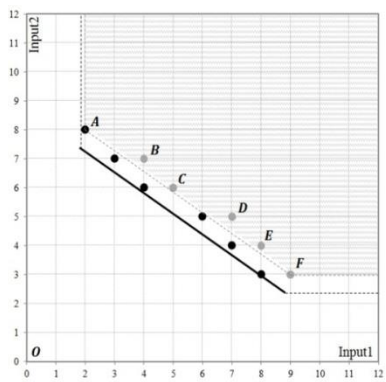


Figure 7: Eights hundredth errors by the scale of A's inputs.

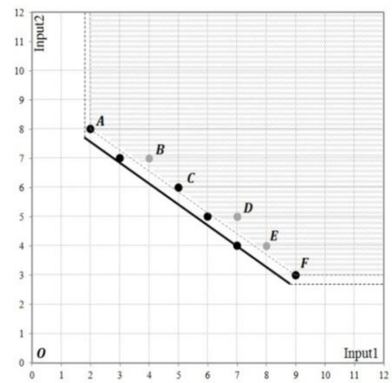
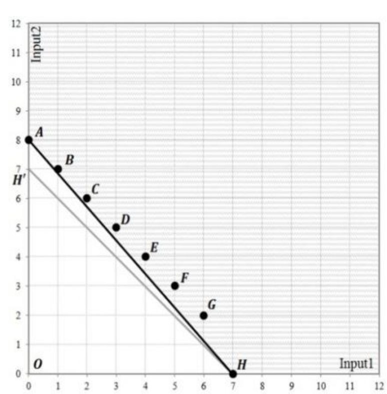


Figure 8: One tenth errors by the scale of minimum inputs.

On the other hand, let us suppose nine DMUs labelled A-H inclusive two inputs and a single constant output according to Table 2 and Figure 9. Assume that the inputs are commensurate and the weights are 1 for each input. The ratio of produced output to used inputs, that is, output/(input1 + input2), are $1/8$ for DMUs A-G and it is $1/7$ for H. However, the technical efficiency integer scores are 1 for A-H by the current MILPs. In other words, those DMUs are technically efficient integer from the Pareto Koopmans definition of efficiency, but the technically efficiency definition cannot depict that the performance of H is better than the other ones [10, 11, 15].

Table 2: The example of eight DMUs.

DMU	A	B	C	D	E	F	G	H
Input 1	0	1	2	3	4	5	6	7
Input 2	8	7	6	5	4	3	2	0
Output	1	1	1	1	1	1	1	1



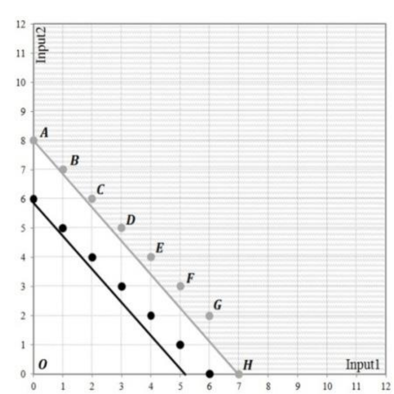


Figure 9: The example of eight DMUs. **Figure 10: Arash Method outcomes.**

From Figure 9, it is also proved that the distance of each DMU to the Farrell frontier is not a harmless technique to discriminate technically efficient DMUs. Because, for instance, A has the same performance with G, but their distances to the Farrell frontier is quite different. Moreover, the inefficient point $(7,1)$ has also the same performance as the technically efficient DMUs A-G, and none of the proposed integer super efficiency models based on the Andersen and Petersen technique [12] is able to arrange these DMUs correctly. Figure 9 also depicts the grey line segment HH' as a valid frontier to measure the efficiency of DMUs A to G and suggests that those DMUs are not efficient in comparison with H, although they are technically efficient integer. In contrast, Figure 10 depicts the results of Integer AM (IAM) where one unit error is introduced in the Farrell frontier (horizontally and vertically) and shows the new technically efficient integer DMUs by black circles. As it can be seen, each new technical efficient integer DMUs have the same score equal to $1/6$. From the score of AM, each DMU is compared with its new target. For instance, AM compares $A(0,8)$ to the point $(0,6)$ and its suggested efficiency score for A is $(1/8)/(1/6)$, that is, 0.75 by 1 degree of freedom (1-DF). All DMUs B to G have also the same efficiency score 0.75 by 1-DF. However, the AM efficiency score for H is $(1/7)/(1/6)$, that is, 0.86. Therefore, AM identifies the best performer among the DMUs and arranges the DMUs as follow, correctly: $H > A = B = C = D = E = F = G$.

As it was proposed in [10], Integer-AM (IAM) is as follows,

$$\max \sum_{j=1}^{m} w_j^- s_j^- + \sum_{k=1}^{p} w_k^+ s_k^+,$$

Subject to

$$\sum_{i=1}^{n} \lambda_i x_{ij} + s_j^- = x_{lj} + \varepsilon_j^-, \forall j,$$

$$\sum_{i=1}^{n} \lambda_i y_{ik} - s_k^+ = y_{lk}, \ \forall k,$$

$$\sum_{i=1}^{n} \lambda_i = 1,$$

$$x_{lj} - s_j^- \geq 0, \forall j,$$

$$\lambda_i \geq 0, \ \forall i,$$

$$s_j^- \geq 0, \ \forall j,$$

$$s_j^- \in \mathbb{Z}_+, \forall j \in M_{int},$$

$$s_k^+ \geq 0, \ \forall k,$$

$$s_k^+ \in \mathbb{Z}_+, \forall k \in P_{int}.$$

$$\text{Targets: } \begin{cases} x_{lj}^* = x_{lj} - s_j^{-*}, \forall j, \\ y_{lk}^* = y_{lk} + s_k^{+*}, \forall k, \end{cases}$$

where $0 \leq \varepsilon_j^- \ll 1$.

$$\text{Score: } A^* = \frac{\sum_{k=1}^{p} w_k^+ y_{lk} \,/\, \sum_{j=1}^{m} w_j^- x_{lj}}{\sum_{k=1}^{p} w_k^+ y_{lk}^* \,/\, \sum_{j=1}^{m} w_j^- x_{lj}^*},$$

where M_{int} and P_{int} are the subsets of the corresponding dimensions that must be integer. Khezrimotlagh et al. [10] exemplified IAM with a numerical example including 39 Spanish airports with four inputs and three outputs, and depicted the robust results of IAM in comparison with the current MILPs. They also *extended IAM to the Integer Kourosh and Arash Model (IKAM) to measure the efficient combinations of DMUs as well as benchmark and rank them.*

CONCLUSIONS

This paper illustrates the shortcomings in the current MILPs and the flaws in the previous structure of DEA and its techniques to benchmark and ranks DMUs inclusive integer and real values. It introduces IAM as a robust technique to measure the efficiency score of DMUs as well as benchmarking and ranking DMUs.

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DEREGULATION, PRODUCTIVITY AND PROFIT IN MEXICAN BANKING

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ABSTRACT

In this paper the relationship between productivity and profit variations is considered. The sources of profit variations have been split into two sources. Therefore, an attempt is made to disclose two effects that bring productivity and profit changes about. Such effects are a total factor productivity change and terms of trade. In addition, the contribution of each effect on profit variations is measured. To this end, a two periods DEA-Malmquist index model is computed. Finally, decomposition process was applied to a set of Mexican banking system data for the 1982-1988 period. The terms of trade adversely affected bank profitability. This adverse outcome was not offset by significant increases in total factor productivity.

Keywords*: Profit decomposition, Malmquist index, Mexican banking.*

INTRODUCTION

In 1982 the Mexican government decreed the nationalization of 58 banks out of 60. This resolution was given in the context of an economic crisis that led the Mexican government to devalue the currency, suspend the payment of debt and stay out of international credit markets.

The era of nationalized banks in Mexico encompassed the 1982-1990 period. However, since 1983 onwards, there were gradually introduced reforms that guided the decisions of the banking sector to a free market system. One of such reforms was that the ownership of private banking assets was limited to 34 percent. Likewise, reforms also carried out a process of consolidation of the banking system to increase operational efficiency. Additionally, the number of banks dropped from 69 to 29.

The aim of this paper is to analyze the causes of bank profitability in the nationalized banking period. It is important to note that during such times Mexican banks underwent a gradual, but sharp, process of deregulation. Moreover, deeper reforms would follow in 1989. On this paper only the period 1982 to 1988, dominated by nationalized banks, with minority private sector is analyzed.

PREVIOUS STUDIES

As far as profit decomposition is concerned, several papers -based on productivity- have been published. Firstly, writtings by Emili Grifell-Tatje and C.A.K. Lovell (1999) pioneered said application to Spanish banks to decompose the returns on six indicators. Based on the Malmquist index the effect of change in productivity, which in turn is divided into technical change effect and operating efficiency change effect was decomposed. Similarly, the activity effect, which includes the product mixture effect, input mixture effect and a scale effect was also separated. Lastly, product price effect was split up too. These authors found out that the combined effect of productivity and activity was positive for Spanish banks during the 1987-1994 period. The price effect was detrimental to Spanish banks for the first six years of the period. In fact, the positive results of the two effects above mentioned -productivity and activity- were almost wiped out by an unfavorable output price effect.

Ten years later, Biresh Kaouru Sahoo and Tone (2009) obtained a profit decomposition by radial and non-radial models in order to get the same kind of indicators that Grifell-Tatje and Lowel obtained for Spanish banks. Nonetheless, the former authors applied such method to Indian banks during the 1998-2005 period. They found that total factor productivity positively contributed to enhance profits. However, activity change negatively affected profits in four out of seven years of the sample. Likewise, price changes adversely affected profitability out of five of the seven years in the sample.

Recently, in 2012 Juo, Jia-Ching Fu, Tsu-Tan and Yu, Ming-Miin worked out a decomposition of profitability model based on a non-oriented slacks based model for Taiwanese banks during the 1994-2002 period. The authors concluded that, on average, the price change effect, technical change and the scale effect contributed positively to bank profits. By contrast, the operating efficiency effect, the joint effect of the product and input mixed effect negatively contributed to generate profits.

METHODOLOGY

Now variables used and the algorithms to obtain profit decomposition are defined. Mexican banking data covers the period 1982-1988, such period corresponds to the nationalized banking system and includes twenty state-owned banks.

Two variables as outputs are included: Credit plus earning assets and other non-interest income. As inputs, deposits, operating costs, other than interest costs and non-performing loans are used. As for prices, we consider the lending rate as the price of credit and interest-earning assets. As for deposits, the deposit reward rate is considered as the price of money kept in banks. In addition, operating expenses and other costs are also pondered. The approach to variable selection is one of intermediation. Likewise, orientation of the model is to output. Additionally, the Malmquist index, as an indicator of change in total factor productivity (dTFP), is worked out.

ALGORITHMS

According to O'Donnell (2009), the following definitions and equations are established:

Efficiency

q_t= Output quantity vector. p_t= Output prices vector

OTE=Output oriented technical efficiency = $\frac{Q_t}{\bar{Q}_t}$ = $D_o^t(x_t, q_t)$

Scale efficiency

OSE= Output oriented scale efficiency = $\frac{\overline{Q_t}/X_t}{Q_t/\overline{X_t}}$

OSE= $\inf_\rho D_o^t(\rho x_t, \rho q_t)$ / $D_o^t(\rho x_t, \rho q_t)$

MIOS=Mix invariant optimal scale

MIX efficiency

OME=Output oriented mix efficiency = $\mathrm{OME} = \frac{\bar{Q}_t}{\hat{Q}_t}$

Where $\hat{Q}_t$ $Q(\hat{q}_t)$ and $\hat{X}_t$ $X(\hat{x}_t)$ are aggregates of $\hat{q}_t$ arg $\max_{q>0}$ $\{Q(q): (x_t, q \in T^t\}$ and $\hat{x}_t$

arg $\min_{q>0}$ $\{X(x): (x_t, q \in T^t\}$.

ROSE =Residual output oriented scale efficiency =$\frac{\frac{\hat{Q}}{X}}{\frac{Q_t^*}{X_t^*}}$

RISE =Residual input oriented scale efficiency =$\frac{\frac{\hat{Q}}{X}}{\frac{Q_t^*}{X_t^*}}$

Where $Q^{\cdot} = Q(q_t^{\cdot})$ and $X^{\cdot} = X(x_t^{\cdot})$ are aggregates of $(x_t^{\cdot}, q_t^{\cdot})$ = arg $\max_{x>0, q>0}$ $\{Q(q)/X(x): (x, q) \in T^t\}$

That is $Q^{\cdot}$ and $X^{\cdot}$ are aggregates output and input quantities at the point of maximum productivity.

RME=Residual Mix Efficiency = $\frac{\frac{\hat{Q}}{\hat{X}}}{\frac{Q_t^*}{X_t^*}}$

Residual mix efficiency (RME) is a measure of the difference between TFP at the point of mix-invariant optimal scale (MIOS) and TFP at the point of maximum productivity (MP).

Total factor productivity (TFP) is denoted at that point $\mathrm{TFP}^{\cdot}{}_t = \frac{Q^{\cdot}{}_t}{X^{\cdot}{}_t}$

Decomposing Productivity

Output oriented decomposition of TFP efficiency

TFPE=$\mathrm{TFP}_t/\mathrm{TFP}_t^*$=$\frac{\frac{Q_t}{X_t}}{\frac{Q_t^*}{X_t^*}}$=$\mathrm{OTE}_t \mathrm{x} \mathrm{OME}_t \mathrm{x} \mathrm{ROSE}_t$

TFPE=$\mathrm{TFP}_t/\mathrm{TFP}_t^*$=$\frac{\frac{Q_t}{X_t}}{\frac{Q_t^*}{X_t^*}} = \mathrm{OTE}_t \mathrm{x} \mathrm{OSE}_t \mathrm{x} \mathrm{RME}_t$

Decomposing TFP

$$TFP_{0t} = [\ TFP_t^* / TFP_0^*] \left[\frac{OTE_t}{OTE_0}\right] \left[\frac{OME_t}{OME_0}\right] \left[\frac{ROSE_t}{ROSE_0}\right]$$

$$TFP_{0t} = [\ TFP_t^* / TFP_0^*] \left[\frac{OTE_t}{OTE_0}\right] \left[\frac{OSE_t}{OSE_0}\right] \left[\frac{RME_t}{RME_0}\right]$$

Profitability Change

$$\pi_{0t} = \left[\frac{P_{0t}}{W_{0t}}\right] [\ TFP_t^* / TFP_0^*] \left[\frac{OTE_t}{OTE_0} \frac{ITE_t}{ITE_0}\right]^{1/2} \left[\frac{OME_t}{OME_0} \frac{IME_t}{IME_0}\right]^{1/2} \left[\frac{ROSE_t}{ROSE_0} \frac{RISE_t}{RISE_0}\right]^{1/2}$$

Total Factor Productivity Index

Output Oriented Malmquist:

$$TFP_{0t}^{0M} = \frac{D_o^t(x_t, q_t)\ \ D_o^0(x_t, q_t)}{D_o^t(x_0, q_0)\ \ D_o^0(x_0, q_0)}$$

RESULTS

An average of results for all 20 banks operating in Mexico in that period is shown below**.** Occasionally average figures seem to be affected by extreme values. Thus, not always results are consistent with equations of origin. For space reasons results relative to input-oriented Malmquist index are excluded.

Table 1. Profit change decomposition (dProf), revenue change (dRev), change in Cost (dCost), output price changes (dP), input price changes (dW), output changes (dQ) and input changes (dX).

Years	dRev	dCost	dProf	dP	dW	dTT	dQ	dX
1983/1982	2.4658	2.5730	0.9573	1.3234	2.0703	0.7771	1.9353	1.4946
1984/1983	1.6924	1.6728	1.0130	0.8552	1.3195	0.6856	2.0388	1.3393
1985/1984	3.8076	3.1517	1.3906	1.5223	4.7208	0.3709	2.5069	0.6754
1986/1985	2.2300	2.2614	0.9872	1.0446	1.8263	0.6205	2.1855	1.3356
1987/1986	2.5845	2.5791	1.0027	0.8620	2.3537	0.4531	3.2447	1.3648
1988/1987	1.3117	1.2697	1.0338	0.7151	1.2462	0.6158	2.2177	1.1268
1989/1988	0.2876	0.2673	1.1246	0.2181	1.2434	0.2328	1.5482	0.2906

By looking at the change in profits, the periods 1982-1983 and 1985-1986 stand out with unwanted results. In such periods the change in costs exceeded revenue change, which was perceived as a sign of banks´ weakness. Moreover, it was also detected in those years a greater increase in input prices than output current value, which negatively affected the terms of trade; hence, reducing banks´ profits.

Table 2. Profit Change (dProf) decomposition. Total factor productivity change (dTFP) and terms of trade change (dTT).

Years	dProf	dTFP	dTT
1983/1982	0.9573	1.5247	0.7771
1984/1983	1.0130	1.6052	0.6856
1985/1984	1.3906	3.8720	0.3709
1986/1985	0.9872	1.7665	0.6205
1987/1986	1.0027	2.8523	0.4531

1988/1987	1.0338	2.0519	0.6158
1989/1988	1.1246	4.8686	0.2328

Table 2 reveals that total factor productivity had a positive effect on the change in banks´ profits. By contrast, during periods 82/83 and 85/86 unfair terms of trade led to adversely affect the change in profits.

Table 3. Total factor productivity change (dTFP) decomposition. Technical Change (dTech) and Efficiency Change (dTFPE).

Years	dTFP	dTech	dTFPE
1983/1982	1.5247	0.9950	1.5848
1984/1983	1.6052	1.1913	1.3918
1985/1984	3.8720	3.1953	1.2111
1986/1985	1.7665	1.5904	1.1297
1987/1986	2.8523	2.1969	1.4329
1988/1987	2.0519	1.4649	2.1905

It is evident from table 3 that while efficiency change in total factor productivity had a positive effect on profitability throughout the period, technical change adversely affected total factor productivity in the period 82/83.

Table 4. Total factor productivity change (dTFP) decomposition: Output oriented technical efficiency change (dOTE), output oriented mix efficiency change (dOME) and residual output oriented scale efficiency change (dROSE).

Years	dTFP	dOTE	dOME	dROSE
1983/1982	1.5247	1.0793	0.9895	1.4669
1984/1983	1.6052	1.1384	0.9794	1.2838
1985/1984	3.8720	1.000	0.9966	1.2152
1986/1985	1.7665	1.0134	0.9859	1.1195
1987/1986	2.8523	1.2270	1.0218	1.1312
1988/1987	2.0519	0.8928	0.9655	2.4086

As long as efficacy of the products is concerned, not only efficiency of scale had always a positive effect on the overall productivity of factors, but also technical efficiency, except for the period 87/88. On the other side, mixed efficiency had a negative effect during the entire lap, except for 86/87 period.

Table 5. Total factor productivity change (dTFP) decomposition. Output oriented technical efficiency change(dOTE), output oriented scale efficiency change (dOSE) and residual mix efficiency change (dRME).

Years	dTFP	dOTE	dOSE	dRME
1983/1982	1,5247	1.0793	1.0857	1.3724
1984/1983	1,6052	1.1384	1.0029	1.2553
1985/1984	3,8720	1.000	1.000	1.2111
1986/1985	1,7665	1.0134	1.0437	1.0652
1987/1986	2,8523	1.2270	0.9912	1.1709

1988/1987	2,0519	0.8928	1.0644	2.1019

From the product orientation point of view, scale efficiency had a positive effect on total factor productivity throughout the span of time analyzed, except for the 86/87 period. The residual mixture efficiency also favored the growth of total factor productivity. As mentioned elsewhere before, technical efficiency favored profits generation throughout the studied term, except for the 87/88 period.

CONCLUSIONS

Immerse in a major economic crisis, Mexico nationalized private banks in 1982. A year later Mexican monetary authorities initiated a set of regulatory reforms that tended to guide decisions to a free banking market. Said measures allowed private capital participation in the banking sector. However, private ownership was severely limited. As a result, a consolidated banking structure showed up, which in turn, substantially reduced the number of banking firms. The aim of this study has been to analyze the causes of bank profitability in the nationalized banking period 1982-1988.

Centralized price controls engendered some banking difficulties in two years within the nationalized banking epoch. Production costs over exceeded bank revenues. Therefore, worsening terms of trade and adversely affecting bank profitability. In fact, this adverse outcome was not offset by significant increases in total factor productivity.

On average, the largest contribution to total factor productivity change was brought about by technological change. Similarly, the change in technical efficiency and residual scale efficiency positively contributed to profit generation. Conversely, the mixed efficiency change observed a detrimental influence on total factor productivity. Nevertheless, residual mixed efficiency change, as well as the scale efficiency change favorable contributed to enhance total factor productivity. Considering the whole period, the terms of trade adversely affected bank profitability. This adverse outcome was not offset by significant increases in total factor productivity.

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ECONOMIC EFFICIENCY AND PRODUCTIVITY IN THE MEXICAN METROPOLITAN AREAS, 1998-2008

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ABSTRACT

This paper deals with technical efficiency and productivity in the medium-sized and big metropolitan zones in Mexico in 1998, 2003 and 2008 by means of Data Envelopment Analysis and the Malmquist index. Metropolises are key territorial units for analysis and action because of their economic, social and political importance. Metropolitan economic efficiency and productivity reveal effective allocation of resources, proficient management, coordinated development and strong competitiveness. We aim at providing information on the economic performance of metropolises and the spatial heterogeneity in Mexico in order to guide further analysis as well as private and public policy projects that support an improved performance of metropolises and the country as a whole.

Keywords*: Productivity; Efficiency; Metropolises; Mexico*

INTRODUCTION

Urban performance involves an array of fundamental aspects of the functioning of cities and metropolises. Therefore it can be assessed across diverse economic and social aspects, and by means of a variety of indicators. The economy is just part of the complex running of cities, but it is one that deserves close attentions due to its implications and relationships with other urban dimensions. From the economic point of view efficiency is a concept that can be employed to evaluate the productive performance of territories. Technical efficiency particularly refers to how close a particular territory is to its optimal production levels, given a production technology and factor endowments. High efficiency at the metropolitan scale means reasonable resource allocation, appropriate management and the coordinated development of various urban social, political and economic aspects, and therefore strong competitiveness (Guo et al., 2011). Since the works in the eighties addressing the urban performance of Chinese cities (Charnes, et al., 1989) and more recently its metropolitan development (Guo, et al., 2011), there has been increasing interest in the economic efficiency of cities, metropolises, regions and countries. Some examples are Charnes et al. (1989), Guo et al. (2011), Emrouznejad (2003), Färe et al. (1994) and Ezcurra et al. (2009). In this literature Data Envelopment Analysis (DEA) and the Malmquist index have been widely used methods for evaluating economic efficiency and productivity change.

This paper addresses the issue of economic performance by examining the efficiency of the big and medium-sized metropolitan zones in Mexico.

Presently Mexico is a predominantly urban society with a degree of urbanization of approximately 70 per cent. In this country urbanization has taken the form of increasing metropolization with the emergence of several cities with characteristics of metropolitan areas. In 2012 the federal government identified fifty nine official metropolitan zones based on data from the 2010 population census. Even though these 59 official Metropolitan Zones (MZs) occupy only 8 per cent of the territory, they concentrate nearly 64 million people which represent almost 57 per cent of national population and 80 per cent of urban population. Furthermore they generate about 75 per cent of national production (SEDESOL, et al. 2012).

Historically there has been significant geographical concentration of population and economic activity in the largest metropolises (Mexico City, Monterrey and Guadalajara). The overconcentration in the three main urban centers began to decline in the 1980s in favour of medium-sized cities. Nonetheless population is still very concentrated in the largest metropolises. According to the 2010 population census the largest MZs are the Metropolitan Zone of Mexico City (MCMZ), Guadalajara (GMZ), Monterrey (MMZ), Puebla-Tlaxcala (PTMZ) and Toluca (TMZ). These top five metropolises have more than one million inhabitants and concentrate more than 50 per cent of metropolitan population. There is also a significant primacy of MCMZ with its 20 million inhabitants. The next five biggest metropolises are industrial cities in the north (Tijuana, Ciudad Juarez and La Laguna) and in the center-north (Leon, Queretaro and San Luis Potosi) all of them with a population of more than one million people. On the contrary the smallest MZs are Tecoman, Ocotlan, Rio Verde, Texiutlan, Acayucan and Moroleon which do not exceed 150 thousand inhabitants each. Similarly economic polarization is very strong because some MZs show greater economic size and dynamism. The size of their economies reflects their productive capacity and/or the effectiveness in the use of resources.

Mexico underwent a deep transformation in its economic model in the 1980s and 1990s derived from the crisis in the import substitution industrialisation that was implemented between the 1940s and 1970s. The economic reforms took place in the form of privatisation, liberalisation and export promotion. Moreno (2000) argues that macroeconomic patterns and adjustments had an influence on the interurban economic performance. Trade liberalization and productive restructuring led to a spatial change resulting into a group of winning subsystems of cities versus a group of disadvantaged subsystems. He identifies as the successful and winning metropolises those located in the northeast (due to its linkages with the US economy), in the gulf (because of the oil-related activity) and in the center and center-west (owing to the more concentrated and specialized productive infrastructure). The heterogeneous metropolitan performance brings about the challenge of extending economic benefits to all metropolises, and the task of evaluating economic spatial disparities.

Even though there is considerable literature on various social and economic aspects at the urban level, little research has been carried out on economic efficiency of cities and metropolitan areas in this country. We aim to assess metropolitan efficiency and productivity change in 1998, 2003 and 2008.

METHODS

The assessment of productive performance and productivity change in the metropolitan zones in Mexico is based on the estimation of technical efficiency and Total Factor Productivity (TFP) change by means of DEA and the Malmquist index.

DEA was presented initially by Rhodes in 1978. It is a non-parametric technique that uses linear programming and principles of frontier analysis to build an efficient frontier or empirical production function using a dataset of similar economic units or decision making units (DMUs) which in this case are represented by metropolitan zones. DEA compares the input-output relations of metropolises by assuming that they use the same kinds of inputs (for instance labour and capital) to produce the same kinds of outputs (product or value added). The metropolises with the best practices determine the maximum output achievable. By measuring the distance to the efficient frontier, an efficiency score is derived for all other metropolises. In other words, the estimated efficiency is a relative score obtained by using the metropolises with the best technological practices as referents.

There are different types of DEA models depending for instance on the objective function (input minimisation to reach a specific output level, and output maximisation for a given set of inputs) and on the assumptions about the returns to scale (constant or variable returns to scale). A traditional output oriented Variable Returns to Scale (VRS) DEA model is estimated. This implies that MZs have the objective of maximising output given their input endowments (from the policy point of view it seems reasonable to expect increases in material surpluses than decreases in capital accumulation and employment).

The Malmquist Index measures the changes in the TFP of a productive unit between two periods, say t and t+1, by calculating the ratios of the distances in each period to a common technology (Coelli et al. 1998). More specifically, the index is based on the calculation of the distance that separates each DMU to the reference technology in each period by using a distance function. These distance functions allow the description of multi-input and multi-output production technologies without specifying a behavioural objective (cost minimisation or profit maximisation) (Coelli et al. 1998). The calculation of distance functions in the Malmquist index makes use of the DEA methodology.

The Malmquist index allows the decomposition of TFP change into the change attributable to an improvement in technical efficiency and the change caused by technical progress. Even though the product of these effects is by definition equal to the Malmquist, the components can have differing directions. A constant returns to scale (CRS) output oriented specification of the Malmquist index is estimated for the MZs in Mexico.

Mexican metropolitan zones are the equivalent to the Decision Making Units (DMU). What we assess is not necessarily metropolises but their aggregate economic activity. We consider economic activity as the aggregate of the construction sector, manufacturing, commerce and services (excepting public services). We include only 30 MZs out of the 59 officially identified; they are the medium-sized and big metropolises - with over 500 thousand inhabitants.

In order to implement DEA the selection of inputs and outputs in this application is based on the indicators that have been used in similar studies and also on the available information. Charnes et al. (1989) use labour (number of staff and workers, exclusive of farm labour), working fund (circulating capital), and investment (new fixes assets and capital construction) as inputs to asses China´s urban performance; the outputs are gross industrial output, profit and taxes and retail sales. Alternatively, capital (fixed assets and liquid capital), human resources (skilled workers), techniques (institutions, rules, skills, information, and knowledge), and natural resources (land, water, minerals) can be input variables whereas outputs can be represented by gross metropolitan product (Guo et al., 2011). Similar to Ezcurra et al. (2009), in our model real gross value added (in 2003 constant prices) is used as the output variable, and labour (occupied workforce) and capital (fixed assets) are the input variables.

DEA analysis requires the homogeneity of inputs and outputs across DMUs; however the mix of skilled and unskilled workers can vary importantly across metropolitan regions, likewise the characteristics of physical capital. Here we impose the strong assumption that capital and labour are homogeneous. Data come from the economic censuses carried out by the National Institute of Statistics, Geography and Informatics (INEGI) for the years 1998, 2003 and 2008. Due to the nature of the techniques only information about quantities is required, and assumptions about the functional form of the production function are not necessary.

RESULTS AND DISCUSSIONS

Table 1 contains the mean efficiency and the efficient metropolises in each period. In 1998 and 2008 there were a total of 23 metro zones showing some degree of inefficiency leading to an average score of 75.6 and 70.82 respectively. In 2003 the number of efficient metro zones increased by one and the mean efficiency is 77.83. According to the estimates of technical efficiency we observe the heterogeneous performance that would be better described as polarised efficiency: there is a small group of efficient metro zones, half of metropolises are under the mean efficiency, and the lowest efficiencies ranges between 31.58 and 35.2.

Among the technically efficient metropolises three showed full efficiency in all periods: Mexico City (the capital city), Saltillo (industrial city in the north) and Poza Rica (coastal city with commercial and industrial activity linked to oil production). Monterrey (second largest metropolitan economy, highly industrialised and located in the north) and Villahermosa (with tourism and oil related activities) reached the efficient frontier en 2003, meanwhile Reynosa (industrial metropolis at the border with the US) and Tampico (industrial and commercial coastal metropolis) located on the efficient production function in 2008. The contrary trend took place in Pachuca (industrial metro zone in the centre) and Xalapa (commercial metro zone) that were efficient only in 1998; Leon and Guadalajara (industrial and commercial oriented cities) were efficient in 1998 and 2003; lastly, Juarez (industrial centre at the border with the US) was efficient only in 2003. At the other end of the spectrum, the most inefficient metropolises were Veracruz in 2003 and Acapulco in 1998 and 2008 (Table A2); both are coastal touristic metropolises which have had important increases in insecurity levels. These results are an indication of the room for large improvements in the performance of the whole system and of most of the individual metropolises which do not reach the optimal production frontier.

Table 1. Efficient metropolitan zones and mean efficiency 1998, 2003 y 2008

	1998		2003		2008	
1	Pachuca	100	Poza Rica	100	Poza Rica	100
2	Poza Rica	100	Villahermosa	100	Reynosa	100
3	Xalapa	100	Juarez	100	Villahermosa	100
4	Saltillo	100	Saltillo	100	Saltillo	100
5	Leon	100	Leon	100	Tampico	100
6	Mexico City	100	Guadalajara	100	Mexico City	100
7	Guadalajara	100	Monterrey	100	Monterrey	100
8			Mexico City	100		
Mean		75.57		77.53		70.82

Source: Developed from the 1999, 2004 and 2008 INEGI economic censuses

Changes in TFP and its components, technical change and efficiency change, provide us with significant information on the productive trends and economic development. The estimations of the Malmquist Index for the Mexican metro zones are summarised in table 2. The average change in total factor productivity experienced by the whole group of MZs was 2.8 per cent by year. Total change is decomposed into 9.0 per cent of technological change, and a decreasing technical efficiency of 5.7 per cent. Therefore the increments in productivity in the Mexican metropolitan zones are the result of technical change rather than improvements in efficiency. Whereas there were increases in technology change between 1998-2003 and 2003-2008, technical efficiency had a modest growth in the period 1998-2003 and an important reduction between 2003 and 2008.

Tabla 2. Malmquist index summary of annual means

All ZMs	Technical efficiency change index	Technology change index	Malmquist productivity change index
1998/2003	1.003	1.040	1.043
2003/2008	0.887	1.142	1.014
All years mean	0.943	**1.090**	**1.028**

Source: Developed from the 1999, 2004 and 2008 INEGI economic censuses

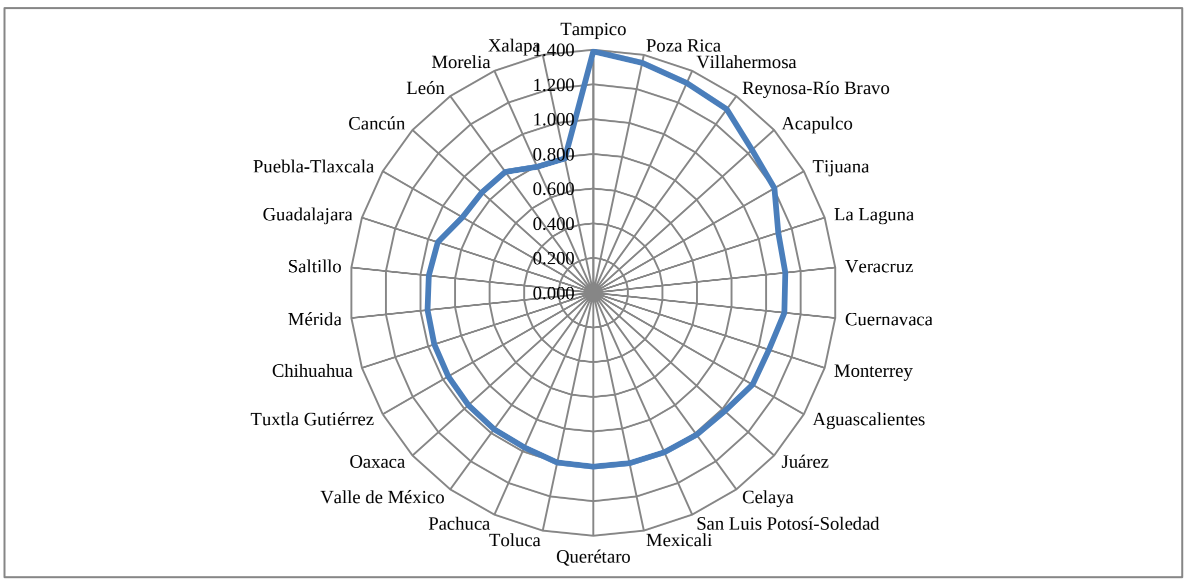

Figure 1. Malmquist productivity in Mexican Metropolitan Zones, 1998-2008

Source: Developed from the 1999, 2004 and 2008 INEGI economic censuses

A review by individual metro zones allows observing very different trajectories as only sixteen MZs had positive changes in TFP (see table A2). Many of these expansions were the result of technological change implemented in the transformation processes of their inputs into outputs combined with some improvements of technical efficiency. In 5 cases TFP development resulted from technical change, and in 1 case it was the result of enhancing technical efficiency. Positive changes in TFP range from 1.390 in Tampico to 1.002 in Queretaro (Figure 1).

CONCLUSIONS

Results show that, in the first place, most of metropolitan economies have some degree of inefficiency. From the policy point of view this opens a window for the design and implementation of economic policies with a metropolitan focus from below as each metro zone has varying and specific characteristics and deficiencies. One problem with this focus is the lack of metropolitan governments, metropolitan governance agencies or municipal coordination. The absence of metropolitan government and governance can somehow become a factor contributing to the productive inefficiency of the majority of metro zones in Mexico. Mexico City is not only the biggest concentration of population and activity, but also the best practice in terms of productive processes in the period 1998-2003.

Productive efficiency problems are not limited to the local level in specific cases but on average technical efficiency in the country also has difficulties. What the metropolitan system faces, as a whole and individually, is a deteriorating panorama in terms of its capacity to generate and maximise its material wealth which puts in danger the economic stability and cohesion. Apart from further analysis, the problems of national and local inefficiency require some kind of private and public policy approach.

An interesting aspect of our efficiency analysis relates to the regional patterns. Longstanding research has addressed the economic spatial differentiation, its evolution and particularly the impact of the structural economic reforms in the eighties and nineties. It has been argued that the north of the country has been benefited from such restructuring due to the locational advantage, closer to the US market. We find that on average the north underwent a positive relative evolution of efficiency; on the contrary the south and centre showed a comparative decrease.

The positive change in the mean TFP in the country has been the outcome of technological change, some of which probably has its origin on foreign direct investment, and whose full benefits have been counterbalance by the negative evolution of technical efficiency. Therefore, the difficulties with productivity change are mostly derived from the increasing technical inefficiency. At the individual level, the differentiation in TFP change is also significant. A total of 16 metro zones had a positive change in their TFP between 1998 and 2008: most of the positive changes in productivity took place in metro zones in the north whereas the rest of metropolises have varying patterns. Even though the overall positive role of technical change has contributed to improvements in TFP, heterogeneity requires some attention to this aspect. Finally we suggest further investigation searching for the explanations of efficiency, as well as productivity change in the metropolitan system and in individual metropolises.

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APPENDICES

Table A1. Results of technical efficiency by metro zone, 1998, 2003, 2008

1998			2003			2008		
Unit	Score	Scale	Unit	Score	Scale	Unit	Score	Scale
Pachuca	**100**	constant	**Poza Rica**	**100**	constant	**Poza Rica**	**100**	constant
Poza Rica	**100**	constant	**Villahermosa**	**100**	constant	**Reynosa-Río Bravo**	**100**	constant
Xalapa	**100**	constant	**Juárez**	**100**	constant	**Villahermosa**	**100**	constant
Saltillo	**100**	constant	**Saltillo**	**100**	constant	**Saltillo**	**100**	constant
León	**100**	constant	**León**	**100**	constant	**Tampico**	**100**	constant
Valle de México	**100**	constant	**Guadalajara**	**100**	constant	**Valle de México**	**100**	constant
Guadalajara	**100**	constant	**Monterrey**	**100**	constant	**Monterrey**	**100**	constant
Morelia	93.84	decreasing	**Valle de México**	**100**	constant	Guadalajara	91.5	increasing
Monterrey	93.61	increasing	Reynosa-Río Bravo	86.06	decreasing	Toluca	87.92	increasing
Mexicali	88.6	decreasing	Mexicali	84.61	decreasing	La Laguna	84.51	increasing
Reynosa-Río Bravo	85.47	decreasing	Tijuana	84.5	increasing	Tijuana	82.76	increasing
Toluca	85.34	increasing	Morelia	84.19	decreasing	Querétaro	81.68	increasing
Puebla-Tlaxcala	80.56	increasing	Querétaro	83.8	increasing	León	81.6	increasing
Villahermosa	79.01	decreasing	Xalapa	82.51	decreasing	San Luis Potosí-Soledad	74.28	increasing
Tuxtla Gutiérrez	76.56	decreasing	Toluca	82.22	increasing	Mexicali	68.75	increasing
Querétaro	73.03	increasing	Cuernavaca	80.29	increasing	Juárez	68.22	increasing
Celaya	69.24	decreasing	Pachuca	78.58	decreasing	Aguascalientes	64.71	increasing
San Luis Potosí-Soledad	68.05	increasing	Oaxaca	74.39	decreasing	Puebla-Tlaxcala	63.85	increasing
Juárez	67.34	decreasing	Tuxtla Gutiérrez	72.25	decreasing	Celaya	59.51	decreasing
La Laguna	67.3	decreasing	Puebla-Tlaxcala	71.72	increasing	Mérida	56.83	increasing
Mérida	66.96	decreasing	La Laguna	70.65	increasing	Cuernavaca	56.76	increasing
Tijuana	61.25	increasing	Tampico	63.7	decreasing	Chihuahua	53.34	increasing
Cancún	60.92	decreasing	San Luis Potosí-Soledad	62.75	increasing	Pachuca	52.31	decreasing
Chihuahua	59.4	decreasing	Aguascalientes	62.68	increasing	Tuxtla Gutiérrez	50.8	decreasing
Oaxaca	58.35	decreasing	Mérida	62.07	increasing	Veracruz	48.01	increasing
Aguascalientes	55.67	decreasing	Celaya	60.06	decreasing	Oaxaca	42.33	decreasing
Tampico	53.76	decreasing	Chihuahua	58.65	increasing	Xalapa	41.85	decreasing
Cuernavaca	52.66	decreasing	Cancún	43.59	increasing	Morelia	39.73	decreasing
Veracruz	38.6	decreasing	Acapulco	42.89	decreasing	Cancún	38.26	increasing
Acapulco	31.58	decreasing	Veracruz	33.74	decreasing	Acapulco	35.21	decreasing
Average	**75.57**			**77.53**			**70.824**	

Table A2. Geometric mean changes in technical efficiency, technology and Malmquist productivity by Metropolitan Zone 1998-2008

	Metropolitan Zone	**Technical efficiency change index**	**Technology change index**	**Malmquist productivity change index**
1	***Tampico***	1.399	0.994	**1.390**

2	***Poza Rica***	1.199	1.129	**1.354**
3	***Villahermosa***	1.199	1.103	**1.322**
4	***Reynosa-Río Bravo***	1.128	1.159	**1.307**
5	***Acapulco***	1.072	1.148	**1.230**
6	***Tijuana***	1.032	1.166	**1.203**
7	***La Laguna***	1.023	1.094	**1.119**
8	***Veracruz***	1.118	0.994	**1.111**
9	***Cuernavaca***	0.992	1.114	**1.105**
10	***Monterrey***	1.066	0.997	**1.062**
11	***Aguascalientes***	1.019	1.039	**1.059**
12	***Juárez***	0.879	1.159	**1.019**
13	***Celaya***	0.942	1.072	**1.010**
14	***San Luis Potosí***	0.981	1.025	**1.006**
15	***Mexicali***	0.868	1.157	**1.004**
16	***Querétaro***	0.958	1.046	**1.002**
17	*Toluca*	0.979	1.021	0.999
18	*Pachuca*	0.845	1.154	0.975
19	*Valle de México*	0.945	1.03	0.973
20	*Oaxaca*	0.834	1.160	0.968
21	*Tuxtla Gutiérrez*	0.832	1.159	0.964
22	*Chihuahua*	0.893	1.077	0.962
23	*Mérida*	0.832	1.154	0.960
24	*Saltillo*	0.982	0.969	0.952
25	*Guadalajara*	0.833	1.132	0.942
26	*Puebla-Tlaxcala*	0.859	1.014	0.871
27	*Cancún*	0.825	1.047	0.864
28	*León*	0.758	1.136	0.861
29	*Morelia*	0.688	1.154	0.794
30	*Xalapa*	0.684	1.155	0.790
	Mean	**0.943**	**1.090**	**1.028**

EFFICIENCY IN THE EUROPEAN BANKING SECTOR: PERIPHERAL VERSUS CORE ECONOMIES

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ABSTRACT

The dual nature of the Eurozone crisis, involving both insolvent sovereigns and private banks, generated distortions in the banking system and fragmentation between the EMU core and the periphery, affecting bank efficiency. There is a large body of literature related to the application of DEA methodology in the banking sector but there is only limited research on the impact of financial crises on bank efficiency while cross-country studies are limited. Moreover, the majority of the studies examine the impact of bank-specific and country-specific factors on efficiency ignoring the above described developments. This paper provides the first attempt to assess the impact of the Eurozone crisis on the bank efficiency with respect to the sector fragmentation.

Keywords*: efficiency, Data Envelopment Analysis, European banking*

INTRODUCTION

The centralization of monetary policy and supervisory powers to the European Central Bank (ECB) was the first step in an effort to create an integrated banking industry with higher degree of competition and improved services to the real economy. However, the structural differences between the economies in the European Monetary Union (EMU) have posed significant obstacles and this task became even harder after the escalation of the sovereign debt and banking crisis.

Beyond its obvious economic advantages, the concept of a monetary union entailed closer links between banks and sovereigns and stronger contagion risks that were not fully perceptible before the burst of the EMU crisis. The low interest rate environment and the single currency framework has enhanced banking competition but simultaneously founded a false perception that credit risk is similar across the different regions, leading to a rapid growth of private credit and increased levels of borrowing amongst the EMU sovereigns. The peripheral economies, which have traditionally been characterized by structural weakness and current account deficits, continued to enjoy an overrated credit status attributed to their Eurozone membership and relied on borrowing from both domestic and foreign banks, mainly those located in the surplus countries of the EMU core. Since late 2009, the increasing risk premia in the sovereign debt and money markets adversely affected the cost and the composition of bank funding. Market access was gradually lost as bank's credit ratings drifted downwards by sovereign rating downgrades, bank balance sheets weakened due to losses on sovereign debt holdings, collateral values declined imposing restrictions on liquidity provision from the markets and the ECB. Euro-peripheral banks confronted risks related to bank runs, capital controls, deposit haircuts or national euro exit and witnessed a large portion of their customer deposits moving to core banks on demand for safety. In response, peripheral banks compelled to raise the interest rates paid on deposits, a strategy which weighed on their profitability. Moreover, stronger austerity and fiscal adjustment in these countries resulted in lower investment, lower demand for loans and, more importantly, increased loan delinquencies. In the absence of uniform and transnational resolution mechanisms, Governments were forced to back commercial banks' creditworthiness against default risk. Thus, while the euro-area banks used to operate in a highly intergraded interbank market their monitoring, creditworthiness and solvency remained highly country-specific.

There is a large body of literature related to the application of DEA methodology in measuring efficiency in the banking sector, however cross-country studies, especially in the EU banking sector, are limited (examples include Lozano-Vivas et al., 2002; Casu and Molyneux, 2003; Beccalli et al., 2006; Casu and Girardone, 2006). Moreover, the majority of the studies examine the impact of bank-specific as well as country-specific factors but there is a lack of studies that account for the impact of the above described developments on the efficiency of the European banks operating in peripheral economies (Greece, Spain, Portugal, Ireland, Italy) compared to banks located in the core economies (Germany, The Netherlands, Austria, Belgium, France). Therefore the aim of the proposed chapter is to address the following objectives:

- To examine the efficiency levels of a large sample of the European commercial banks.

- To conduct a cross-country comparison in order to examine how the unfolding of the EU debt crisis affected bank efficiency and whether it benefitted specific regions.

METHODS

In the present study bank efficiency measurement is based on Data Envelopment Analysis (DEA) methodology. DEA is a non-parametric technique that uses mathematical programming to estimate the relative efficiency of the decision making units (DMU) by determining a production frontier which is made up by the most efficient banks. DEA's major advantage is that it does not require dealing with assumptions on the distribution of the variables included as inputs and outputs. Furthermore, DEA permits the inclusion of inputs and outputs which are not supposed to have a pre-specified relationship and the measurement of inputs and outputs could be in different units.

In the present study the DEA input-oriented VRS (variable returns to scale) is used in order to evaluate the efficiency of the banks in the Euro zone:

$$\min_{\theta,\lambda} \theta$$

$$\begin{aligned} &s.t. \\ &-y_i + Y\lambda \geq 0 \\ &\theta x_i - X\lambda \geq 0 \\ &\lambda \geq 0 \\ &\sum \lambda = 1 \end{aligned}$$

where Y is a M×N matrix of output quantities and X is a K×N matrix of input quantities assuming that the firms uses M outputs and K inputs, yi is a M×1 vector of output quantities for the i-th bank, xi is a K×1 vector of input quantities for the i-th bank, λ is a N×1 vector of constants and θ is the efficiency score of the bank i. The efficiency score obtained varies between 0 and 1. The solution of this linear programming problem for each bank provides the efficiency score, with θ=1 indicating that it lies on the frontier and thus is perfectly efficient, while firms with θ<1 exhibit inefficiencies compared with the firms on the frontier.

Data were obtained from the Bankscope database and after excluding inconsistent observations and by using the Wilson (1993) outliers detection method we ended-up with a final sample of 430 banks per year, on average. Personnel expenses, fixed assets and total customer deposits (Maudos and Pastor, 2003, Casu and Molyneux, 2003, Chortareas et al. 2013) are used as inputs, and loans and other earning assets as outputs (Casu and Girardone, 2004, 2006, Chortareas et al. 2013).

RESULTS AND DISCUSSION

The results obtained from the empirical analysis based on the input-oriented DEA with variable returns to scale of the whole dataset are presented in table 1 and graph 1. The results reveal that from 2005 until 2008 there was a downward tendency of the efficiency scores of the banks in the Euro zone and banks from Luxemburg and Ireland show a relatively stable efficiency scores. Banks from Greece, Cyprus, Portugal and Slovakia show the lowest efficiency rates and vary between 0.04 and 0.08. On the other hand, banks in Estonia, France, Germany, Ireland and Malta are the most efficient ones with an efficiency of more than 0.25.

Regarding bank efficiency in the peripheral economies (Greece, Spain, Portugal, Ireland, Italy) it is observed that on average they underperform compared to banks located in the core economies (Germany, The Netherlands, Austria, Belgium, France). More specifically, banks from the peripheral economies display an average efficiency score of 0.19 while banks from the core economies display an average score of 0.23. Both groups of banks exhibit low efficiency scores on average. The results also show that moving from 2005 to 2008 there is a downward tendency of the efficiency scores in the European banking sector. Moreover, banks from the peripheral economies show an upward tendency in their efficiency scores between 2008 and 2012 while in core economies it is observed the same impact but with the difference that is stronger: banking efficiency in the core economies increased from 0.16 in 2008 to 0.27 in 2012 returning to efficiency levels before the crisis. Instead average efficiency in the periphery increased from 0.16 to 0.24, a result which mainly is attributed to the banking sector of Ireland.

Table 1: Efficiency in the European banking sector

Country	2005	2008	2012
AUSTRIA	0.1709851	0.1328533	0.1967809
BELGIUM	0.2750921	0.1155252	0.2954854
CYPRUS	0.0480403	0.0472361	0.0496865
ESTONIA	0.5392558	0.2253759	0.2756997
FINLAND	0.1114113	0.1333238	0.3629702
FRANCE	0.2536211	0.1893614	0.2888006
GERMANY	0.2794085	0.195666	0.3641863
GREECE	0.066674	0.0359215	0.0862702

IRELAND	0.4522239	0.4392759	0.5692769
ITALY	0.1647386	0.1899575	0.2357441
LUXEMBOURG	0.0856365	0.1356652	0.10354
MALTA	0.3725364	0.3138545	0.2480966
NETHERLANDS	0.3174092	0.1926449	0.2354244
PORTUGAL	0.0861341	0.0632884	0.0950536
SLOVAKIA	0.0592027	0.0427495	0.0705635
SLOVENIA	0.1232025	0.0870197	0.0896484
SPAIN	0.1117838	0.1011029	0.2244588

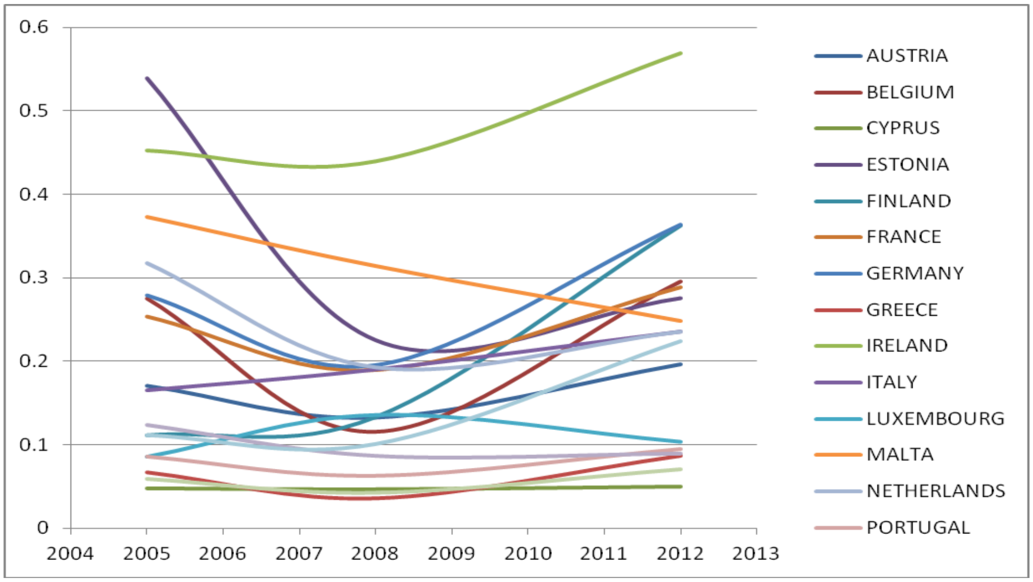

Figure 1: Graphical representation of the efficiency scores in the in the European banking sector

CONCLUSIONS

The present study evaluates the efficiency of the European banking sector using DEA and focuses on the identification of divergence in the performance between peripheral and core banks. The results reveal that banks in the peripheral economies underperform on average the banks in the core economies, and provide strong evidence that the impact of the Eurozone crisis has helped the banks in the core economies to increase their efficiency levels and recover more quickly.

Future research could focus on the empirical examination of the specific factors impeding peripheral banks to achieve higher efficiency scores compared to core banks and the identification of the structural differences between the banking industries of the aforementioned groups.

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EFFICIENCY MEASUREMENT OF PASSENGER PORTS WITH DATA ENVELOPMENT ANALYSIS AND UTILIZING MALMQUIST PRODUCTIVITY INDEX

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ABSTRACT

Efficiency measurement of decision making units (DMUs) is vital for effective management of these units. The aim of this research is to measure the efficiencies of four participating passenger ports comparatively and to evaluate the changes occurred in their efficiencies during the period of eight years from 2003 to 2010. To measure the time dependent efficiency levels of each port, Data Envelopment Analysis (DEA) based Malmquist Productivity Index has been utilized in this research. By utilizing the Malmquist Productivity Index; (i) efficiency scores for each port for every year, (ii) average efficiency scores for each year for all the ports, and (iii) average efficiency scores for each port over the time period had been measured. The results show that average efficiency scores by years did not follow a stable trend and fluctuated. Another finding is that during eight year period, only two participating passenger ports performed beyond the efficiency frontier. The study shows that efficiency measurement of passenger ports with DEA and utilizing Malmquist Productivity Index would result with better indicators about port efficiency and can be used by decision makers for better decisions.

Keywords*: Efficiency, Data Envelopment Analysis, Malmquist Productivity Index, passenger ports*

INTRODUCTION

Passenger ports have minor importance for regional economies because of their relatively smaller trading volumes compared to freight ports. This is why passenger ports attract less attention in efficiency measurement (Güner, et al., 2012; Vaggelas and Pallis, 2010). Although lots of studies have been performed to measure the efficiencies of freight ports (Tongzon, 2001; Baysal, et al., 2004; Roll and Hayuth, 2006), only a few studies have been performed for passenger ports (Vaggelas and Pallis, 2010). This paper aims to contribute to the literature in this area.

METHODS

Various mathematical techniques have been developed to measure the efficiencies of different decision making units (DMUs). These mathematical techniques can be classified into two categories according to whether they are parametric or non-parametric. Parametric techniques include Stochastic Frontier Approach (SFA), Distribution-Free Approach (DFA) and Thick Frontier Approach while non-parametric techniques include Free Disposal Hull (FDH) and Data Envelopment Analysis (DEA).

Non-parametric methods aim to measure the distance of decision making units to the efficiency frontier by utilizing linear programming techniques. These methods are more advantageous than parametric ones because they don't need to take the behavioral assumptions of decision making units into consideration (İnan, 2000).

Data Envelopment Analysis (DEA) is the most preferred non-parametric technique to measure the efficiencies of DMUs' comparatively (Tahir ve Yusof, 2011). DEA detects an efficiency frontier by accepting the most efficient decision making unit as a reference point and evaluates the other DMUs efficiencies comparatively according to their distances to this reference point (Kutlar ve Babacan, 2008). As the most preferred non-parametric technique, DEA has been utilized for various DMUs from football teams (Haas, 2003) to ports (Tongzon, 2001; Estache, vd., 2004).

Basic DEA can be modeled as follow;

θ = efficiency

u = weight of i th output

y = quantity of i th output

v = weight of i th input

x = quantity of i th input;

Objective Function:

$$max\ \theta = \sum_{r=1}^{n} u_r y_r$$

$$max\ \theta = u_1y_1 + u_2y_2 + \cdots + u_ny_n$$

(1)

Maximization of total output

Constraints:

$$\sum_{i=1}^{m} v_i x_i = 1$$

$$v_1x_1 + v_2x_2 + \cdots + v_mx_m = 1$$

(2)

Equation of total input to 1

$$\sum_{r=1}^{n} u_r y_r - \sum_{i=1}^{m} v_i x_i \leq 0$$

$$(u_1y_1 + u_2y_2 + \cdots + u_ny_n) - (v_1x_1 + v_2x_2 + \cdots + v_mx_m) \leq 0$$

(3)

Output - Input

$$u_1, u_2, \ldots, u_n \geq 0 \qquad \textbf{(4)}$$

$$v_1, v_2, \ldots, v_m \geq 0 \qquad \text{Non negativity}$$

Basic DEA model is a usable technique for most cases. But it is deficient in dynamic situations where dependence to the time occurs because of static structure (Cooper et al., 2007). This is an important limitation for basic DEA. To overcome this limitation, Malmquist Productivity Index (MI) has been developed and used. MI has also been used for the time dependent efficiency measurement of ports by various researchers (Melchor, 1999; Tongzon, 2001; Estache, vd., 2004).

Malmquist productivity index is a comparative statistics that examines the changes in the efficiency of a decision making unit between two time periods (Cooper vd., 2007). To measure the MI, two main concepts "catching-up" and "frontier-shift" effects must be defined.

Catching-up effect (C) refers to the improvement or deterioration degree of a DMUs' efficiency scores between two time periods and it can be calculated by dividing first time efficiency score to second time efficiency score. Thus, changes in the efficiency score can be determined. On the other hand, frontier-shift effect (F) refers to the shifting rate of efficiency frontier between two time periods and evaluates the each DMUs' t-time input-output mix regard to the next time (t+1). Frontier-shift effect calculated by taking geometric average of each DMUs' relative efficiencies to t+1 values. Thus, relative change in the efficiency frontier can be determined. At last, time-dependent efficiency scores of each DMUs' can be measured by multiplying the catching-up (C) and frontier-shift (F) effects.

A Malmquist productivity index can be modeled as follow;

$$C = \frac{\theta_j^{t+1}}{\theta_j^t}$$

(5)

(C): Catching-up effect

θ_j : Efficiency score

$$F = \sqrt{\frac{\delta^t(x_i, y_r)^t}{\delta^{t+1}(x_i, y_r)^t} \times \frac{\delta^t(x_i, y_r)^{t+1}}{\delta^{t+1}(x_i, y_r)^{t+1}}}$$

(6)

(F): Frontier-shift effect

$$MI = \frac{\theta_j^{t+1}}{\theta_j^t} \times \sqrt{\frac{\delta^1(x_i, y_r)^t}{\delta^2(x_i, y_r)^t} \times \frac{\delta^1(x_i, y_r)^{t+1}}{\delta^2(x_i, y_r)^{t+1}}}$$

(7)

MI: Malmquist Productivity Index

In this research, to evaluate the changes in efficiency scores of four passenger ports in an eight year time period, DEA based Malmquist productivity index has been utilized. After mathematical modeling of the problem, Win4DEAP software has been used to solve the problem.

DATA COLLECTION

This research encompasses four passenger ports that are located and operating in Aegean and Mediterranean shores. All of these ports were privatized in 2003 and this study subject to the post privatization years between 2003 and 2010. Data used in this study have been gathered from Republic of Turkish Prime Ministry Privatization Administration.

ANALYSIS AND RESULTS

Before the measurement of efficiency, input and output metrics in this model must be determined. Table 1 shows the input and output metrics that has used in this research. As can be seen from Table 1, this study used two input (labor and total expenses) and three output (passenger calls, ship calls and total income) metrics.

Table 6. Input and output metrics

Input	Unit	Output	Unit
Labor	Quantity	Passenger Calls	Tones
Total expenditures	Turkish Lira	Ship Calls	Quantity
		Total income	Turkish Lira

After determination of input and output metrics and gathering of related data, efficiency scores can be calculated. Mathematical model of the problem was introduced in previous section. After modeling the problem mathematically, DEA based Malmquist Productivity Index has been operated by Win4DEAP software.

DEA based Malmquist Productivity Index analysis are shown in Table 2. According to this table, when we evaluate the mean scores of seven-years of each port, it is possible to rank four ports according to their scores as follow; PP4 (1,163) > PP3 (1,130) > PP2 (0,958) > PP1 (0,852). This result shows that, during the eight year period, PP4 is the most efficient port while PP1 is the least.

On the other hand, in seven years period, average efficiency scores had increased in 2004, 2005, 2007, and 2009 (average scores are over 1) while average efficiency scores had decreased in 2006, 2008, and 2010 (average scores are below 1).

Table 7. Total factor productivity scores

TFPCH*	2004	2005	2006	2007	2008	2009	2010	*mean*
PP1**	0,877	1,027	1,037	1,128	0,690	0,788	0,570	*0,852*
PP2	1,019	1,247	0,560	1,116	0,839	1,091	1,017	*0,958*
PP3	1,607	1,080	0,729	1,129	0,988	1,328	1,259	*1,130*
PP4	1,034	1,229	1,188	1,137	1,043	1,240	1,296	*1,163*
mean	*1,104*	*1,142*	*0,842*	*1,127*	*0,879*	*1,091*	*0,986*	

* Total Factor Productivity Change

** Passenger Port

Table 2 also shows the individual MI scores of each port by years. Changes in total factor productivity scores visualized in Figure 1. As can be seen from Figure 1, TFPCH scores by years did not follow a stable trend and fluctuated.

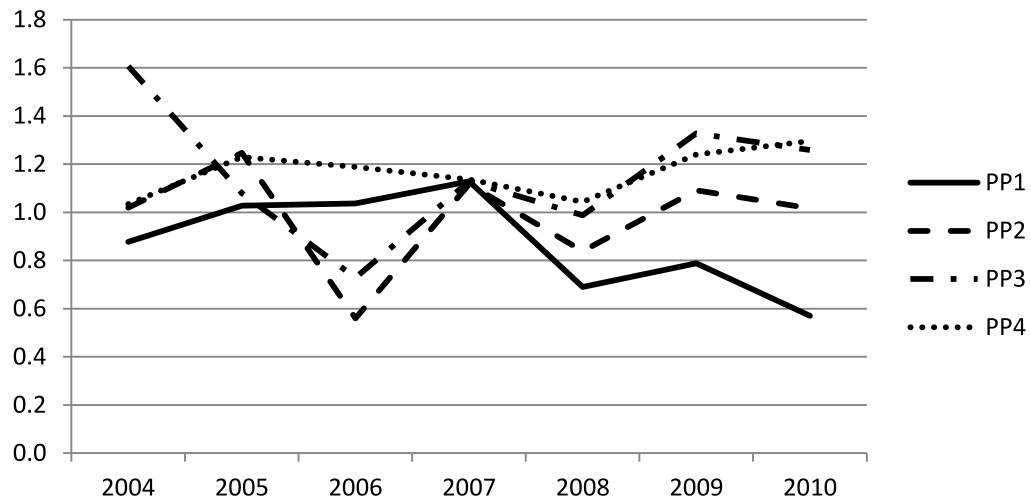

Figure 2. Fluctuation of TFPCH scores of each port

FURTHER ANALYSIS

Total productivity index scores are composed of efficiency differences and technological changes between each year. Indeed, total factor productivity scores are calculated by the multiplying of efficiency changes and technological changes (Formulation 7). So, these two factors should also be considered together to understand the dynamics of total productivity scores.

The meaning of catching-up effect score exceeding 1 is that efficiency score is increasing compared the previous year. If the score is 1, it means there is no difference between current and previous year. If the score is less than 1, then the efficiency is decreasing from previous to current year. Increasing catching-up score can be interpreted as firm's effectiveness is approaching to perfect. Efficiency scores of each port can be seen in Table 3. According to this table, efficiency scores are over 1 in 2004, 2006, and 2008. On the other hand, efficiency score are below 1 in 2005, 2007, 2009, and 2010.

Table 8. Efficiency Change Scores

EFFCH*	2004	2005	2006	2007	2008	2009	2010	*mean*
PP1	1,000	0,631	1,585	1,000	0,911	0,685	0,378	*0,813*
PP2	1,000	1,000	1,000	1,000	1,000	1,000	0,792	*0,967*
PP3	1,669	0,977	1,625	0,896	1,116	1,000	1,000	*1,149*
PP4	1,000	1,000	1,000	1,000	1,000	1,000	1,000	*1,000*

mean	*1,137*	*0,886*	*1,267*	*0,973*	*1,004*	*0,910*	*0,739*	

* Efficiency Change

The meaning of frontier-shift effect score exceeding 1 is that production frontier shifts up compared the previous year (Dinçer, 2008). If the frontier-shift score is 1, it means there is no difference between current and previous year. If the score is less than 1, then the production frontier shifts down from previous to current year. Technological change scores of each port can be seen in Table 4. According Table 4, technological change scores are over 1 in 2005, 2007, 2009, and 20010. On the other hand, technological change scores are below 1 in 2004, 2006, and 2008.

Table 9. Technological Change Scores

TECHCH*	2004	2005	2006	2007	2008	2009	2010	mean
PP1	**0,877**	**1,628**	**0,654**	**1,128**	**0,758**	**1,151**	**1,509**	**1,048**
PP2	1,019	1,247	0,560	1,116	0,839	1,091	1,284	0,990
PP3	**0,963**	**1,105**	**0,449**	**1,260**	**0,885**	**1,328**	**1,259**	**0,984**
PP4	1,034	1,229	1,188	1,137	1,043	1,240	1,296	1,163
mean	**0,971**	**1,289**	**0,665**	**1,159**	**0,875**	**1,199**	**1,334**	

* Technological Change

Afterwards the evaluation of efficiency changes and technological changes together, now it is possible to set forth the reasons of fluctuations in total productivity scores. Increase in total factor productivity index score in 2004 resulted from efficiency change while increases in 2005, 2007, and 2009 arouse from increases in technological change. On the other hand, decrease in total factor productivity index scores in 2006 and 2008 arouse from decreases in technological change while decrease in 2010 arouse from decrease in efficiency change.

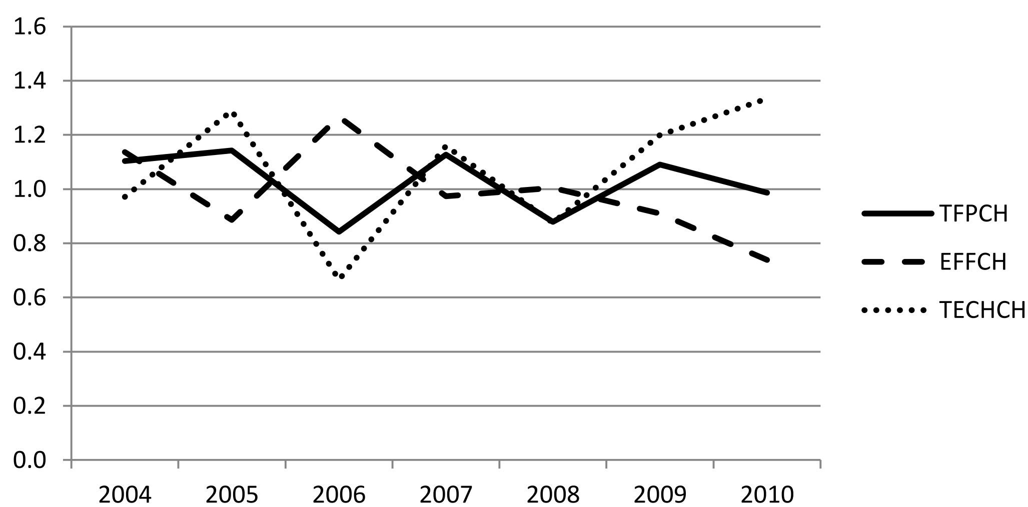

Figure 3. Changes in Average Efficiency Scores

IMPLICATIONS, LIMITATIONS, AND CONCLUSIONS

In this study, a time dependent model, which measures the efficiencies of passenger ports comparatively, has been developed. For this, DEA based Malmquist Productivity Index had been utilized and four Turkish passenger ports has been ranked according to their efficiency scores. Those results may serve to compare these ports among themselves and the same model can also be used to compare other passenger ports' efficiencies.

One limitation of this research is the inadequate number of input and output metrics. More input and output metrics would allow more accurate results. Although it is relatively easy to collect data for a certain year, it is not easy to derive data for a longitudinal study. To improve this model, more variety of other input and output would be helpful.

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EFFICIENCY-BASED PERFORMANCE EVALUATION USING DATA ENVELOPMENT ANALYSIS

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ABSTRACT

In today's manufacturing environment, productivity analysis is significant in order to monitor their progress for enterprises. Data Envelopment Analysis (DEA) is a very effective method for measuring the relative efficiencies of a set of decision making units (DMUs) which uses multiple inputs to produce multiple outputs. In this paper, the efficiency problem in factory units in defence industry based on materials' lateness purchasing which is caused the customer demands couldn't meet on time is examined. There is a lot of criteria affecting this trouble and this situation gives a rise to conflict among departments due to couldn't be determined the causes of the problem. In order to solve this challenge, DEA non-parametric method in which the set of inputs and outputs are evaluated together is preferred in this study. Firstly, DMUs are detected from related departments such as Production Planning and Control, Material Management, Research & Development and Technology and Quality Management. At continuation of this study, homogeneous inputs and outputs for DMUs are defined. As a result, it is expected to find out ineffective DMUs in order to make them more productive, and decrease the inactive times caused by materials absence.

Keywords: *Data Envelopment Analysis, efficiency, purchasing*

INTRODUCTION

Changing economic conditions have challenged many companies to reduce cost, improve quality and responsiveness to meet fierce competition. So that, there is an increasing concern among organizations to study level of efficiency with which they work relative to their competitors. It is important for the firms that they provide the maximum output which can be achieved with any possible combination of inputs. Data Envelopment Analysis (DEA) provides calculating apparent efficiency levels using multiple inputs and outputs involved in many activities within a group of organizations. Because of this feature, DEA opens up possibilities for use in cases which have been resistant for other approaches. So, a great variety of applications of DEA have been seen in performance measurement and benchmarking of bank branches, schools, hospitals, etc. (Botti et al., 2009; Lin et al., 2009; Tyagi et al., 2009; Alexander et al. 2010). The studies using DEA are summarized in the following.

Specially focus on bank branches, Paradi and Zhu (2013) offer a study for DEA researchers. Their paper surveys 80 published DEA applications in 24 countries/areas. Key issues related to the design of DEA models in these studies are discussed. Much advice is included on how to design future experiments and studies in this domain.

Considering for assessing and managing the relative performance of productivity driven organizations that operate in unstable environments, Samoilenko and Osei-Bryson (2013) present a DEA-centric decision support system (DSS) that provides facilities. The design of their DSS was guided by a set of system requirements that are highly relevant to a productivity driven organization's efforts to identify and evaluate multiple productivity models in order to select the most suitable one for the given organization.

Du et al. (2010), motivate by a production-planning problem regularly faced by the central decision-making unit to arrange new input and output plans for all individual units in the next production season when demand changes can be forecasted. Two planning ideas have been proposed in their paper. One is optimizing the average or overall production performance of the entire organization, measured by the CCR efficiency of the average input and output levels of all units. The other is simultaneously maximizing total outputs produced and minimizing total inputs consumed by all units. According to these two ideas, they develop two DEA-based production planning approaches to find the most preferred production plans. All these individual units, considered as decision- making units (DMUs), are supposed to be able to modify their input usages and output productions. A simple numerical example and a real world data set are used to illustrate these approaches.

From the perspective of the output efficiency, Li (2011) evaluates the output efficiency of university human resource collecting data of 42 universities. These findings reflect the human resources of the output current problems on improving efficiency of resource use, to solve the employment problems of college students have certain significance. Similarly, Sohn and Kim (2012) examine two main problems of the existing incentive systems in academia using an example of a professor evaluation system that ignores the input aspect and focusing only on the short-term performance. By applying the super-efficiency DEA and considering multi-period output, it is showed that the input factors and the time trend of outcomes need to be incorporated for the fair evaluation of professors and their research performance.

As seen literature review above, DEA is useful tool in complex situations where there are multiple outputs and inputs. In this paper, the efficiency problem in factory units in defense industry based on purchasing of materials' lateness which is caused to not meeting the customer demands timely manner is examined. There is a lot of criteria affecting this trouble and this situation gives a rise to conflict among departments due to couldn't be determined the causes of the problem. In order to solve this challenge DEA non-parametric method in which the set of inputs and outputs are evaluated together is preferred in this study.

The structure of the rest of the paper is: In the next section, DEA methodology is introduced and the techniques are explained. Then, application of DEA in a factory is presented. Finally, some conclusions and discussions are addressed in the last section.

DATA ENVELOPMENT ANALYSIS

Data Envelopment Analysis (DEA) is non-parametric method for measuring the relative efficiencies of homogenous set of decision making units. In DEA, the examined organization unit converting inputs into outputs is regarded as decision making units so called DMUs.

DEA identifies the most efficient unit or best practice unit comparing DMUs and measures efficiency relative to the best practice. It calculates resource savings that can be achieved by making each inefficient unit as efficient as the most efficient unit. Hence, it isn't determined whether a DMU is absolutely efficient. However, DEA compare several DMU output-to-input ratios and determine that one unit is more or less efficient than another so called benchmarking. Sherman and Zhu (2006) indicate the main advantages of DEA in the following:

- It can readily incorporate multiple inputs and outputs and, to calculate technical efficiency, only requires information on output and input quantities.
- Possible sources of inefficiency can be determined as well as efficiency levels.
- By identifying the 'peers' for organizations which are not observed to be efficient, it is seen that they provide a set of potential role models that an organization can look to, in the first instance, for ways of improving its operations.
- Data Envelopment Analysis, except a linear form, does not require a functional form relating inputs and outputs.
- Inputs and outputs can have different units. In this situation, any hypothesis and converter are not being required to use.

In summary, DEA captures the relationships between multiple inputs and outputs by creating weighted based on the best practice performance in the peer group and makes possible performance comparison.

There are two basic models of DEA; the first one is CCR (Charnes, Cooper and Rhodes) model proposed by Charnes *et al.* (1978). In the CCR model, the model's objective is to maximize the ratio of the weighted outputs to weighted inputs for DMUs and restricting this ratio to be less than or equal to 1 for all DMUs. Therefore, all the DMUs receive an efficiency score between 0 and 1 and the efficient ones take the value of 1. Assuming that there are *n* DMUs, each with *m* inputs and *s* outputs, the relative efficiency score of a DMU_p is obtained as seen below.

$$\max = \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_i x_{ip}}$$

k= 1 to s,

j=1 to m;

i= 1 to n,

$$\frac{\sum_{k=1}^{s} v_k y_{ki}}{\sum_{j=1}^{m} u_j x_{ji}} \leq 1$$

$$v_k \geq 0;$$

$$uj \geq 0$$

y_{ki} = quantity of output k prodced by DMU i,

v_k = weight given to output k,

x_{ji} = quantity of input *j* utilized by DMU i,

u_j = weight given to input j.

Since this model is nonlinear, it is converted into a linear model by setting the weighted inputs of DMU_p to a constant value. Besides, the benchmarks for improvement of inefficient DMU can be obtained from the dual form. Table 1 shows linear model and dual form.

Table 1. The models of CCR

Linear Model	Dual Form
$\max = \sum_{k=1}^{s} v_k y_{kp}$ $\sum_{j=1}^{m} u_j x_{jp} = 1$ $\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0$ $v_k, u_j \geq 0$	$\min = \Phi$ $\sum_{i=1}^{n} \lambda_i x_{ji} - \Phi x_{jp} \leq 0$ $\sum_{i=1}^{n} \lambda_i y_{ki} - y_{kp} \geq 0$ $\lambda_i \geq 0$ Φ = efficiency score, λ_s = dual variables

DEA also allows for computing the necessary improvements in the inefficient unit's input and outputs to make it efficient. Note that DEA is primarily a diagnostic tool and does not prescribe any strategies to make the inefficient unit efficient (Talluri, 2000). Such improvement strategies should be suggested from managers by understanding the operations of the efficient units.

As the second model of DEA, BCC (Banker, Charnes and Cooper) model proposed by Banker *et al.* (1984) is one of the extensions of the CCR model. The main difference between these two models, the DEA-BCC model is that the former allows for perhaps a more realistic assumption of variable returns-to-scale, in contrast to the constant returns-to-scale assumed in the DEA-CCR model (Cullinane & Wang, 2007).

EVALUATING THE EFFICIENCY OF PERFORMANCE IN A FACTORY USING DEA

This study is carried out in a factory in defense industry**.** In this factory, there is purchasing problem based on long time of process and materials' lateness which prevents to meet on time the customer demands. For deciding the purchase of materials, there are four related departments such as Research & Development and Technology (RDT), Production Planning and Control (PPC), Materials Management (MM) and Quality Management (QM) departments.

RDT department is responsible for projects from the beginning to end. It determines the technical specifications of the materials and generating the materials processing forms making time studies. When the material cannot be bought because of the number of inadequate supplier, RDT must reconstitute specifications and technical documents due to apply the law on public procurement.

PPC department is responsible for making annual product plans and prepare purchasing material lists using product tree datas. Besides, PPC department coordinates the manufacturing workshops to produce the goods on time to fulfill customers' demands.

MM department is responsible for stock control, shipping, preparing tender offers and purchasing the materials on time. For all tender offers which are rejected based on quality problems, MM department must reconstitute tender documents.

QM department is responsible for whether purchased materials and used measuring instruments are compatible to technical specifications and functional test procedures or not.

Material procurement is the responsibility of those four departments'. Depending on shortage and lateness of materials, the troubles such as ineffective time in manufacturing workshops and assembly lines and conflicts among departments occur in the factory. That means the factory's resources cannot be used effectively. For increasing the efficiency of these departments which have common multiple inputs and outputs, DEA is used to solve the problem in this study. This paper aims to determine inactive DMUs in order to turn them active. In this study, it is determined inputs and outputs as follows and Table 2 displays the values of these actually produced by DMUs of factory.

Inputs:

- Staff Number: It is determined to measure the adequacy of the existing staff.
- Department's budget: It is determined to evaluate efficiency of budget utilization.
- Waste time due to lack of material: For this input, the evaluation of PPC department is different from the other departments. The waste time for PPC is calculated as required time for manufacturing the goods which don't handle according to the production plan because of lack of material. For the other departments, re-production time is calculated as waste time.
- *Outputs:*
- Departments' expenditures: This output indicates total annual cost of each department.
- Number of items which are met on time: Considering all relevant departments, it is calculated as number of items of purchased, completed, controlled and delivered in timely manner. Note that item indicates customers' all demands includes in products and spare parts.
- Number of items which aren't met on time: This output indicates customers all demands' which aren't met on time. For example; for QM department, the output means that number of items aren't in requested specification.

Table 2: The actual values of inputs and outputs of DMUs

	INPUTS			OUTPUTS		
DMUs (related departments)	Staff Number	departments' budgets (Euro/Year)	waste time due to lack of material (Hour / Year)	departments' expenditures (Euro/Year)	number of items which are met on time	number of items which aren't met on time
PPC	28	89.259.709	76.670	84.796.723	1.631.471	-1.376
QM	98	125.404.531	58.406	191.181.230	2.385.456	-25.576
RDT	49	51.161.003	45.700	47.835.538	1.230.043	-13.985
MM	71	60.072.816	54.890	84.796.723	1.043.677	-259.949

In this study, the results were obtained with using CCR model within "Frontier Analyst 4" solver of software. It is seen that the efficiency of MM department is 58% as well as the other departments' are

100%. In other words, MM department is the inefficient department in the factory. Table 3 shows target values and potential improvements of MM department in detail. The “target” column shows the amount of inputs and outputs that the MM department should be using in order to be efficient. The “potential improvement” column shows how much, in percentage terms, MM department’s use of inputs or outputs needs to change by in order for it to be efficient. The table shows that MM department should reduce its use of staff from 71 to 42, a reduction of almost 42% as an input value. Besides, analysis of the outputs, it should be reduction of number of items which aren't met on time almost 96%, waste time due to lack of material almost 41%. The other output of number of items which are met on time should be increase almost 9%.

Table 3: Potential improvements for MM Department

Variable	Actual	Target	Potential Improvement
Staff number	71,00	41,42	-41,66%
Departments' budgets	60.072.816,00	60.072.816,00	0,00%
Departments' expenditures	84.796.723,00	84.796.723,00	0,00%
Number of items which are met on time	1.043.677,00	1.133.920,04	8,65%
Number of items which aren't met on time	-259.949,00	-10.025,09	-96,14%
Waste time due to lack of material	54.890,00	32.622,36	-40,57%

In order to become as efficient as the other departments, staff structure of MM department should be examined. The majority of staff mightn’t have enough adequacies in terms of technical knowledge. In order to solve this problem, job analysis should be updated and work positions of staff should be reorganized. The management of purchasing process and the used technology and/or size of the unit should be examined. Besides, managerial expertise can be provided from efficient units to the inefficient ones. The adjustments in purchasing process will provide improvements especially on the output of number of items which aren't met on time.

CONCLUSIONS

Considered to give rise to more performance businesses of companies, efficiency is one of the most important concepts and concerned with how to use limited resources more economically. As a benchmarking approach to study efficiency, DEA compares decision making units taking used resources into account, identifies best units and the inefficient units in which real efficiency improvements are possible.

In this paper, DEA application for solving the purchasing problem is proposed. By using DEA, it was identified the inefficient unit as MM department together with target values for inputs and outputs. This helps to use determined resources of inefficient department more active and economical in the factory and hence provide improvement in productivity.

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ESTIMATING DIRECTIONAL RETURNS TO SCALE FOR BASIC RESEARCH INSTITUTES IN CHINESE ACADEMY OF SCIENCES

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ABSTRACT

This paper aims to investigate the directional returns to scale for 16 basic research institutes in Chinese Academy of Sciences (CAS). In comparison with the classic returns to scale analysis, which only provides information of input-output change along the diagonal direction, our methods have the following advantages: (1) we can identify the regions of increasing (constant, decreasing respectively) directional returns to scale for each of the basic research institutes. This information is very useful for these institutes future planning; (2) we find that the directional congestion effect occurs in several of the research institutes for some directions other than the diagonal direction.

Keywords*: Efficiency of Research institute; returns to scale; directional returns to scale; congestion; directional congestion*

INTRODUCTION

This paper aims to estimate the directional returns to scale (RTS) of the 16 basic research institutes in CAS in 2010. RTS is an important issue in the analysis of an organizational performance, which can help decision-makers (DMs) decide if the size of the organization should be expanded or reduced. RTS is a classic economic concept that is tied to the relationship between scale of production factors and variation of outputs. The RTS measures the change rate of output(s) with that of all input(s) proportionally (Pindyck and Rubinfeld, 2000). There are three types of RTS in production processes, which are classified as constant returns to scale (CRS), or decreasing returns to scale (DRS), or increasing returns to scale (IRS) if the change of outputs is the same, or less, or more than the proportional change of the inputs, respectively. In some real applications, however, the change in scale is often caused by the input change in unequal proportions as to be seen later. Therefore, Yang (2012) introduces directional RTS from a global and local (directional scale elasticity) perspective under the Pareto preference, and gives mathematical formulations of directional RTS for the directions other than the diagonal, which will be used to estimate the directional returns to scale (RTS) for the 16 basic research institutes in CAS in 2010.

METHODS

In Liu et al. (2011) discussions are taken to select the most suitable indicators for the DEA based evaluations. In this work we will still use them for analyzing the directional RTS for these basic research institutes. These indicators include: (1) input indicators: Staff and Research Expenditure (Res.Expen.); (2) output indicators: SCI publications (SCI Pub.), High-quality publications (High Pub.) and Graduate

Enrollment (Grad.Enroll). Input-output data of 16 basic institutes in CAS in 2010 is shown in Table 1 as follows.

Table 1. Input-output data of 16 basic institutes in CAS in 2010.

DMU	Inputs		Outputs			
	Staff (FTE)	*Res.Expen. (RMB million)*	*SCI Pub. (Number)*	*High Pub. (Number)*	*Grad.Enroll. (Number)*	*Exter.Fund. (RMB million)*
DMU1	252	117.945	436	133	184	31.558
DMU2	37	29.431	243	127	43	15.3041
DMU3	240	101.425	164	70	89	33.8365
DMU4	356	368.483	810	276	247	183.8434
DMU5	310	195.862	200	55	111	12.9342
DMU6	201	188.829	104	49	33	60.7366
DMU7	157	131.301	113	49	45	72.5368
DMU8	236	77.439	8	1	44	23.7015
DMU9	805	396.905	371	118	89	216.9885
DMU10	886	411.539	607	216	168	88.5561
DMU11	623	221.428	314	49	89	45.3597
DMU12	560	264.341	261	79	131	41.1156
DMU13	1344	900.509	627	168	346	645.415
DMU14	508	344.312	971	518	335	205.4528
DMU15	380	161.331	395	180	117	90.0373
DMU16	132	83.972	229	138	62	32.6111

Data Source: (1) Monitoring data of institutes in CAS, 2011; (2) Statistical yearbook of CAS, 2011.

Note: These data were derived from these institutes in the period of Jan.01,2010~Dec.31,2010.

Yang (2012) proposed the definition of directional scale elasticity in economics in the case of explicit production functions with multiple inputs and multiple outputs as follows.

$$e\left(Y_0, X_0\right)=\frac{d\beta}{dt}\Big|_{t=0}=-\sum_{i=1}^{m}\frac{\partial F}{\partial x_i}x_i\omega_i \Big/ \sum_{r=1}^{s}\frac{\partial F}{\partial y_r}y_r\delta_r\Big|_{(Y_0,X_0)} \qquad (1)$$

where $F\left(Y_0, X_0\right)=0$ denotes the production function and $\sum_{i=1}^{m}\omega_i=m$; $\sum_{r=1}^{s}\delta_r=s$; t, β are input and output scaling factors respectively.

The estimation of RTS of DMUs (Decision making units) using DEA (Data Envelopment Analysis) method is investigated first by Banker (1984) and Banker et al. (1984). Almost all the existing RTS measurements in DEA models are based on the definition of RTS in the DEA framework made by Banker (1984). Yang (2012) argued that due to the complexity of research activities in research institutions, it often can be observed that production factors are not necessarily tied together proportionally. Based on this observation, they introduced directional RTS from a global and a local (directional scale elasticity) perspective under the Pareto preference, and provided mathematical formulations of directional RTS and corresponding models for the directions other than the diagonal. In addition, he demonstrated that the traditional RTS is a special case of the directional RTS in the diagonal direction. In the DEA framework, the definition of directional RTS is provided based on production possibility set (PPS) as follows.

Definitions 1 (Directional RTS): Assuming $DMU(Y_0, X_0) \in PPS$ and $X_0 \in R_m^+, Y_0 \in R_s^+$, we let

$$\beta(t) = \max\left\{\beta \middle| \left(\Omega_t X_0, \Phi_\beta Y_0\right) \in PPS, t \neq 0\right\}$$

where $\Omega_t = diag\{1+\omega_1 t,...,1+\omega_m t\}$ and $\Phi_\beta = diag\{1+\delta_1\beta,...,1+\delta_s\beta\}$, $diag\{\square\}$ denotes the diagonal matrix. $(\omega_1,...,\omega_m)^T$ ($\omega_i \geq 0, i=1,...,m$) and $(\delta_1,...,\delta_s)^T$ ($\delta_r \geq 0, r=1,...,s$) represent inputs and outputs directions respectively and satisfy $\sum_{i=1}^{m}\omega_i = m; \sum_{r=1}^{s}\delta_r = s$ where t, β are input and output scaling factors respectively. We let

$$\rho^- = \lim_{t\to 0^-}\frac{\beta(t)}{t} \quad (2) \qquad\qquad \rho^+ = \lim_{t\to 0^+}\frac{\beta(t)}{t} \quad (3)$$

Then we have: (a) if $\rho^- > 1$ (or $\rho^+ > 1$) holds, then increasing directional RTS prevails on the left-hand (or right-hand) side of this point (Y_0, X_0) in the direction of $(\omega_1,\omega_2,...,\omega_m)^T$ and $(\delta_1,\delta_2,...,\delta_s)^T$; (b) if $\rho^- = 1$ (or $\rho^+ = 1$) holds, then constant directional RTS prevails on the left-hand (or right-hand) side of this point (Y_0, X_0) in the direction of $(\omega_1,\omega_2,...,\omega_m)^T$ and $(\delta_1,\delta_2,...,\delta_s)^T$; (c) if $\rho^- < 1$ (or $\rho^+ < 1$) holds, then decreasing directional RTS prevails on the left-hand (or right-hand) side of this point (Y_0, X_0) in the direction of $(\omega_1,\omega_2,...,\omega_m)^T$ and $(\delta_1,\delta_2,...,\delta_s)^T$.

Based on **Definition 1**, the following method is used to estimate the directional RTS (Yang, 2012). For a strong efficient DMU(X_0, Y_0) on the strongly efficient frontier in BCC-DEA model, its directional scale elasticity can be determined through the following Model (4):

$$\begin{aligned}
&\bar{\rho}(\underline{\rho}) = \max(\min)\frac{V^T W X_0}{U^T \Delta Y_0} \\
&s.t.\begin{cases}
U^T Y_j - V^T X_j + \mu_0 \leq 0, j=1,...,n \\
U^T Y_0 - V^T X_0 + \mu_0 = 0 \\
V^T X_0 = 1 \\
U \geq \mathbf{0}, V \geq \mathbf{0}, \mu_0 \text{ free}
\end{cases}
\end{aligned} \qquad (4)$$

where $U=\left(u_1,u_2,...,u_s\right)^T$ and $V=\left(v_1,v_2,...,v_m\right)^T$ are vectors of multipliers, and $\Delta = diag\left\{\delta_1,\delta_2,...,\delta_s\right\}$ and $W = diag\left\{\omega_1,\omega_2,...,\omega_m\right\}$ are matrixes of inputs and outputs directions respectively and satisfy $\sum_{i=1}^{m}\omega_i = m$ and $\sum_{j=1}^{s}\delta_j = s$.

Based on the optimal solutions of Model (4), we have the following procedure for determining the directional RTS of DMU$\left(X_0,Y_0\right)$ in the direction of $\left(\omega_1,...,\omega_m\right)^T$ and $\left(\delta_1,...,\delta_s\right)^T$.

(1) The RTS to the "right" of DMU$\left(X_0,Y_0\right)$: (a) $\underline{\rho}\left(X_0,Y_0\right)>1$, increasing directional RTS prevails; (b) $\underline{\rho}\left(X_0,Y_0\right)=1$, constant directional RTS prevails;(c) $\underline{\rho}\left(X_0,Y_0\right)<1$, decreasing directional RTS prevails;

(2) The RTS to the "left" of DMU$\left(X_0,Y_0\right)$: (a) $\bar{\rho}\left(X_0,Y_0\right)>1$, increasing directional RTS prevails; (b) $\bar{\rho}\left(X_0,Y_0\right)=1$, constant directional RTS prevails; (c) $\bar{\rho}\left(X_0,Y_0\right)<1$, decreasing directional RTS prevails; (d) if Model (1) has no optimal solution, there is no data to determine the directional RTS to the "left" of DMU$\left(X_0,Y_0\right)$.

For inefficient or weakly efficient DMUs, we can project them onto the strongly efficient frontier using DEA models so that we can estimate the directional RTS to the "right" and "left" of them according to the directional RTS of these projections.

Model (4) is a fractional programming and difficult to solve, so we transform it into an equivalent mathematical programming (Model (5)) through Charnes-Cooper transformation (Charnes et al., 1962). Solving Model (5), we can obtain the directional RTS of DMU$\left(X_0,Y_0\right)$.

In the process of analyzing RTS, the concept of congestion effect is often useful. Congestion means the reduction of one (or some) input(s) will result in the increase of maximum possible of one (or some) output(s) under the premise that other inputs or outputs do not become deteriorated (Cooper et al, 2004).

$$\bar{\rho}\left(\underline{\rho}\right)=\max(\min)\Gamma^T X_0$$
$$s.t.\begin{cases}\Lambda^T\Delta^{-1}Y_j-\Gamma^T W^{-1}X_j+\mu_0^{'}\le 0, j=1,...,n\\ \Lambda^T\Delta^{-1}Y_0-\Gamma^T W^{-1}X_0+\mu_0^{'}=0\\ \Gamma^T W^{-1}X_0=t\\ \Lambda^T Y_0=1\\ \Gamma\ge\mathbf{0},\Lambda\ge\mathbf{0},t\ge 0,\mu_0^{'}\text{ free}\end{cases} \qquad (5)$$

$$\max\theta=\theta_0$$
$$s.t.\begin{cases}\sum_j\lambda_j x_{ij}=x_{i0}, i=1,...,m\\ \sum_j\lambda_j y_{rj}-s_r^+=\theta_0 y_{r0}, r=1,...,s\\ \sum_j\lambda_j=1\\ \lambda_j,s_i^-,s_r^+\ge 0, r=1,...,s; i=1,...,m; j=1,...,n\end{cases} \qquad (6)$$

Essentially, congestion describes the issue of excessive inputs (Wei and Yan, 2004). Färe and Grosskopf (1983, 1985) investigated congestion using quantitative methods and proposed corresponding DEA models to deal with this issue. Soon after that, Cooper et al. (1996) proposed another model to study congestion. Cooper et al.(2001) compared the similarities and differences of the above two models. Wei and Yan (2004) and Tone and Sahoo (2004) built a new DEA model based on the new production possibility set (PPS) under the assumption of weak disposal to detect the congestion of DMUs. The above methods are all based on the idea of radial changes in all inputs. Yang (2012) argued that due to the complexity of research activities in research institutions, it often can be observed that production factors are not necessarily tied together proportionally, and he introduced the concept of directional congestion under the Pareto preference, and mathematical formulations and models for the directions other than the diagonal. The methods he proposed are as follows.

For a strong efficient DMU$\left(X_0,Y_0\right)$ on the strongly efficient frontier of the production possibility set (PPS) determined in Model (6), its directional scale elasticity can be determined through the following Model (7). We transform Model (7) into an equivalent mathematical programming (Model (8)) through Charnes-Cooper transformation (Charnes et al., 1962) as follows.

$$\bar{\rho}\left(\underline{\rho}\right)=\max(\min)\frac{V^TWX_0}{U^T\Delta Y_0}$$
$$s.t.\begin{cases} U^TY_j-V^TX_j+\mu_0\le 0, j=1,\dots,n \\ U^TY_0-V^TX_0+\mu_0=0 \\ V^TX_0=1 \\ U\ge \mathbf{0}, V, \mu_0 \text{ free} \end{cases} \quad (7)$$

$$\bar{\rho}\left(\underline{\rho}\right)=\max(\min)\Gamma^TX_0$$
$$s.t.\begin{cases} \Lambda^T\Delta^{-1}Y_j-\Gamma^TW^{-1}X_j+\mu_0^{'}\le 0, j=1,\dots,n \\ \Lambda^T\Delta^{-1}Y_0-\Gamma^TW^{-1}X_0+\mu_0^{'}=0 \\ \Gamma^TW^{-1}X_0=t \\ \Lambda^TY_0=1 \\ \Lambda\ge \mathbf{0}, t\ge 0, \Gamma, \mu_0^{'} \text{ free} \end{cases} \quad (8)$$

Based on the results of Model (8), we have the following procedure for determining the congestion effect of a strongly efficient DMU$\left(X_0,Y_0\right)$ on strongly efficient frontier of $P_{convex}\left(X,Y\right)$ in the direction of $\left(\omega_1,\dots,\omega_m\right)^T$ and $\left(\delta_1,\dots,\delta_s\right)^T$.

(1) If there exists optimal solution in Model (8) and the optimal value of objective function $\underline{\rho}\left(X_0,Y_0\right)<0$, directional congestion effect occurs to the "right" of the DMU$\left(X_0,Y_0\right)$. If these does not exist optimal solution in Model (8), there is no data to determine the directional congestion effect to the "right" of DMU$\left(X_0,Y_0\right)$.

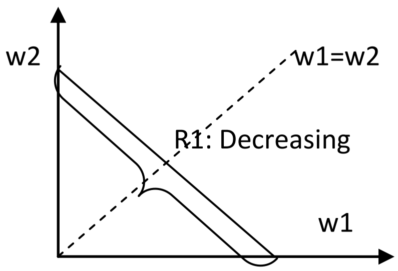
(2) If there exists optimal solution in Model (8) and the optimal value of objective function $\bar{\rho}\left(X_0,Y_0\right)<0$, directional congestion effect occurs to the "left" of the DMU$\left(X_0,Y_0\right)$. If these does not exist optimal solution in Model (8), there is no data to determine the directional congestion effect to the "left" of DMU$\left(X_0,Y_0\right)$.

For inefficient or weakly efficient DMUs, we can project them onto the strongly efficient frontier using DEA models so that we can detect the directional congestion effect to the "right" and "left" of them according to those of those projections.

RESULTS AND DISCUSSIONS

DIRECTIONAL RTS

Firstly, we determine the efficient frontier EF using input-based BCC-DEA model with radial measurement. Secondly, we can determine the directional RTS of 16 projected basic research institutes in CAS in 2010 using our methods in Section 2. We take DMU_1 as example. Without loss of generality, we set the outputs direction as $\delta_1 = \delta_2 = \delta_3 = \delta_4 = 1$. See Figure 1 ~ Figure 2 for details.



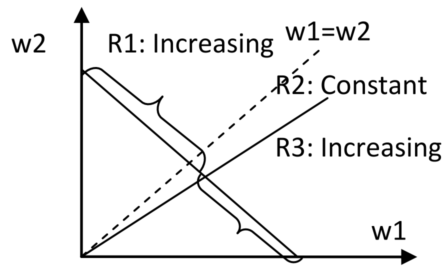


Figure 1: Directional RTS to the right of DMU_1 **Figure 2: Directional RTS to the left of DMU_1**

Through the above analysis, we have the following findings. For DMU_1, on the basis of existing inputs, if Staff and Res. Expen. increase in any proportion (under Pareto preference), decreasing directional RTS prevails on DMU_1, i.e., DMU_1 locates on the region with decreasing directional RTS in any direction of inputs increase. See Figure 1. If Staff and Res. Expen. decrease in radial proportion, increasing directional RTS prevails. If the proportion of Staff and Res. Expen. locates in R1 and R3 in Figure 2, increasing directional RTS prevails. If the proportion of inputs decrease locates in R2, constant directional RTS prevails. See Figure 2.

Similarly, we can have the directional RTS to the “right” and “left” of other DMUs. It is clear that our approach can provide more complete (not just in the diagonal direction) RTS information.

DIRECTIONAL CONGESTION EFFECT

Firstly, we detect the congestion effect of 16 projected basic research institutes using WY-TS model (Wei & Yan, 2004; Tone & Sahoo, 2004) based on the input-output data of these institutes. We can see that congestion effect occurs on DMU_3, DMU_8, DMU_9, DMU_{10}, DMU_{11}, DMU_{12}, DMU_{15} and DMU_{16}. Secondly, we can analyze the directional congestion effect of the above DMUs using our methods mentioned in Section 2. We take DMU_{15} as example. Without loss of generality, we set the outputs direction as $\delta_1 = \delta_2 = \delta_3 = \delta_4 = 1$ and we can compute the directional congestion effect of these two DMUs in different inputs directions. See Table 7 for details.

Table 7. Directional congestion effect of DMU_{15} in different inputs directions.

DMUs	ω_1	ω_2	$\underline{\rho}$ (Lower bound)	$\overline{\rho}$ (Upper bound)	Directional congestion effect (right)	Directional congestion effect (left)
DMU15	0.3	1.7	2.05	6.71	No	No
	0.5	1.5	1.72	5.03	No	No
	0.7	1.3	1.09	3.35	No	No
	0.9	1.1	0.37	1.67	No	No

1	1	0	1.13	No	No
1.1	0.9	-0.55	0.85	Yes	No
1.3	0.7	-1.74	0.50	Yes	No
1.5	0.5	-3.40	0.16	Yes	No
1.7	0.3	-5.06	-0.18	Yes	Yes

Based on the above analysis, we can find that congestion effect occurs on DMU_{15} when using WY-TS model – in fact this means that congestion can occur in the diagonal (strong congestion) or other (weak congestion) directions. From its directional congestion analysis, we can know that whether directional congestion effect occurs in certain directions (e.g., $\omega_1 = 1.7, \omega_2 = 0.3; \delta_1 = \delta_2 = \delta_3 = \delta_4 = 1$). On the other hand, for the same DMU, there are some directions (e.g., $\omega_1 = 0.3, \omega_2 = 1.7; \delta_1 = \delta_2 = \delta_3 = \delta_4 = 1$) where congestion does not occur. These are important details for the institute planning. Similarly, we can analyze the directional congestion effect for other DMUs.

CONCLUSIONS

This paper aims to investigate the directional returns to scale of 16 basic research institutes in CAS. Firstly, the input-output indicators are selected, including Staff, Research Expenditure, SCI papers, High-quality papers, Graduates training and external funding. Secondly, the methods proposed by Yang (2012) are introduced to analyze the directional returns to scale, optimal input direction and the effect of directional congestion for the basic research institutes in CAS. Based on our analysis, we have the following findings: (1) we can detect the regions of increasing (constant, decreasing respectively) directional RTS for each of the basic research institutes; (2) we find that the directional congestion occurs in certain directions in several of the basic research institutes. On this occasion, the outputs of these institutes will decrease with the inputs increase in the directions.

ACKNOWLEDGEMENTS

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ESTIMATING EFFICIENCY AND PRODUCTIVITY GROWTH OF THE FLOUR MILLS OF THE GRAIN SILOS AND FLOUR MILLS ORGANISATION (GSFMO) IN SAUDI ARABIA

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Abstract

The Grain Silos and Flour Mills Organisation (GSFMO) is a monopoly milling organisation in Saudi Arabia. However, the organisation has been facing financial problems for a number of years. In addition, there is a variation in the human and machine productivity between all branches, as well as rising the costs over time. The aim of this paper is to estimate the technical (TE) of nine flour mills of the GSFMO (1988-2011), using Data Envelopment Analysis (DEA) and explain variation in efficiency levels between the mills. Productivity growth for 2008-2011 is also estimated. Both primary data (interviews with branch managers) and secondary data issued by the GSFMO were utilised. Presenting results estimated using DEA approach, this paper shows that under variable returns to scale (VRS) input orientated (output orientated) mean TE ranged from 93.16% (93.21%) to 98.77% (98.79%), and under constant returns to scale (CRS), it ranged from 91.72% to 97.63%. Regarding productivity growth results for the period (2008-2011), no consistent patterns were found across branches in the mean total factor productivity growth (TFPG), technical change (TC), and efficiency change (EC).

***Keywords**: Technical efficiency; Data Envelopment Analysis; Constant Returns to Scale; Variable Returns to Scale; Total Factor Productivity Growth.*

INTRODUCTION

Wheat is one of the most important commodities and holds a strategic economic significance for Saudi Arabian agriculture. For this reason, the GSFMO, which is one of the main manufacturing and strategic industries with a crucial role to play in the Saudi food security, was established. The organisation is responsible for the milling industry and aims to prepare wheat for human consumption (GSMFO, 2010).

Analysing the current situation of flour mills in the GSFMO, a number of issues have been identified, including the monopoly of the organisation of the milling industry in the Kingdom of Saudi Arabia and the wide variation in performance, as well as the financial losses incurred each year despite the governmental annual support. Similarly, while the silos' storage capacity has remained the same, the amount of wheat used has increased. Hence, the proportion of storage capacity of the silos has steadily decreased relative to the amount of wheat used. The imbalance between storage capacity of the silos and the amount of wheat used across all branches has led to an increased movement of wheat between the branches, resulting in extra transportation costs for the organisation and a rise in the average unit cost of producing flour.

In addition, there has been a constant upward trend in the costs of flour production, with increases in the average costs of salaries and wages, operating costs, and maintenance costs per tonne of flour produced over the 1988-2011 period. Naturally, this increase in the unit cost of flour means reduced economic efficiency of the GSFMO's mills. This may then require a re-evaluation of the capital assets of the organisation and the operation of the resources used in the milling industry in to improve technical and economic efficiency. In recent years, the Saudi Arabian government has pursued a policy of economic reform and structural change, including the privatisation policy of the GSFMO, allowing the private sector access into the milling industry in 2003. However, in light of the losses incurred by the organisation, the private sector has not ventured into the industry, and consequently the GSFMO is still under the management and control of the state.

Previous studies exploring variation in efficiency within the agricultural and food production industries include approaches using Data Envelopment Analysis (DEA) (Coelli *et al*., 2002; Begum *et al.*, 2009) and Stochastic Frontier Analysis (SFA) (Willson *et al*, 2001, Bekele and Belay, 2007).

AIM AND OBJECTIVES OF PROJECT

This paper aims to estimate technical efficiency (TE) of the flour mills, explain variation in this efficiency and estimate productivity growth. The specific objectives are:

1) To analyse the production activities of the GSFMO (1988-2011).
2) To estimate productivity growth (2008-2011).
3) To measure the technical, allocative and economic efficiency of the GSFMO's branches, using Data Envelopment Analysis (DEA) and to explain variation in efficiency levels.
4) To provide recommendations and policies to improve the financial situation and operation of the flour mills.

RESEARCH METHODOLOGY AND DATA SOURCES

DATA COLLECTION

This paper uses primary data (interviews with branch managers) and secondary data published by the GSFMO during 1988-2011, specifically the reports issued by the management of internal controls and mills' records of the 22 mills which are distributed over nine branches; namely, Riyadh, Qassim, Hail, Jeddah, Tabuk, Aljouf, Dammam, Almadinah and Khamis Mushayt. The paper uses three inputs (amount of wheat, machine hours, and number of workers) and one output (amount of flour).

METHOD OF ANALYSIS

The DEA (Farrell, 1957) approach to estimating TE has been used when measuring efficiency of the flour mills. DEA analysis was undertaken using PIM Software and pooled data in this paper.

RESULTS AND DISCUSSION

MEAN TE OF ALL BRANCHES USING DEA

A review of the data contained in Table 1 shows that under CRS, mean TE ranges between a minimum of 91.72% in the Khamis Mushayt branch and a maximum of 97.63% in the Almadinah during the period from 1988 to 2011. Khamis Mushayt branch achieved mean TE of 91.72% and can increase the output by 8.28% without having to augment the inputs in the milling industry, or reduce inputs by this amount to achieve the same output. It appears then that the Khamis Mushayt branch has underutilised a portion of its resources, resulting in increased cost of flour production by 8.28% under CRS.

Under input-oriented VRS, mean TE for the various branches of the GSFMO ranged from a low of 93.16% in the Dammam branch to 98.77% for the Jeddah branch during the period 1988 to 2011. This shows that the Jeddah branch achieved the greatest level of efficiency under VRS. On the other hand, the Dammam branch has been shown to have the lowest TE, and has to reduce its inputs by 6.84%. It has also been shown that the Jeddah branch has underutilised a smaller fraction of its resources, which leads to increased cost of production of flour by only 1.23%, relative to optimal TE as measured under VRS.

In addition, under output-oriented VRS, mean TE for the various branches of the GSFMO ranged from a low of 93.21% in the Dammam branch up to 98.79% for the Jeddah branch during the period 1988 to 2011.

In respect to TE of branches under input-oriented VRS, it has been shown to be lower than those estimates under output-oriented VRS except for the Aljouf branch. Similarly, the Tabuk branch has an equal value estimate under both input- and output-oriented VRS; however, differences between these estimates are not substantial. It can be clearly inferred that the TE under VRS for the GSFMO branches was greater than its counterpart estimate for the same branches under CRS. These results confirm the findings of Begum *et al.* (2009), Alrwis and Francis (2003), and Bhagavath (2009), where VRS scores were shown to be higher than those under CRS.

Table 1: Mean technical efficiency for all branches during the period 1988-2011

Branch	Technical Efficiency (TE)	Technical Efficiency(TE)	
	CRS- Input and output oriented	VRS- Input oriented	VRS- Output oriented
Riyadh	94.47	95.64	95.7
Jeddah	97.07	98.77	98.79
Dammam	92.49	93.16	93.21
Qassim	95.13	95.41	95.48
Khamis	91.72	93.26	93.4
Tabuk	97.59	98.04	98.04
Almadinah	97.63	97.75	97.97
Hail	94.37	94.43	94.47
Aljouf	94.7	95.96	95.95
Mean	95.02	95.82	95.89

Examining TE for each branch, some branches have been found to be inefficient. For example, in 1992, Dammam was inefficient in terms of machine hours. For it to be efficient, it should decrease the number of machine hours by 61.11%, or increase its output by 49.39%, using the same input (Figure 1).

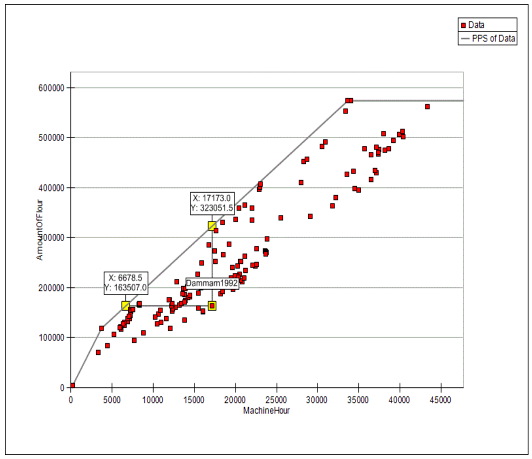

Figure 1: TE of the Dammam branch in terms of machine hours (1992)

Examining data from the interviews, the high TE achieved may be ascribed to the excellent condition of the equipment, sophisticated machinery and road worthy transportation. In addition, only a few managers have had the opportunity to gain qualifications by attending training courses in the field of milling industry technology. On the other hand, low TE can be ascribed to the fact that most branch managers have very limited experience in the milling industry, the number of machine breakdown hours and old machinery in some branches.

RESULTS OF PRODUCTIVITY GROWTH FOR ALL BRANCHES UNDER OUTPUT-ORIENTED CRS

MEAN TOTAL FACTOR PRODUCTIVITY GROWTH (TFPG), TECHNICAL CHANGE (TC) AND EFFICIENCY CHANGE (EC) (2008-2011)

The results generated are only for the studied period of four years (2008-2011), and therefore, these estimated results would not be expected to necessarily replicate results from the previous period (1988-2011) because of the more restricted sample size. With regard to the year 2009, for example, all branches achieved 100% efficiency during the studied period (2008-2011); meanwhile, efficiency for the same year was found to be different for the various branches, according to the overall period (1988-2011).

Reviewing the productivity change in the various branches of the GSFMO during the period from 2008 to 2011 under output-oriented CRS, it is shown that there is no change in TC in the Riyadh, Qassim, Tabuk, Almadinah and Hail branches, while there was an increase for Jeddah, Dammam and Khamis branches with an average rate of 0.67% per annum for each. On the other hand, TE decreased in the Hail branch by 0.33% (Table 2).

With respect to EC in the various branches, there was no change in terms of efficiency in the Riyadh, Jeddah, Dammam and Almadinah branches, while there was an increase in the Qassim and Khamis of 3% and 0.33% respectively. However, EC decreased at an equal rate of 0.67% for each of the Tabuk and Aljouf branches, while it also declined at the Hail branch (0.33%).

No change in TFPG for the Riyadh and Almadinah branches is observed during the period, while TFPG increased at an identical rate (0.67%) for the Jeddah, Dammam and Khamis branches, and 3.33% in the

Qassim branch. Finally, TFPG decreased by 0.67% in the Tabuk and Aljouf branches, and also in the Hail branch by 1.0%. As already shown, the period spanning from 2008 to 2011 did not see any change in terms of TC, EC, and TFPG in the Riyadh and Almadinah branches, while it increased in Khamis Mushayt and declined in Hail.

Moreover, when productivity growth was estimated for each period (2008-2009, 2009-2010 and 2010-2011), it is shown that the 2008-2009 was the highest increase with 3% TC in Jeddah and Dammam, while EC was 14%, and TFPG was 15% in Qassim during the same period. Compared to the other periods, the highest decrease was in the 2009-2010 period with 2% (TC) in Jeddah and Khamis, and 5% (in EC and TFPG) in both Qassim and Dammam branches. As for the Riyadh and Almadinah branches, there was no change in TC, EC and TFPG in each period (Table 2).

Table 2: Total factor productivity growth (TFPG), technical change (TC) and efficiency change (EC) for all branches (2008-2011)

Branch	Year	TC	EC	TFPG	TC%	EC%	TFPG%
Riyadh	2008-2009	1	1	1	0	0	0
	2009-2010	1	1	1	0	0	0
	2010-2011	1	1	1	0	0	0
	Mean	1	1	1	0	0	0
Jeddah	2008-2009	1.03	1.01	1.05	3	1	5
	2009-2010	0.98	1	0.98	-2	0	-2
	2010-2011	1.01	0.99	0.99	1	-1	-1
	Mean	1.0067	1	1.0067	0.67	0	0.67
Dammam	2008-2009	1.03	1.03	1.05	3	3	5
	2009-2010	0.99	0.95	0.95	-1	-5	-5
	2010-2011	1	1.02	1.02	0	2	2
	Mean	1.0067	1	1.0067	0.67	0	0.67
Qassim	2008-2009	1.01	1.14	1.15	1	14	15
	2009-2010	0.99	0.95	0.95	-1	-5	-5
	2010-2011	1	1	1	0	0	0
	Mean	1	1.03	1.0333	0	3	3.33
Khamis	2008-2009	1.03	1.04	1.07	3	4	7
	2009-2010	0.98	0.97	0.95	-2	-3	-5
	2010-2011	1.01	1	1	1	0	0
	Mean	1.0067	1.0033	1.0067	0.67	0.33	0.67
Tabuk	2008-2009	1.01	1	1.01	1	0	1
	2009-2010	0.99	0.98	0.97	-1	-2	-3
	2010-2011	1	1	1	0	0	0
	Mean	1	0.9933	0.9933	0	-0.67	-0.67
Almadinah	2008-2009	1	1	1	0	0	0
	2009-2010	1	1	1	0	0	0
	2010-2011	1	1	1	0	0	0
	Mean	1	1	1	0	0	0
Hail	2008-2009	1	1.01	1.01	0	1	1
	2009-2010	0.99	0.97	0.96	-1	-3	-4
	2010-2011	1	1.01	1	0	1	0
	Mean	0.9967	0.9967	0.99	-0.33	-0.33	-1

CONCLUSIONS

Given the lack of previous studies on the milling industry in Saudi Arabia, combined with the future prediction of shortages and a decline in the agricultural activities in the Kingdom, this paper aims to understand how to make the GSFMO more efficient and therefore assist the national economy in general.

As such, this research has set out to estimate TE and TFPG of the flour mills of the GSFMO in Saudi Arabia and to explain the efficiency variation levels between the various branches.

Using the PIM software in the DEA analysis, input- and output-oriented TE were estimated under the specifications of CRS and VRS. Under CRS, DEA yielded lower TE scores than VRS. For example, the mean TE under CRS reached a minimum of 91.72% in Khamis branch and a maximum of 97.63% in Almadinah. In addition, under output-oriented VRS, mean TE for the various branches of the GSFMO ranged from a low of 93.21% in the Dammam branch up to 98.79% for the Jeddah branch. Similarly, under input-oriented VRS, mean TE for the various branches of the GSFMO ranged from a low of 93.16% in the Dammam branch up to 98.77% for the Jeddah branch during the period 1988 to 2011.

To analyse TFPG in the various branches of the GSFMO, the PIM software was also utilised for a four year period. (2008-2011). The mean results of TFPG confirmed that in spite of the increase in TFPG, TC, and EC in some branches, there was no change in TFPG, TC, and EC for both Riyadh and Almadinah branches. Similarly, there was a decrease in the TC, EC and TFPG in the Hail branch. However, the scope of this paper is limited with respect to the estimation of productivity growth since it was based on a small sample size (four years only), while results could have been made more robust if the PIM software allowed unbalanced data.

Based on the aforementioned results and planned further research which will seek to compare DEA and Stochastic Frontier Analysis (SFA) approaches, this paper will provide recommendations and policies to improve the economic operation of the mills to help the government implement the privatisation policy and facilitate entry of the private sector to the Saudi milling industry.

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EVALUATING THE EFFICIENCY OF FACULTIES IN QASSIM UNIVERSITY USING DATA ENVELOPMENT ANALYSIS

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ABSTRACT

This paper investigates the efficiency of eighteen faculties in Qassim University (FQU) . The aim of the paper is estimate and analyze the efficiency in (FQU) for the academic year 2011-2012. Using the number of students enrolled, the number of teachers and staff as inputs, and The total number of students with a bachelor's degree and a number of research as outputs, We use The output oriented model with variable return to scale to estimate efficiency score. The result showed that (10) FQU or 55.5% are efficient with average 0.88 in term of variable return to scale efficiency. FQU obtained average scale efficiency 0.68 and only three FQU get the optimum size.

Keywords: *University Evaluating, efficiency, scale efficiency, Data Envelopment Analysis.*

INTORDUCTION

Qassim University was established in 2004 by merging two Qassim branches of Imam Mohammad Ibn Saud Islamic University and King Saud University. Since the establishment of the university, it has experienced a remarkable growth in enrollment and a significant expansion of faculty and its administrative staff. The number of male and female students registered at university during 2010-11 approached 50,000 and number of faculty members and staff reached well over 4,000. At present the university encompasses 28 colleges both for male and female students. This rapid expansion Qassim University should be accompanied by a rational exploitation for these possibilities so as to raise the performance indicators and minimizing wastage of human and material resources.

The aims of this paper is estimate and analyze the efficiency in 18 (FQU) for the academic year 2011-2012 using data envelopment method.

Although there are numerous studies have estimated the efficiency of universities in different countries around the world using various parametric and non-parametric methods especially in developed economics like United States (Kokkelenberg et al. 2008), the United Kingdom (Izadi et al. 2002, Flegg et al. 2004, Glass et al. 2006), Canada (McMillan and Chan 2006) and Australia (Abbott and Doucouliagos 2003, Worthington and Lee 2008) , Another group of papers has estimated the efficiency of departments within a university (Johnes and Johnes 1993, Tauer et al. 2007, Kao and Hung 2008) and of a given academic programme across universities (Colbert et al. 2000). But we saw there are a few or a rare studies in Arabs countries especial in Saudi Arabia, so our paper is fulfill this gap.

The rest of paper as follow: section two provides a brief overview of the methodology, section three discuss data and results and final section concludes.

DATA ENVELOPMENT ANALYSIS

Data Envelopment Analysis (DEA) has been a technique for measuring the relative efficiency of decision making units (DMUs) with multiple inputs and multiple outputs (Charnes et al., 1978, 1994; Banker et al., 1984). The method has become popular in university performance measurement (Prichard , 1990; Youn & Park, 2009). In fact, there are literally various kinds of DEA methods such as constant return to scale (CRS), variable return to scale (VRS), (Cooke & Zhu 2005). DEA measures the efficiency of the decision making unit (DMUs) by the comparison with best producer in the sample to drive compared efficiency. DEA submits subjective measure of operational efficiency to the number of homogenous entities compared with each other, through a number of samples unit which form together a performance frontier curve envelopes all observations. So, this approach called Data Envelopment Analysis. (Al- Delaimi & al-Ani, 2006). In this paper we adopted The output oriented model with variable return to scale to estimate efficiency score, this model developed by Banker et al. (1984):

$$\theta^* = \max_{\theta,\lambda} \theta$$

$$s.t. \quad \theta x_{io} \leq \sum_{j=1}^{n} \lambda_j x_{ij} \quad i = 1, \ldots, m$$

$$y_{ro} \geq \sum_{j=1}^{n} \lambda_j y_{rj} \quad r = 1, \ldots, s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \quad \forall j$$

where x_{ij} and y_{rj} denote the levels of the *i*th input and *r*th output of the *j*th university, $j = 1, \ldots, n$. The first two constraints require that the performance of a given university o in terms of its inputs x_{io} and outputs y_{ro} is located within a production possibility set defined by the envelopment of all data points. The last two constraints, where λ is an $N\times 1$ vector, allow for variable returns to scale by imposing a convexity restriction which generates a frontier in the form of a convex hull of intersecting planes.

DATA AND RESULTS

The data which have been used in this paper have been taken from the Higher Education Statistics Center of Saudi Arabia. The variables used are the number of students enrolled, the number of teachers and staff as inputs, and The total number of students with a bachelor's degree and a number of research as outputs. (appendix 1). DEAP software has been used for analyzing the information. Table 1 show the efficiency sore of eighteen Faculties in Qassim University.

The results show that the mean of CRS TE and VRS TE are 0.61 , 0.88 respectively , in turn only three faculties are full efficient in term CRS TE , and ten in term VRS TE, which mean about 55% are efficient. The mean of scale efficiency is 0.68 , only three faculties are work in optimal size , two work in increasing return to scale and thirteen work in decreasing return to scale , this refer that about 72% Qassim faculties are excess economic size.

Table 1. Efficiency Score in Faculties of Qassim University

Faculties	CRS TE	VRS TE	Scale efficiency	
Economics and Administration	0.501	1	0.501	drs
Education	0.822	1	0.822	drs
Sharia and Islamic Studies	0.286	1	0.286	drs
Pharmacy	1	1	1	-
Human Medicine	0.874	1	0.874	drs
science	1	1	1	-
Dentistry	0.713	1	0.713	irs
Arts and Sciences Rass	0.387	1	0.387	drs
Arts and Sciences in Buraidah	0.443	1	0.443	drs
Education for Girls - Buraidah	1	1	1	-
Applied Medical Sciences	0.907	0.971	0.934	drs
Arts and Sciences Balbkiria	0.722	0.91	0.793	drs
Agriculture and Veterinary Medicine	0.683	0.897	0.762	drs
Arts and Sciences Anayzah	0.255	0.81	0.315	drs
Engineering	0.527	0.766	0.689	irs
Computer	0.478	0.577	0.829	drs
Arabic Language And Social Studies	0.151	0.509	0.297	drs
Designs and home economics	0.208	0.369	0.563	drs
mean	0.609	0.878	0.678	

Source : The output of DEAP software ver. 2.1

CONCLUSIONS

This paper investigates the efficiency of eighteen Faculties in Qassim University (FQU) for the academic year 2011-2012. The results showed only three faculties are full efficient in term CRS TE , and ten in term VRS TE, which mean about 55% are efficient. The mean of scale efficiency is 0.68 , only three faculties are work in optimal size , two work in increasing return to scale and thirteen work in decreasing return to scale , this refer that about 72% Qassim faculties are excess economic size. So we can conclude that most of Qassim faculties exceed the optimal size and produce decreasing return to scale , this can be explained by rapid growth in enrollment and a significant expansion of faculty and its administrative staff, Therefore, we believe that academic expansion in Qassim univesity should be gradually in order to ensure efficient use of limited resources.

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Appendix 1. Input and output of in Faculties of Qassim University

Faculties	Inputs			Outputs	
	students enrolled	**staff**	**teachers**	**bachelor's degree**	**research**
Economics and Administration	2974	27	196	453	56
Education	2514	84	138	76	107
Computer	885	27	117	20	31
Agriculture and Veterinary Medicine	1780	75	112	197	70
Sharia and Islamic Studies	4232	77	310	520	76
Pharmacy	346	16	48	6	28
Human Medicine	582	199	218	89	40
science	1497	32	88	119	83
Arabic Language And Social Studies	1837	49	222	286	9
Engineering	305	20	117	166	6
Dentistry	196	16	87	24	11
Arts and Sciences Balbkiria	2451	74	84	303	55
Arts and Sciences Rass	8209	45	184	920	43
Arts and Sciences in Buraidah	8303	67	187	1071	1
Arts and Sciences Anayzah	4521	90	174	574	27
Education for Girls - Buraidah	438	7	35	452	29
Designs and home economics	1162	14	86	188	4
Applied Medical Sciences	428	44	75	36	31

Source : Higher Education Statistics Center

EVALUATING THE PERFORMANCE OF PUBLIC HEALTH CARE SERVICES PROVISION: AN ANALYSIS OF THE MUNICIPALITIES OF MATO GROSSO STATE, BRAZIL

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ABSTRACT

The public health care system in Brazil (SUS) is designed to be universal and equitable. To cover almost 200 million people, it demands a great amount of public resources. To improve the resource application on health care, we propose a framework to assess performance of this system. In addition, we verify whether contextual variables affect the level of efficiency and test the hypothesis of constant returns to scale, by using non-parametric tests in an outlier corrected environment. The methodological approach is based on two-stage Data Envelopment Analysis (DEA). The sample comprises the municipalities of Mato Grosso state, Brazil, in 2011. The results indicate that the municipalities of Mato Grosso have an average 76.8% of technical efficiency in the resources application. An average, the adoption of best management practices observed in the state would allow the expansion of 30.2 % on provision, access and quality of services. Finally, we confirm the hypothesis of the presence of scale economies. Thus, the adoption of best management practices, the scale adequacy (by managerial centralization), and the alignment of public health preventive policies can be emphasized to increase efficiency.

Keywords*: Data Envelopment Analysis, Bootstrap, Health care, Public services, Brazil.*

INTRODUCTION

The public health care system in Brazil (SUS) is designed to be universal and equitable. To cover almost 200 million people, it demands a great amount of public resources. The resources destination to SUS is ensured by the Brazilian Constitution. Since 2012, with an additional Law, the Federal, regional and local governments must allocate part of its budget to provide public health care services. The Federal government must destine an amount of resources equal to the value expended in the last year plus the nominal variation of the Gross Domestic Product (GDP), while the regional (States) and local (cities and towns) governments must allocate 12% and 15%, respectively, of its budgets for public health care services provision.

In Brazil, the local (cities and towns) governments are the main responsible for the public health care management system. They are supposed to apply and manage all the resources destined to provide public health care services. To improve the resource application on health care, we propose a framework to assess performance of this system. In addition, we verify whether contextual variables affect the level of efficiency and test the hypothesis of constant returns to scale, by using non-parametric tests in an outlier corrected environment. This last step is important because the inefficiency can be related to exogenous factors, besides management failures, that local government cannot control, like suggested by Sampaio de Sousa et al. (2005).

Indeed, in Brazil, the literature suggest the existence of a strong scale economies effect in the demand and provision of general public services, in other words, increasing the public services provision is related to decreasing marginal costs or big cities would be more efficient in the public services provision than the smaller ones.

Sampaio de Sousa et al. (2005) evaluated, for Brazil, the municipal efficiency level in providing general public services and Mendes e Sampaio de Sousa (2006, 2007) estimated, using a median voter's framework, also for Brazil, the demand for general and health care and education public services, respectively. In the three papers, evidence of the presence of scale economies in municipal level was found.

Mendes e Sampaio de Sousa (2006) claim that these empirical evidences contradict the "Brecht Law", this Law postulate that areas where there are greater population density have the tendency of greater *per capita* expenditures to provide public services. In fact, these results agree to a new theoretical framework based on crowding functions. The baseline of this argument lies in the presence of scale economies in the public services provision, making possible an inverse relationship between population density and *per capita* expenditure and, in consequence, a direct relationship between population size and efficiency (REITER; WEICHENRIEDER, 1997 apud MENDES; SAMPAIO DE SOUSA, 2006).

The Mato Grosso State, located in the Center West region of Brazil, was chosen like the study case of this paper. A non negligible part of the state was recently occupied, so since 1970 the share of the national population that resides in the state increased from 0.65% to 1.6% currently, that represents the third largest population growth in the country. Among the States with the fastest relatively population growth, Mato Grosso was the one that had the greatest population growth, since 1970 the resident population has increased 5 times, mainly due to migration of people to the State. Therefore, it appears that the State has suffered great pressure both by application of resources as the demand for public health care services becoming a relevant case to be investigated.

In this context, the purpose of this study is to propose a framework to measure efficiency in providing public health care services and apply it to the municipalities of Mato Grosso State. As a second step we analyze, through regression analysis, whether the causes of inefficiency are concentrated in the direct management of resources or conditions outside the control of local governments would be affecting the levels of municipal efficiency.

The empirical strategy is the main innovation of this paper. The outlier detection tests and also the returns to scale tests allow a robustness efficiency estimation, like the bootstrap resample technique in the regression model generates "better" coefficients with robust standard errors. Thus, the model used can be applied to analyze the efficiency in the public health care services provision over different situations/regions.

METHODS

Analysis Techniques. The methodological approach of this study is based on two-stage Data Envelopment Analysis (DEA). This approach joins the efficiency measure through Data Envelopment Analysis (DEA) with regression analysis, using the efficiency index like a dependent variable.

For the efficiency estimation of the municipalities of Mato Grosso State in providing public health care services, we test the hypothesis of constant returns to scale CRS (CCR), proposed by Marinho and Façanha (2000) and Marinho (1998, 2003). This hypothesis is based in the fact that health care organizations work with some unused capacity given the unpredictability of demand or the inability to transfer demand to other health care units.

For outlier detection we use the *leverage* estimator, proposed by Sampaio de Sousa e Stosic (2005), which is based in the Euclidian distance measure to verify how distant one efficiency frontier to another is. If a municipality is very distance from the frontier, when this municipality is not included in the estimation, this is evidence that this city is an outlier.

In an outlier corrected environment, we want to define what is the best efficiency estimator (CCR versus BCC) to asses public health care services provision, so we use the Simar and Wilson (2002) S_1 and S_2 tests and we also use the Kolmogorov and Smirnov non-parametric test, suggested by Banker and Natarajan (2004).

The result of the last step, the efficiency measure, will be used like a dependent variable in a regression analysis to explore the presence of a scale economies effect in providing public health care services. To regression estimation we use the #1 Simar and Wilson's (2007, p.41) algorithm.

Data. The data for this study were extracted from the SUS database (DATASUS) and from the Brazilian Institute of Geography and Statistics (IBGE) database. The reference year was 2011 and the data correspond to the 141 municipalities of the Mato Grosso State, Brazil.

Measures – Public health care services Inputs and Outputs. Based on Ozcan (2008) we measure the public health care services provision by four types of output: treated cases (outpatient procedures and hospital admissions) weighted by a service-mix complexity index, home visits (doctors and nurses), immunization (vaccines applied) and two indicators: one indicator of access (under 1, mortality rate) and one indicator of quality (hospital mortality rate). Like inputs we use two types of measures: capital (number of hospitals, beds and outpatient capacity) and total expense with health care.

Measures – Contextual variables. To verify the presence of a scale economies effect in providing public health care services we use four contextual variables: *per capita* Gross Domestic Product (GDP) and total population (both in logarithm measure), urbanization rate and population density. In fact, if there is a scale economies effect, these variables should present a positive direct and statistically significant relationship for the efficiency index. We also included other nineteen control variables related to income, demography, education, infra structure, climate and geography to control for other effects that could influence the efficiency level.

RESULTS AND DISCUSSIONS

Outlier Detection and returns to scale. Just one city (Jangada) was identified like an outlier, in other words, this city has a level of influence over the efficiency frontier beyond of acceptable, so this city was excluded of analysis.

For the returns to scale, the hypothesis that the production function in providing public health care services present constant returns to scale CRS was confirmed. Table 1 shows the returns to scale tests results.

Table 1: Returns to scale tests and critical values, H_0: CRS; H_1: VRS.

Tests	Test Statistics	Critical Values		
	Mean	**10%**	**5%**	**1%**
Simar and Wilson's S_1	**0.831**	0.642	0.582	0.434
Simar and Wilson's S_2	**0.834**	0.828	0.826	0.820
Kolmogorov-Smirnov	**0.000**	0.103	0.115	0.137

Thus, we use the CRS model with output orientation to measure the efficiency level in the public health care services provision in the Mato Grosso State.

Performance Assessment. Table 2 shows the efficiency results for the CRS model with output orientation.

Table 2: Municipal distribution by efficiency ranges (E)

Ranges	**CRS Technical Efficiency (Nº municipalities)**
E < 0.1	0
0.1 ≤ E < 0.2	0
0.2 ≤ E < 0.3	1
0.3 ≤ E < 0.4	5
0.4 ≤ E < 0.5	11
0.5 ≤ E < 0.6	13
0.6 ≤ E < 0.7	20
0.7 ≤ E < 0.8	24
0.8 ≤ E < 0.9	20
0.9 ≤ E < 1.0	12
E = 1.0	34
Total	140
Efficiency measures:	
Mean	0.768
Standard Deviation	0.198
Coefficient of variation	25.79%

Under the constant returns to scale assumption, we verify that, among the sample of 140 municipalities, 34 reached the maximum level of efficiency. The average level of inefficiency was 0.302 [1-(1/0.768)], which means that the municipalities can increase, in average, 30.2% of its public health care services access, quality and provision, keeping constant the expenditures. It is noteworthy that the municipalities that achieved maximum technical efficiency cannot increase the provision of services. However, others can do it using like reference those with efficiency equal to one.

Scale Effect. Table 3 shows the influence of the contextual variables on the level of efficiency. Two procedures are described, one using a Tobit estimator and another according to the #1 Simar and Wilson's algorithm.

Table 3: Efficiency determinants in providing public health care services, Mato Grosso, Brazil, 2011

Variáveis	Tobit Estimator			Simar and Wilson Estimator		
	coeficient		std. dev.	coeficient		std. dev.
Constant	-3.64565	***	1.33728	-2.69657	***	0.48524
ln_pc_GDP	0.07233		0.04873	0.06240	***	0.01615
ln_total_population	0.22245	***	0.03497	0.17474	***	0.01266
Urbanization_rate	0.28377		0.18827	0.19827	***	0.06612
Population_density	-0.00082		0.00089	-0.00039		0.00040
R^2	0.42477			0.42244		
F test	3.56916	***		3.53529	***	

*t test (α: 10%); ** t test (α: 5%); *** t test (α: 1%).

The strong influence of the environment on the public health care services provision in Mato Grosso is evidenced by the significance of the factors considered, in other words, ignoring this fact could lead to a resources application below the optimum level of efficiency.

The variables included to capture the scale effect were relevant to explain the efficiency, but the population density was not. The *per capita* GDP, the population and the urbanization rate presented a strong positive relationship to the level of efficiency, confirming the hypothesis raised by this and other cited articles. These results suggest, according to Mendes and Sampaio de Sousa (2006) that the large number of small cities prevents the exploitation of economies of scale, inherent characteristic of public services, limiting a more efficient resource application and the increase in the health care services provision with decreasing average costs.

Regarding the control variables, although many present significant relationships, its low magnitude indicates a much lower impact on the level of efficiency than the characteristics of scale. Often, socioeconomic variables that are outside the direct control of managers affect the efficiency of the municipalities in the provision of health care services. Thus, the study of the determinants of efficiency is of great importance for the definition of actions through public policies to improve performance of municipalities.

CONCLUSIONS

The analysis emphasizes that efficient cities offer greater number of public health care services with lower costs compared to the other cities. With reference to the efficient municipalities is possible to obtain significant gains in the provision of public health care services in the State. Given the calculated efficiency index, if the municipalities are projected to the efficient frontier, would be possible to obtain an average gain of 30.2% in the provision, quality and access to public health care services. The existence of repressed demands makes this increase necessary.

The analysis of contextual determinants of efficiency reinforced the findings already obtained. It was found that the efficient municipalities are generally larger, both in economic as in population terms, compared to the other cities. These results led to the confirmation of the hypothesis that there are economies of scale in the provision of public health care services.

Actions like the centralization of services in addition to the formation of local health care services provision consortiums could help to improve the efficiency in the resources allocation. Other States already have this mechanism, called Health Care Inter-municipal Consortium to centralize the health care provision management and increase efficiency.

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EVALUATION OF TURKISH AIRPORT EFFICIENCIES USING DATA ENVELOPMENT ANALYSIS AND MOORA METHOD

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ABSTRACT

In this study, performance of 40 Turkish Airports is evaluated by using Data Envelopment Analysis (DEA) and MOORA metod (Multi-Objective Optimization on basis of Ratio Analysis). The best possible parameters reflecting the capacity of an airport infra-structure is selected and they are used in DEA model, which is solved by using Win4deap software. In the DEA model, the most efficient results are obtained in terms of output oriented maximization. In this study the inputs that effect performance are defined as number of personnel and number of apron. The outputs are number of passenger, cargo movements, total plane movements. The efficient airports are derived by using the data of years 2000-2004 from State Airports Authority Directorate General (DHMI) annual statistics. Actual and target values for each airport are calculated and discussed by taking efficient airports as a reference set for the inefficient ones.

Key Words: *Airports efficiency, Multi-objective optimization on basis of ratio analysis, Data Envelopment Analysis.*

INTRODUCTION

Data Envelopment Analysis (DEA) by Charnes, Cooper and Rhodes [1978] is a method for evaluating the relative efficiency of comparable entities referred to as Decision Making Units (DMU). The summary of the main characteristics of DEA method are to be able to identify the sources and the level of inefficiency for each DMU and their evaluated efficiencies are relative efficiencies since the level of efficiency of each DMU is obtained with respect to the other units, and making no assumptions on the variables.

CCR AND BCC MODELS

When performing DEA, the first step is to decide whether to use a CRS or a VRS model since DEA gives you the choice. The essence of the CRS model is the ratio of maximization of the ratio of weighted multiple outputs to weighted multiple inputs. The original model developed by Charnes, Cooper and Rhodes(CCR model) was applicable when characterized by constant returns to scale(CRS). Banker, Charnes and Cooper(BCC model, 1984) extended the CCR model to account for technologies that show variable returns to scale(VRS). The technical efficiency score (in both CRS and VRS models) equal one implies full efficiency. On the other hand, if the score is less than one it indicated technical inefficiency.

MOORA (MULTI-OBJECTIVE OPTIMIZATION ON BASIS OF RATIO ANALYSIS) METHOD:

A new method is proposed for multi-objective optimization with discrete alternatives: MOORA (Multi-Objective Optimization on the basis of Ratio Analysis). This method refers to a matrix of responses of alternatives to objectives, to which ratios are applied. A well established other method for multi-objective optimization is used for comparison, namely the reference point method. Later on, it is demonstrated that this is the best choice among the different competing methods. In MOORA the set of ratios has the square roots of the sum of squared responses as denominators. These ratios, as dimensionless, seem to be the best choice among different ratios. These dimensionless ratios, situated between zero and one, are added in the case of maximization or subtracted in case of minimization. Finally, all alternatives are ranked, according to the obtained ratios.

METHOD AND DISCUSSIONS

For the analysis of the specified inputs and outputs using Win4deap software with the entry of the CCR and BCC models obtained in the effective values are summarized below.

FOR 2010-2011 CCR RESULTS AND REFERENCE SETS TABLE

For example, as shown in Table , in 2010 the reference sets of Dalaman are Atatürk airport and Antalya airport. Therefore, for Dalaman airport to become efficient, it can learn best practices from these departments.λ 1=0,111 and λ 4=0,010 show the proportions contributed by Atatürk airport and Antalya airport to the point used to evaluate Dalaman. Further, it is observed that DMU 20(Diyarbakır) is the most recurring benchmark. It was referenced for 34 times, which means that there are 34 departments which could learn from DMU20 best practices and thus become efficient. The same can be said about the other recurring benchmarks like DMU1 was referenced for 25 times.

FOR 2010-2011 COMPARISON BETWEEN ACTUAL AND TARGETED VALUES TABLE

In this study, the targeted value of a variable represents the amount to which a given DMU can decrease its consumption of that specific variable. If inefficient departments can reduce their inputs or outputs to the corresponding target levels, then, they would become efficient. In general, departments in performance of ineffective Turkish Airports need to reduce their inputs number of personnel and number of apron in order to become efficient.

FOR THE RANKING RESULTS OBTAINED USING THE MOORA METHOD TABLE

According to the calculation results in 2010 with referans point, ranking order of alternatives is as follows:Antalya > Atatürk > Adnan Menderes > …… > Ağrı > Balıkesir . This means that the fourth alternative, Antalya, is the best solution with the overall performance index of 0,46996, and the fortieth alternative, Balıkesir, is the worst with the result of 0,89378.According to both methods in 2010 and 2011, Ratio System and *The Full Multiplicative Form*,Atatürk airport is chosen above the other airports.

Table 1: 2010-2011 CCR results and reference sets

DMU	SKORE		RANK		Reference set(λ)			
	2010	2011	2010	2011	2010		2011	
ATATÜRK	1,000	1,000	1	1	DMU1 1,000		DMU1,000	
ESENBOĞA	0,417	0,403	11	9	DMU1 0,093	DMU20 4,162	DMU1 0,080	DMU20 4,085
A.MENDERES	0,550	0,545	8	5	DMU1 0,128	DMU20 2,406	DMU1 0,113	DMU20 2,478
ANTALYA	1,000	1,000	1	1	DMU4 1.000		DMU4 1,000	
DALAMAN	0,320	0,278	19	20	DMU1 0,111	DMU4 0,010	DMU1 0,098	DMU20 0,034
ADANA	0,286	0,280	21	19	DMU1 0,102	DMU20 0,077	DMU1 0,108	
TRABZON	0,688	0,400	6	10	DMU1 0,008	DMU20 1,373	DMU1 0,035	DMU20 0,581
MİLASBODRUM	0,349	0,339	15	14	DMU1 0,070	DMU4 0,038	DMU1 0,076	DMU4 0,022
S.DEMİREL	0,349	0,486	16	7	DMU1 0,015	DMU20 0,136	DMU1 0,019	DMU20 0,205
N.KAPADOKYA	0,155	0,097	28	36	DMU20 0,155		DMU1 0,002	DMU20 0,102
ERZURUM	0,150	0,160	29	30	DMU1 0,022	DMU20 0,051	DMU1 0,020	DMU20 0,107
GAZİANTEP	0,369	0,394	14	11	DMU1 0,014	DMU20 0,552	DMU1 0,012	DMU20 0,666
ADIYAMAN	0,297	0,034	20	40	DMU20 0,099		DMU1 0,002	DMU20 0,005
AĞRI	0,002	0,288	40	16			DMU20 0,096	
BALIKESİR	0,015	0,078	39	38	DMU20 0,002		DMU20 0,014	
B,YENİŞEHİR	0,165	0,207	27	25	DMU1 0,009	DMU20 0,118	DMU1 0,009	DMU20 0,192
ÇANAKKALE	0,340	0,228	17	22	DMU20 0,113		DMU1 0,004	DMU20 0,109
DENİZLi-ÇARDAK	0,128	0,144	31	32	DMU1 0,003	DMU20 0,069	DMU1 0,003	DMU20 0,098
ÇORLU	0,728	0,663	5	4	DMU1 0,070		DMU1 0,071	
DİYARBAKIR	1,000	1,000	1	1	DMU20 1.000		DMU20 1,000	
ELAZIĞ	0,564	0,341	7	13	DMU20 0,376		DMU1 0,001	DMU20 0,299
ERZİNCAN	0,473	0,120	10	33	DMU20 0,158		DMU1 0,007	DMU20 0,026
VAN F.MELEN	0,389	0,447	13	8	DMU1 0,017	DMU20 0,256	DMU1 0,017	DMU20 0,348
HATAY	0,539	0,511	9	6	DMU1 0,010	DMU20 0,230	DMU1 0,006	DMU20 0,317
K.MARAŞ	0,089	0,322	34	15	DMU20 0,060		DMU20 0,107	
KARS	0,173	0,173	26	27	DMU1 0,007	DMU20 0,072	DMU1 0,006	DMU20 0,080
KAYSERİ	0,331	0,390	18	12	DMU1 0,027	DMU20 0,060	DMU1 0,027	DMU20 0,161
KONYA	0,846	0,222	4	23	DMU20 0,564		DMU1 0,013	DMU20 0,157
B,KÖRFZ	0,051	0,119	37	34	DMU1 0,003	DMU20 0,007	DMU1 0,006	DMU20 0,039
MALATYA	0,263	0,281	23	18	DMU1 0,019	DMU20 0,037	DMU1 0,017	DMU20 0,102
MARDİN	0,415	0,152	12	31	DMU1 0,006	DMU20 0,103	DMU1 0,001	DMU20 0,062
MUŞ	0,249	0,218	24	24	DMU1 0,002	DMU20 0,096	DMU1 0,002	DMU20 0,091
MERZİFON	0,092	0,066	33	39	DMU20 0,038		DMU20 0,031	
S.ÇARŞAMBA	0,275	0,288	22	17	DMU1 0,021	DMU20 0,093	DMU1 0,021	DMU20 0,267
SİİRT	0,034	0,161	38	29	DMU20 0,011		DMU20 0,054	
SİNOP	0,204	0,168	25	28	DMU20 0,068		DMU1 0,007	DMU20 0,056
ŞANLIURFA	0,103	0,090	32	37	DMU1 0,009	DMU20 0,002	DMU1 0,006	DMU20 0,024
SİVAS	0,066	0,114	36	35	DMU1 0,004	DMU20 0,007	DMU20 0,027	
TOKAT	0,131	0,184	30	26	DMU20 0,044		DMU20 0,061	
UŞAK	0,086	0,264	35	21	DMU20 0,029		DMU20 0,088	

Table 2: 2010-2011 Comparison between actual and targeted values

DMU	Number Of Passenger		Cargo Movement		Plane Movement		Number Of Personel		Number Of Apron	
	2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
ATATÜRK	0	0	0	0	0	0	0	0	0	0
ESENBOĞA	589086,5	1158694,3	134602,0	156390,8	0	0	248,7	292,6	0	0
A.MENDERES	0	0	102568,0	115399,7	2932,5	2855,6	119,0	143,4	0	0
ANTALYA	0	0	0	0	0	0	0	0	0	0
DALAMAN	0	0	53420,8	51970,5	5459,8	3557,1	0	0	0	0
ADANA	537435,4	753466,3	62363,5	77891	0	0	0	0	0,122	1,633
TRABZON	158530,1	30709,3	15056,9	24527,9	0	0	30,3	0	0	0
M.BODRUM	0	0	44564,8	48824,8	0	0	0	0	0,992	0,947
S.DEMİREL	625058,8	990846,5	16189,8	24255,8	0	0	0	0	0	0
N.KAPADOKYA	26443,6	63478,23	0	424,5	0	0	0	0	0	0
ERZURUM	0	69937,33	15297,3	17336,1	0	0	0	0	0,157	0,078
GAZİANTEP	200615,5	272184,8	8305,3	8125,6	0	0	0	0	0	0
ADIYAMAN	0	0	0	519,455	0	00	0	0	0	0,831
AĞRI	0	0	0	0	44	0	33	0	0	0
BALIKESİR	0	0	0	0	0	0	0	0	0	0
B.YENİŞEHİR	34998,1	524146,9	8690,6	11244,9	0	0	0	0	0	0
ÇANAKKALE	0	234838,8	0	4923,8	0	0	0	0	0	0
D. ÇARDAK	67248,7	7411,757	2563,1	2508,8	0	0	0	0	0	0
ÇORLU	2178817,5	2598124,2	50517,7	60154,5	0	0	0	0	0	1,598
DİYARBAKIR	0	0	0	0	0	0	0	0	2,818	0
ELAZIĞ	0	0	0	0	0	57,054	0	0	0	0
ERZİNCAN	0	49777,1	0	5131,1	80,6	0	17,3	0	0	0,663
VAN F.MELEN	22448,1	146466,7	11104,3	12849,6	0	0	0	0	0	0
HATAY	77239,9	63613,2	5556,0	2540,9	0	0	0	0	0	0
K.MARAŞ	0	0	3,906	0	0	0	0	0	0	0
KARS	0	0	4447,3	6396,9	174,7	545,2	0	0	0	0
KAYSERİ	12929,4	19828,5	14195,1	17836,3	0	0	0	0	0,174	0
KONYA	199694,7	133030,8	1856,0	12024,3	0	0	36,9	0	0	0
B,KÖRFEZ	66825,7	202373,6	2653,0	6871,2	0	0	0	0	0,480	0,431
MALATYA	138823,8	198223,2	13245,0	16291,9	0	0	0	0	0,332	0,086
MARDİN	20934,9	2395,209	3338,0	0	0	0	0	0	0	0
MUŞ	33145,6	0	233,1	65,3	0	14,115	0	0	0	0
MERZİFON	0	0	81,4	0	0	36,129	0	0	0	0
S.ÇARŞAMBA	117772,4	70125,87	13670,0	16210,1	0	0	0	0	0	0
SİİRT	591,2	8118,501	7,8	150,430	0	0	18,1	4,504	0	0
SİNOP	0	0	25,2	3,938	0	0	0	8,478	0	0
ŞANLIURFA	68286,6	24032,15	6524,8	5085,34	0	0	0	0	0,718	0,696
SİVAS	25842	16169,07	2849,8	4611,46	0	0	0	0	0,549	0,640
TOKAT	0	16951,58	12,6	209,672	0	0	21,9	8,763	0	0
UŞAK	0	0	23,9	0	0	0	26,9	0	0	0

Table 3: The ranking results obtained using the MOORA method

AİRPORTS	Ratio System				Reference Point				The Full Multiplicative Form			
	2010 Ratio	Rank	2011 Ratio	Rank	2010 Ratio	Rank Min	2011 Ratio	Rank Min	2010 Ratio	Rank	2011 Ratio	Rank
ATATÜRK	1,44147	1	1,44443	1	0,57816	2	0,591629	1	1,05368E+14	1	1,4136E+14	1
ESENBOĞA	-0,46001	40	-0,4560	40	0,80953	4	0,817062	18	8,69817E+11	4	1,08854E+12	4
A.MENDERES	-0,10385	35	-0,0974	36	0,80407	3	0,810483	2	2,06489E+12	3	2,73386E+12	3
ANTALYA	0,52271	2	0,52173	2	0,46996	1	0,567231	6	2,98934E+13	2	4,02611E+13	2
DALAMAN	-0,17985	38	-0,1990	38	0,84478	5	0,853215	12	4,62748E+11	7	4,29399E+11	7
ADANA	-0,21113	39	-0,2350	39	0,85890	7	0,864483	3	2,70222E+11	9	2,92511E+11	10
TRABZON	-0,03540	17	-0,0797	34	0,87494	8	0,875893	38	4,86516E+11	6	3,39956E+11	9
MİLASBODRUM	-0,12551	36	-0,1197	37	0,85754	6	0,860353	28	4,44178E+11	8	5,66411E+11	5
S.DEMİREL	-0,05538	26	-0,0432	28	0,89349	33	0,894666	32	152052246,1	31	78106968,38	37
N.KAPADOKYA	-0,07685	30	-0,0540	31	0,89212	24	0,893223	30	1110420826	26	974982143,4	28
ERZURUM	-0,13416	37	0,01772	13	0,88731	15	0,888474	17	15352746424	20	18786040887	17
GAZİANTEP	-0,08115	32	0,17378	5	0,88245	12	0,882793	19	89496268542	13	1,56804E+11	11
ADIYAMAN	-0,02844	11	-0,0491	29	0,89295	28	0,8945	4	1980751078	24	32265399,02	39
AĞRI	-0,03357	15	-0,0317	25	0,89378	39	0,893653	5	0	39	199955228,2	32
BALIKESİR	-0,01591	6	0,00700	15	0,89378	40	0,894758	7	0	39	76178509,09	38
B.YENİŞEHİR	-0,09499	33	-0,0830	35	0,89378	38	0,893432	9	665783,7104	37	591332130	29
ÇANAKKALE	-0,02748	10	-0,0065	16	0,89359	34	0,894447	10	131292584,5	33	1049867687	27
DENİZLİÇARDAK	-0,05752	27	-0,0530	30	0,89280	27	0,893435	13	794967299,3	27	464329294,3	31
ÇORLU	-0,04328	21	0,32105	3	0,87897	9	0,88203	11	24060024064	19	5,5267E+11	6
DİYARBAKIR	0,00873	3	0,09522	8	0,88122	11	0,88186	14	7,2427E+11	5	3,93728E+11	8
ELAZIĞ	-0,04688	23	-0,0202	22	0,88935	19	0,889773	15	39988273684	16	15686634737	18
ERZİNCAN	-0,03080	12	0,15798	6	0,89247	25	0,893064	16	5049199804	23	12449148464	19
VAN F.MELEN	-0,04167	20	0,08662	9	0,88548	14	0,885824	40	98297291839	12	1,1207E+11	12
HATAY	-0,01426	5	-0,0128	18	0,88743	16	0,888244	20	1,21272E+11	11	21728935313	16
K.MARAŞ	-0,04428	22	0,04546	11	0,89328	31	0,894005	21	144710008	32	8353503223	20
KARS	-0,05433	25	0,19119	4	0,88989	20	0,891493	22	9650426670	21	3558561128	22
KAYSERİ	-0,04092	19	-0,0595	33	0,88072	10	0,881502	23	1,48191E+11	10	2441500885	24
KONYA	-0,03936	18	0,03478	12	0,88881	18	0,889684	24	76824540542	15	23579337201	15
B,KÖRFEZ	-0,07255	29	-0,0590	32	0,89340	32	0,894396	8	34540847,83	34	149805790,4	33
MALATYA	-0,05270	24	0,05271	10	0,88799	17	0,890148	25	33431982225	18	33801693574	14
MARDİN	-0,01387	4	-0,0067	17	0,89072	21	0,893775	26	37908408143	17	1962044256	25
MUŞ	-0,02624	8	0,01035	14	0,89210	23	0,893192	29	6109123383	22	6950275697	21
MERZİFON	-0,03451	16	-0,0277	24	0,89327	30	0,8945	27	236008394,1	30	91174055,28	36
S.ÇARŞAMBA	-0,09704	34	0,13732	7	0,88438	13	0,884977	31	51137964445	14	88860867141	13
SİİRT	-0,02628	9	-0,0190	21	0,89377	37	0,894607	33	15781,05263	38	128702304,8	35
SİNOP	-0,02305	7	-0,0160	19	0,89326	29	0,894316	34	622757164,6	28	548631771	30
ŞANLIURFA	-0,08112	31	-0,0413	27	0,89191	22	0,893062	36	1732998436	25	1547724965	26
SİVAS	-0,06754	28	-0,0184	20	0,89266	26	0,892918	35	413281736,5	29	2756953367	23
TOKAT	-0,03170	13	-0,0231	23	0,89367	36	0,894589	37	15615159,53	34	130671343	34
UŞAK	-0,03266	14	-0,0346	26	0,89365	35	0,894705	39	13860096,92	36	18572188,06	40

CONCLUSIONS

This research used the input minimizing Data Envelopment Analysis approach to measure the technical efficiency of Turkish Airports departments. The DMUs of the research are 40 departments and the study covered the period (2010-2011). The results of CCR model have an average of 34,2% and 31,6 %. 3 DMUs are 100% efficient in CCR. The potential improvements are then evaluated for each inefficient DMU. It was found that cargo movements needs the most improvement in outputs and number of personnel needs the most improvement in inputs. We found the same result with MOORA and DEA. Atatürk, Antalya and Diyarbakır are effective for both method.

MOORA is assisted by a second method, the reference point method with a maximal objective reference point, which can control and certify the outcomes of MOORA.

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EVALUATION OF TURKISH AIRPORTS EFFICIENCIES USING DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Only incoming and outgoing values of the airport company are not enough and correct to provide effectiveness comparison. Thus, benchmarking and measuring the companies which has big company cost and set by big capital are important to maintain companies' activities effectively. In this study, performance of Turkish Airports is evaluated by using Data Envelopment Analysis (DEA). In this study the inputs that effect performance are operating expenses, average number of employees, distance to city center, car parking capacity, sum of general purpose tools and sum of all vehicles. The outputs are annual average flight, number of passengers, cargo plus mail (embarked plus disembarked, in tones), operating revenue, TL. The efficient airports are derived by using the data of years 2007-2011 from State Airports Authority Directorate General (DHMI) annual statistics.

Keywords: *Data Envelopment Analysis, Malmquist, Efficiency of airport*

INTRODUCTION

Turkey, located at an intersection across continents, has an important and strategic place in international air transport[1]. Aviation industry in recent years due to the change and developments have emerged as the searches for structural model. In recent years all over the world and Turkey, options to be financed by the public outside of airports and businesses are becoming increasingly common across the logic of profit from airports which are major investments.

Data Envelopment Analysis, one of the non-parametric efficiency measurement methods, is a special kind of linear programming and is used for measuring efficiency of business relatively. The aim of Data Envelopment Analysis is to find input- output combination which products maximum output using minimum input.

MALMQUIST PRODUCTIVITY INDEX

Before introducing the MPI, we describe the notion of distance function and production technology. Let x^t and y^t denote the input and output vectors at time period t and $P^t\left(x^t\right)=\left\{y^t : x^t \text{ can produce } y^t\right\}$ model the production technology. Shephard [2] defined an output distance function $D^t\left(x^t, y^t\right)$ as follows:

$$D^t\left(x^t, y^t\right)=\min\left\{\theta:\left(y^t/\theta\right)\in P^t\left(x^t\right)\right\},\ t=1,\ \ldots,\ T$$

This function indicates a maximal proportional expansion of the output vector given an input vector. On the basis of the output distance function, Caves et al. [3] introduced the following MPI to measure the relative growth (or change) of a DMU's productivity between two consecutive periods with respect to the reference technology.

$$M^{t} = \frac{D^{t}\left(x^{t+1}, y^{t+1}\right)}{D^{t}\left(x^{t}, y^{t}\right)}, M^{t+1} = \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t}, y^{t}\right)}$$

Where M^{t} (or M^{t+1}) measures the productivity growth between periods t and $t+1$ using the technology in period t (or $t+1$) as the reference technology. To avoid an arbitrary choice of reference technology, and the two indexes are not necessarily equal, it is common to define the MPI to be the geometric mean of M^{t} and M^{t+1} as follows:

$$MPI = \left[\frac{D^{t}\left(x^{t+1}, y^{t+1}\right)}{D^{t}\left(x^{t}, y^{t}\right)} \times \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t}, y^{t}\right)}\right]^{1/2}$$

where MPI greater than, equal to, or less than 1 implies productivity growth, stagnation, or

decline between periods t and $t+1$.

If $MPI > 1$ the growth could arise from several sources. On the one hand, the DMU did improve its efficiency relative to the reference unit. On the other hand, the level of the available production technology was enhanced. Either way, to better understand the sources of growth, Fare et al. [4] decomposed the preceding MPI into two terms as follows.

$$MPI = \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^{t}\left(x^{t}, y^{t}\right)} \times \left[\frac{D^{t}\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^{t}\left(x^{t}, y^{t}\right)}{D^{t+1}\left(x^{t}, y^{t}\right)}\right]^{1/2}$$

The term outside the bracket captures EC (efficiency change), or catching-up change; the term inside the bracket captures TC (technical change). The distinction between these two kinds of changes can be illustrated by treating the DMU as using exogenously determined technology that forms the efficiency frontier. Given the frontier, EC measures whether the observation has moved closer to or farther from the frontier over time, while TC measures whether the frontier has expanded or contracted. Note that these two kinds of changes are independent of each other; there can be TC without EC, and vice versa. With respect to TC, the first term measures the shift on the frontier at the data observed in period $t+1$, whereas the second measures that shift observed in period t.

DEA (DATA ENVELOPMENT ANALYSIS)

DEA, non-parametric method of evaluating relative efficiencies for groups of similar units in point of view of the produced product and service, was introduced by Charnes, Cooper and Rhodes [5]. The summary of the main characteristics of DEA method are to be able to identify the sources and the level of inefficiency for each DMU and their evaluated efficiencies are relative efficiencies since the level of efficiency of each DMU is obtained with respect to the other units, and making no assumptions on the variables [5],[6].

In DEA there are many models which can be used to measure of efficiency, and these models are derived from the ratio models in which the weighted sum of efficiency outputs are measured as the ratio to the weighted sum of inputs [5]. Considering as n units each of which has m inputs denoted by $x_{ij}\ (i=1,2,\ ...\ ,m)$ and s outputs denoted by $y_{rj}\ (r=1,2,\ ...\ ,s)$, the mathematical programming problem of ratio form can be given as follows:

$$\begin{aligned}
&\max\ \sum_{r=1}^{s} u_r y_{ro} \Big/ \sum_{i=1}^{m} v_i x_{io} \\
&\quad \sum_{r=1}^{s} u_r y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij} \le 1 \quad j=1,2,\ ...\ ,n \\
&\quad u_r, v_i \ge 0
\end{aligned} \tag{1}$$

Where u_r and v_i are the input and the output weights respectively. Equating measured DMU's weighted sum of inputs ($\sum_{i=1}^{m} v_i x_{io}$) to 1, the fundamental efficiency model, CCR Model is obtained.

$$\begin{aligned}
&\max\ h_j = \sum_{r=1}^{s} u_r y_{ro} \\
&\quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad j=1,2,\ ...\ ,n \\
&\quad \sum_{i=1}^{m} v_i x_{io} = 1 \\
&\quad u_r, v_i \ge 0 \quad i=1,2,\ ...\ ,m\ ;\ r=1,2,\ ...\ ,s
\end{aligned} \tag{2}$$

This model is known as input oriented CCR model. As the efficiency of DMUs is measured by this model, the model is needed to be solved for each DMU i.e. n times. Optimal goal function gives the efficiency score of corresponding DMU. Each DMU whose efficiency score equals to 1, $h_j = 1$, is evaluated as efficient. Similarly output oriented CCR model can be given as follows:

$$\begin{aligned}
&\min\ h_j = \sum_{i=1}^{m} v_i x_{io} \\
&\quad -\sum_{r=1}^{s} u_r y_{rj} + \sum_{i=1}^{m} v_i x_{ij} \ge 0 \qquad j=1,2,\ ...\ ,n \\
&\quad \sum_{r=1}^{s} u_r y_{ro} = 1 \\
&\quad u_r, v_i \ge 0 \quad i=1,2,\ ...\ ,m\ ;\ r=1,2,\ ...\ ,s
\end{aligned}$$

In DEA, variables are needed to be separated as input and output. The discrimination of variables as input and output is dependent on their effect on the unit. Retzlaff-Roberts showed that it will be more accurate to use the concept of positive effective and negative effective variables instead of input and output variables. They proposed that variables whose increase provides the better evaluation of unit are taken as positive effective, in contrast variables whose decrease provides the better evaluation of unit are taken as negative [7].

In DEA, DMUs are ranked according to efficiency scores obtained at the end of the analysis. DMU that has the highest efficiency score occurs at the first place while DMU that has the lowest efficiency score occurs at the last place. However, since efficiency score of all DMUs that are efficient in DEA are assigned as "1", it is not possible to rank efficient units between each other. DEA can be used only for ranking inefficient DMUs and in order to abolish this disadvantage various methods were developed [8].

AN APPLICATION

In this study performance of 27 Turkish Airports is evaluated by using Data Envelopment Analysis (DEA). These airports;

1.İstanbul Atatürk H.	8.Trabzon H.	15.Çardak H.	22.Mardin H.
2.Ankara Esenboğa H.	9.Süleyman Demirel H.	16.Diyarbakır H.	23.Muş H.
3.Adnan Menderes H.	10.Nevşehir H.	17.Elazığ H.	24.Samsun H.
4.Antalya H.	11.Erzurum H.	18.Erzincan H.	25.Sivas H.
5.Dalaman H.	12.Gaziantep H.	19.Kars H.	26.Tekirdağ H.
6.Milas Bodrum H.	13.Bursa Yenişehir H.	20.Kayseri H.	27.Ferit Melen H.
7.Adana H.	14.Çanakkale H.	21.Malatya H.	

Inputs;	**Outputs;**
X1: Operating expenses X2: Average number of employees X3: Distance to city center X4: Car parking capacity X5: Sum of general purpose tools X6: Sum of all vehicles	Y1: Annual average flight Y2:Number of passengers Y3:Cargo plus mail, embarked plus disembarked, in tones Y4: Operating revenue

The efficiency variations for the period 2007-2008 are given in the table below:

	effch	**techch**	**pech**	**sech**	**tfpch**	**no**	**effch**	**techch**	**pech**	**sech**	**tfpch**
1	1.00	1.062	1.00	1.00	1.062	**15**	0.138	1.084	0.205	0.672	0.149
2	0.919	0.969	0.930	0.988	0.890	**16**	0.968	1.114	0.963	1.005	1.078
3	1.011	1.034	1.049	0.965	1.046	**17**	1.028	1.100	1.00	1.028	1.131
4	1.00	1.056	1.00	1.00	1.056	**18**	0.938	1.077	0.732	1.282	1.010
5	0.995	0.996	0.969	1.027	0.991	**19**	0.713	1.222	1.00	0.713	0.871
6	1.099	1.240	1.095	1.004	1.363	**20**	0.582	1.048	1.00	0.582	0.610
7	0.941	1.073	1.00	0.941	1.010	**21**	0.975	1.110	0.979	0.996	1.082
8	0.484	1.107	0.680	0.712	0.536	**22**	0.878	1.110	1.00	0.878	0.974
9	1.563	1.109	1.855	0.842	1.732	**23**	0.353	1.221	1.00	0.353	0.431
10	1.613	1.029	1.609	1.003	1.660	**24**	0.335	1.062	0.354	0.945	0.355
11	0.357	1.062	0.385	0.927	0.379	**25**	1.219	1.100	1.00	1.219	1.341
12	0.945	1.115	0.956	0.989	1.054	**26**	0.973	0.991	0.919	1.059	0.965
13	1.047	1.107	1.053	0.995	1.159	**27**	0.865	1.109	1.00	0.865	0.959
14	0.469	1.058	1.00	0.469	0.496	**mean**	0.776	1.086	0.885	0.877	0.843

The efficiency variations for the period 2008-2009 are given in the table below:

	effch	techch	pech	sech	tfpch	no	effch	techch	pech	sech	tfpch
1	1.00	1.126	1.00	1.00	1.126	**15**	1.288	1.079	0.921	1.399	1.390
2	0.962	1.036	0.950	1.012	0.996	**16**	0.968	1.163	1.039	0.933	1.126
3	1.017	1.031	0.941	1.080	1.048	**17**	1.079	1.678	1.00	1.079	1.810
4	1.00	0.982	1.00	1.00	0.982	**18**	0.970	1.125	0.846	1.147	1.091
5	0.982	0.938	1.019	0.964	0.921	**19**	0.365	1.110	1.00	0.365	0.405
6	0.930	1.163	0.950	0.979	1.082	**20**	1.202	1.034	1.00	1.202	1.242
7	0.961	1.040	1.00	0.961	0.999	**21**	1.122	1.544	1.142	0.983	1.733
8	0.937	1.082	1.052	0.891	1.014	**22**	0.834	1.562	1.00	0.834	1.304
9	0.568	1.396	0.511	1.111	0.793	**23**	0.443	1.201	1.00	0.443	0.532
10	0.855	1.132	0.984	0.869	0.968	**24**	2.990	2.723	2.825	1.058	8.140
11	1.064	1.001	1.263	0.843	1.065	**25**	0.496	2.034	1.00	0.496	1.009
12	0.860	1.312	0.832	1.034	1.129	**26**	1.546	2.343	1.088	1.421	3.622
13	0.651	1.899	0.652	0.999	1.237	**27**	0.962	1.305	1.00	0.962	1.255
14	0.843	1.158	1.00	0.843	0.976	**mean**	0.919	1.286	0.996	0.923	1.182

The efficiency variations for the period 2009-2010 are given in the table below:

	effch	techch	pech	sech	tfpch	no	effch	techch	pech	sech	tfpch
1	1.00	1.044	1.00	1.00	1.044	**15**	1.906	0.665	5.298	0.360	1.266
2	1.035	1.082	1.019	1.016	1.120	**16**	0.832	1.010	1.00	0.832	0.840
3	1.003	1.073	0.939	1.068	1.075	**17**	0.646	0.899	1.00	0.646	0.581
4	1.00	1.266	1.00	1.00	1.266	**18**	3.233	0.750	5.157	0.627	2.424
5	0.997	1.050	1.069	0.933	1.047	**19**	6.627	0.884	1.00	6.627	5.858
6	1.013	1.110	0.966	1.049	1.125	**20**	2.723	1.042	1.00	2.723	2.837
7	1.107	1.045	1.00	1.107	1.156	**21**	0.427	0.815	0.420	1.019	0.348
8	1.053	1.133	0.989	1.065	1.193	**22**	0.929	0.823	1.00	0.929	0.764
9	5.010	0.654	4.652	1.077	3.276	**23**	3.960	0.849	1.00	3.960	3.363
10	1.090	0.906	0.910	1.197	0.987	**24**	0.459	0.449	1.00	0.459	0.206
11	1.195	0.987	1.160	1.030	1.179	**25**	0.226	0.810	0.169	1.337	0.183
12	1.384	0.898	1.385	0.999	1.242	**26**	1.00	0.468	1.00	1.00	0.468
13	1.078	0.894	7.357	0.147	0.964	**27**	1.185	0.955	1.00	1.185	1.131
14	0.691	0.883	1.00	0.691	0.610	**mean**	1.184	0.882	1.184	1.00	1.044

CONCLUSIONS

This study applies DEA and the MPI to measure the efficiency and productivity of airports in the Turkey. We selected 27 airports to study their performance over the period from 2007 to 2011; the input variables are operating expenses, average number of employees, distance to city center, car parking capacity, sum of general purpose tools, sum of all vehicles and the output variables are annual average flight, number of passengers, cargo plus mail, embarked plus disembarked in tones, operating revenue. Because airports can have a far-reaching impact on a region's economic development, this poster's primary objective is to characterize findings that may help improve the efficiency and productivity of an airport's operations.

As a result of MPI method, S. Demirel Airport in terms of change in efficiency is the best-performing airport by increasing the effectiveness to %73.2 from 2007 to 2008. Samsun Çarşamba Airport in terms of change in efficiency is the best-performing airport by increasing the effectiveness to %714 from 2008 to 2009. Kars Airport in terms of change in efficiency is the best-performing airport by increasing the effectiveness to %485.8 from 2009 to 2010. Elazığ Airport in terms of change in efficiency is the best-performing airport by increasing the effectiveness to %233.2 from 2010 to 2011.

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I-MEET FRAMEWORK FOR THE EVALUATION E-GOVERNMENT SERVICES FROM ENGAGING STAKEHOLDERS' PERSPECTIVES

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ABSTRACT

I-MEET is an Integrated Model for Evaluating E-government services Transformation from stakeholders' perspectives. It is based on an integration of concepts from value chain management and business process transformation to optimize the system-wide value chain of providers and users simultaneously. It aims to align stakeholders on a common global value against traditional disintegrated approaches where each stakeholder optimizes its e-service local value at the expense of others. The measured variables are derived from the literature and focused groups. They are then categorized into cost and risk (Inputs) and (benefit and opportunity) Outputs after a validation process based on Structured Equation Models using a sample of 1540 user-responses of e-services in the UK. Finally, Data Envelopment Analysis is conducted to derive an aggregated of an e-service satisfaction value using the various inputs and outputs. The empirical results demonstrate that data-derived weights for aggregating indicators are variable rather than fixed across e-services. The novelty of the assessment approach lies in its capability to provide informed suggestions to set targets to improve an e-service from the perspective of all engaging users. Hence it provides a better transformation of public administration services and improved take up by citizens and businesses.

***Keywords**: Data Envelopment Analysis; Electronic Government Service; Performance Measurement; Stakeholders; Structured Equation Modelling, United Kingdom, Qatar, Lebanon.*

INTRODUCTION

E-government is defined as: utilizing the internet and the world-wide-web for delivering government information and services to citizens (United Nations, 2001). An e-government service (e-service) involves many stakeholders such as citizen, non-citizen and business users; government employees; information technology developers; and government policy makers, public administrators and politicians (Rowley, 2011). E-government is also a complex dynamic socio-technical system encompassing several issues starting from governance; policy development, societal trends; information management; interaction; technological change; to human factors (Dawes, 2009). Consequently, the evaluation of such e-services becomes a challenging task due to several factors related to e-government information and communication system (e-system) as well as stakeholders. Each stakeholder has different interests, costs, benefits and objectives that impact users' satisfaction and e-service take-up. The achievement of one set of specific e-government objectives for one stakeholder may result in the non-achievement of another set of specific e-government objectives for another stakeholder (Millard, 2008). This challenge in balancing the interests of various stakeholders and interest groups was also emphasized by Kelly and Nielsen (2011) with a highlight on the lack of user-centricity which has been recently recognized by some government officials such as the Swedish Minister Ann-Karin Halt who said "...agencies have a good internet presence, but their internet solutions are often designed to meet the agency's need rather than the citizens' needs".

Recently, Lee et al. (2008) reported that e-government has been delivered at a high cost for the tax payer with many successes and failures and a little use by citizens. Their statement can be supported by Eurostat (2009) reports showed that the information technology expenditures in 2008 for the United Kingdom, 27 European States, United States and Turkey are 3.7%, 2.4%, 3.3%, and 0.9% of their national Gross Domestic Product, respectively. Moreover, the e-government take-up (use) by individuals aged between16 and 74 in the United Kingdom, 27 European States, and Turkey, are 30%, 35% and 8% of their population respectively. Lee et al (2008) also listed other hindering factors; the large bureaucratic public sector structures which are grounded in years of tradition, thus unable e-government: to embrace change; create environment for innovation; establish tools to measure users' satisfaction and identify best benchmarks to improve performance. Moreover, Millard et al, (2006) highlighted the lack of a proper measurement strategy for objectives. They suggested that operational output objectives related to the roll-out of e-government services need to be evaluated and measured in relations to specific outcome objectives to increase user satisfaction and e-service take-up; thus stipulating that high quality e-services would increase users' satisfaction and take-up, decrease administrative burden, and increase back-office efficiency. Additionally, Irani, et al. (2005) emphasized the potential of long term savings and improved service quality levels that can be achieved by the development of an efficient e-government infrastructure to facilitate electronic delivery of services to citizens. However, this potential requires e-government to focus on: innovation and structural reform; rethinking the way in which e-services are done; simplifying and reengineering the organizational process in order to achieve high quality user-centric e-services.

In e-government practice, the evaluation of e-services is never simple due to the tremendous complexity in public performance measurement, availability of information on e-government policy and administrative efficiency indicators. According to the review of customer satisfaction approaches in FreshMinds (2006), traditional performance measurement of government services are often based on modification of customer satisfaction indices (such as ACSI: American customer satisfaction index, or EPSI: European customer satisfaction index), standardized survey instruments (such as CMT: Canadian common measurement tool); and scale conversion methodologies (Miller and Miller, 1991). All these measurement approaches conduct surveys and operate at a similar level of depth in terms of asked questions, but they do differ in terms of breadth and coverage. They use fixed weights for each measured variable associated with each factor to devise an overall satisfaction score. In our view, there are few main points that may go against the appropriateness of such practical approaches. First e-service users are not customers; they cannot buy better quality e-services at higher prices due to the non-existence of market competition in e-government. Second, customer satisfaction indices are measured based on perceived and expected quality of services. Alternatively, users' satisfaction should be a function of the quality of online interactions, reliability, personalization and other opportunities that come out of an e-service. Finally, the perception of high risk when using e-commerce service might be more than that with e-service. As a result, there have been a few research initiatives to develop a citizen satisfaction model (CSM) for e-services, (Kim et al., 2005; Welch et al., 2005; Lee at al. 2008; Wang et al. 2005). These models focus on e-government measures for different purposes, perspectives and countries (Jaeger and Bertot, 2010). They also employ statistical approaches to establish relationships and predict satisfaction trends (Chan et al., 2010; Irani et al., 2007, 2008; Wang and Liao, 2008; and Weerakkody and Dhillon, 2008). They may not suggest a systematic process to e-service managers to design better services. They are descriptive rather than prescriptive approaches in nature. For a recent review on an analysis of methodologies utilized in e-government research from a user satisfaction perspective with e-services, we refer to Irani et al (2012).

Given the above diversity of e-government measurement models and mentioned challenges, there has been no formal agreement on a common international framework for evaluation; there is no single view of how such measurement indicators should be designed, or maintained relevant and practical over time. The integration of citizen' use of e-services is absent from most measurement frameworks (United Nations, 2010). Hence, an *Integrated Model for Evaluating E-government services Transformation* – IMEET project was initiated with the support of Qatar National Research Fund (QNRF**)** to develop a global agreement on a consistent framework to measure e-government services and to include measures on all stakeholders namely, users and providers. In this paper, we aim to develop a standard for the evaluation of an e-service based on both e-system characteristics and user's behaviour from users' online experience to measure users' satisfaction using a Data Envelopment Analysis. The reasons to measure each stakeholder value within I_MEET framework are mainly due to conflict of interests, need to align various stakeholders on common goals and recommend improvements at macro and micro levels from different perspectives, Osman et al (2013). Please note that citizen/users are used interchangeably in the paper. The main objectives of the paper are as follows:

- To develop an alternative satisfaction measure using Data Envelopment Analysis (DEA) efficient frontier methodology. DEA considers simultaneously the multiple measures on outputs (benefits, outcome, and personal opportunity factors) generated from the e-system with the multiple measures on inputs risk and cost to users in order to determine the aggregate measure on satisfaction. Thus the satisfaction measure would reflect an overall efficiency and effectiveness of the e-service.
- To experimentally validate that the relationships among Cost-Risk inputs, Benefit-Opportunity outputs and users' satisfaction are statistically significant using real-data collected on users of five e-services in the UK with a new enhanced questionnaire, see Appendix. The experiment would provide an additional proof of the relationships validity of the COBRA (Cost-Risk and Benefit-Opportunity Analysis) framework that was initially proposed and validated on a sample of Turkish data in (Osman et al 2011, 2014).

- To illustrate how DEA results can generate recommendations for managers to re-design and improve e-services from the citizen's perspective.
- To call for the re-assessment of current United Nations e-government indices that use fixed weights for indicators to derive weights based on our findings that users' stakeholder prefer to have variable weights reflecting their interests.

METHODS

In this section, we shall first illustrate an e-service and the engaging stakeholders; the identification process of the set of inputs and outputs with special focus on users, the data collection process, the statistical validation process, and the Data Envelopment Analysis. In this paper, our methodology is developed from the engaging users' perspective. However the I-MEET framework is developed from the perspective of all stakeholders. Stakeholders' groups include users/citizens; businesses; public administrators (employees and politicians); Government agencies; E-government project managers; design and IT developers; suppliers and IT developers; research and evaluators. Rowley (2011). I-MEET is a mission-driven interconnected framework based on the five main components that are shown in Figure 1: Mission and desired values of Government; the involved internal stakeholders; the affected External stakeholders; the offered E-service(s); the Operating resources support and the decision making support system (DMSS). The DMSS performs the business intelligence analysis to determine the desired e-service values. It is also the dashboard for the deceleration and acceleration control process to guide the improvement of e-services in various evaluation dimensions.

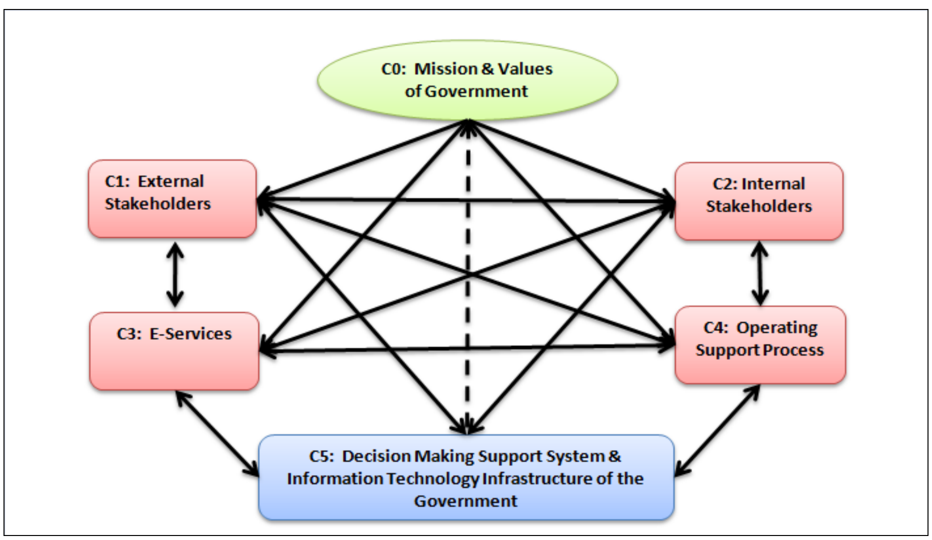

Figure 1: The main interconnected components of I-MEET framework

The I-MEET evaluation process starts by the identification of the e-service to access, and the engaged stakeholders group which provides the real-experience data on the e-service to evaluate. In this paper, we consider the users group which had real interactions and experience with the identified e-service to evaluate. An e-service is delivered using an e-system which is considered a black-box process to users (external stakeholders). The black-box process is the concern of governments and agency providers (internal stakeholders). It is normally designed according to providers' strategic initiatives, objectives and desired public values. The providers inject various input resources to provide outputs and outcomes to the all stakeholders including users. However, the users provide inputs to an e-system during online interactions to receive e-system's outputs and outcomes. This interaction process during the actual engagement with an e-service is a white-box process to users. The inputs and outputs of the white-box process are the main concern of users that influence the users' satisfaction. Figure 2 illustrates the interaction process between a user and an e-system to obtain an e-service. Thus, an e-service can be defined as the complete cycle of stages starting from the first interaction to request a service through the various input/output online activities while engaging with an e-system to the final delivery of the service according to the user's desired output and outcome.

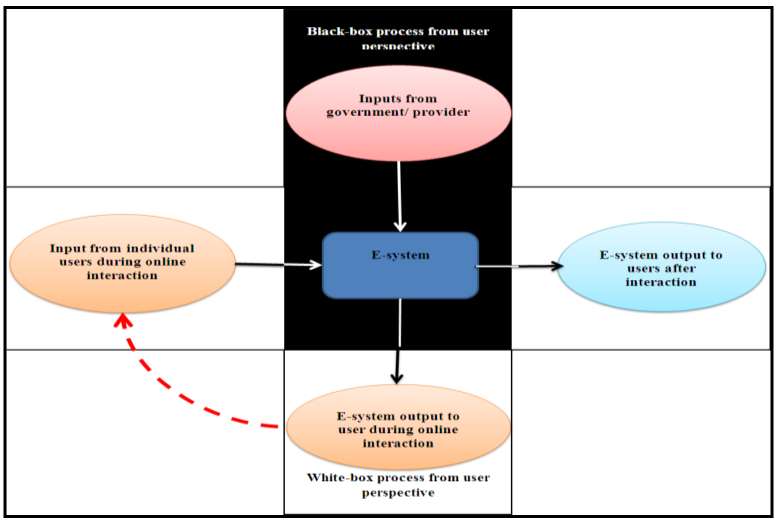

Figure 2: The interactive process between user and e-service.

The identification process of the set of inputs and outputs from user's perspective was based on a systematic approach where a set of measurable indicators was derived from conducting focused groups with various stakeholders and the available literature, Irani et al (2012). Three workshops were held in Qatar, Lebanon and UK with different stakeholders -users, providers and academics- to generate a questionnaire from users' prospective consisting of 60 questions. The data collection process started by identifying a list of five e-services, namely, Benefits, Retirement and Financial or Job Seekers support; Driving License Queries; Healthcare Information; Local Government and Tax Information. The data collection was conducted by a private agency over a six months period. The statistical validation process was conducted to validate the set of input and output variables using COBRA - the cost-opportunity and benefit-risk analysis- framework in Figure 3. The COBRA framework was proposed to validate the measurement scale of a set of measured variables and their relationships to users' satisfaction on a sample of Turkish e-services, Osman et al (2011, 2014). The COBRA validation process was based on a structured equation modelling and a confirmatory factor analysis in order to group measured variables into a set of fewer COBRA categories. The prediction of users' satisfaction to users' inputs as predicators was found to follow the following significant relationship:

$$\text{Satisfaction} = 1.9 + 0.385 \times \text{Opportunity} + 0.026 \times \text{Benefit} - 0.023 \times \text{Risk} - 0.287 \times \text{Cost}.$$

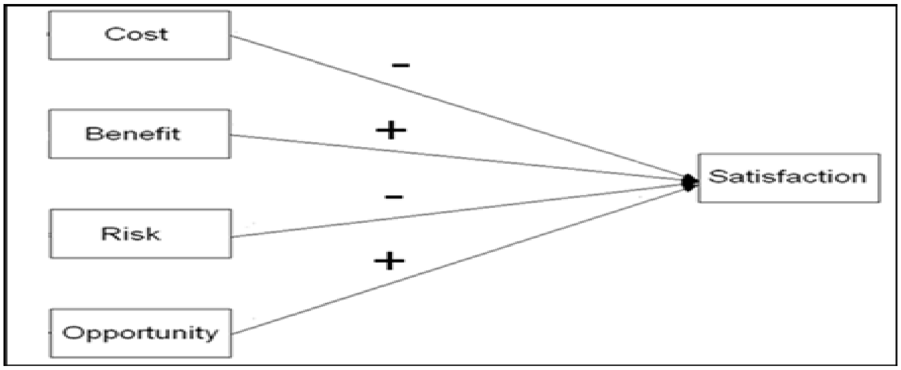

Figure 3: A COBRA illustration of measurable predictors to user' satisfaction.

Finally, the main analytical component of the I-MEET is a decision making support component which is based on Data Envelopment Analysis. It acts like a dash broad that will provide tradeoffs among competing indicators and provide guidance on how to accelerate and decelerate the I-MEET processes in order to achieve the main goals from the evaluation process for transforming an e-service.

Data Envelopment Analysis (DEA) is a non-parametric linear programming approach for multifactor productivity performance analysis. It evaluates the relative efficiencies of a homogeneous set of decision-making units (DMUs) where each DMU (e-service) utilizes multiple inputs and resources (cost and risk variables) to produce multiple outputs and outcomes (benefit and opportunity variables). The efficiency score of a unit is measured by an aggregate function defined as the ratio of the total weighted outputs to the total weighed inputs. A unit with an aggregate efficiency score of 1 (slack values =0) is considered to be efficient (satisfying users) and a score of less than 1 indicates that the e-service unit is inefficient (dissatisfying users). The original DEA *constant return to scale* model (DEA-CRS) was developed by Charnes et al. (1978). It assumes that a proportional change in inputs does result in a similar proportional change in outputs. The DEA-CRS model needs to be executed as many times as the number of decision making units in order to determine an aggregate efficiency score for each e-service. The weights for each e-service are optimized in the best interest of the e-service being evaluated subject to the aggregate ratio of each e-service in the set does not exceed a value of 1. Figure 4 provides a mathematical formulation for the primal DEA output-oriented model based on a constant return to scale on the left side and its associated envelopment dual model on the right. In this formulation, given n e-services where p (p =1, …, n) is the e-service being evaluated, m represents the number of inputs (cost and risk variables) and s represents the number of outputs (benefit and opportunity variables), y_{ki} is the amount of output k generated by e-service i, and x_{ji} is the amount of input required by e-service i, and v_k, u_j are the weights given to output k and input j respectively. The output-oriented productivity measure of e-service p can be obtained by maximizing the numerator of ($\sum_{j=1}^{s} v_k y_{kp} / \sum_{i=1}^{m} u_j x_{jp}$) and setting its denominator equals to 1 as shown in the first constraint in the formulation. The second set of n constraints achieves the relative concept; obtained by imposing no aggregate ratio value to any unit should exceed one. Similarly, a primal input-oriented model can be obtained by minimizing the dominator while setting the numerator equals to 1.

Primal DEA-CSR: Output-Oriented Model	Envelopment DEA-CSR: Input-Oriented Model
$Maximize \sum_{k=1}^{s} v_k y_{kp}$ s.t. $\sum_{j=1}^{m} u_j x_{jp} = 1$ $\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0 \; ; \forall i = 1, \dots, n$ $v_k \,, \quad u_j \geq 0 \quad \forall \, k, j$	$Minimize \; \emptyset$ s.t. $\sum_{i=1}^{n} \lambda_i x_{ji} \leq \emptyset x_{jp} \quad ; \forall j = 1, \dots, m$ $\sum_{j=1}^{m} \lambda_j y_{ki} \geq y_{kp} \quad ; \forall k = 1, \dots, s$ $\lambda_i \geq 0 \quad ; \forall i = 1, .., n$

Figure 4*:* Constant Return to Scale DEA (Primal) and Envelopment DEA (Dual).

For every inefficient unit, DEA identifies a set of efficient units that can be utilized as benchmarks for improving inefficient ones. Benchmarks can be easily obtained by employing the envelopment DEA-CRS input-oriented model when the number of DMUs is very high due to its computational efficiency. A DEA variable return to scale (DEA-VRS) model was developed by Banker et al. (1984). It assumes variable changes in outputs, unlike proportional changes in DEA-CRS. The envelopment DEA-VRS model can be obtained by adding a constraint $\sum_{j=1}^{n} \lambda_i = 1$ to the envelopment input-oriented model DEA-CRS model, where λ represents the dual variables to identify the benchmarks for inefficient units.

DEA was considered as one of the big idea in the history of research in service operations (Chase and Apte, 2007). DEA applications in service operations include: examination of efficient use of different types of enterprise information in the realization of strategic performance (Bendoly et al, 2009); assessing the relative efficiency of local government in Portugal (Afonso and Fernades, 2008); efficient service location design for a government agency in the State of Michigan (Narasimhan et al, 2005); evaluation of efficiency of units within a large-scale network of petroleum distribution facilities (Ross and Droge, 2004); performance assessment of joint maintenance shops in the Taiwanese army (Sun, 2004); evaluation of the relative efficiency of nurses (Osman et al, 2010); For more details on DEA theory, models and applications please refer to Cooper at al. (2007).

RESULTS AND DISCUSSIONS

The users' online experience was captured from responses of 1540 UK real-time users of the five identified e-services. Enough time was allowed to collect more than 300 responses per e-service, see Table 1. Table 2 provides description of the data and their grouping. The set of 60 questions in the questionnaire were divided into two parts. Part one contained 49 questions related the users' e-service experience for measuring the users' value of satisfaction. These questions were further subdivided into a set of 4 factors and associated sub- categories to generate recommended improvements. The value of each variable was obtained by averaging the Likert scale responses of the included questions. Part two contained the other 11 questions to collect bio-data in order to identify the characteristics of satisfied/dissatisfied users for managerial actions.

Table 1: Summaries of e-service names and responses size per an e-service

E-Service name	Size of responses
Benefits, Retirement & Financial or Job Seekers support	310
Driving License Queries	305
Healthcare Information	310
Local Government	306
Tax Information	309
All E-service	1540

Table 2: Grouping of questions in the questionnaire in factors and sub-categories.

Factor/Group	Included Questions	No of questions
Cost		14
Time	1-7, 19	8
Money	8, 9, 10, 20, 21, 23	6
Risk		11
Finance	11,12, 13,14, 15	5
Personal	16, 17, 18, 34, 35, 36	6
Benefit		11
Information	28,30-33, 47	6
Service	24-27, 29	5
Opportunity		13
Technical	44-46, 48, 49	5
Service	22, 37-43	8

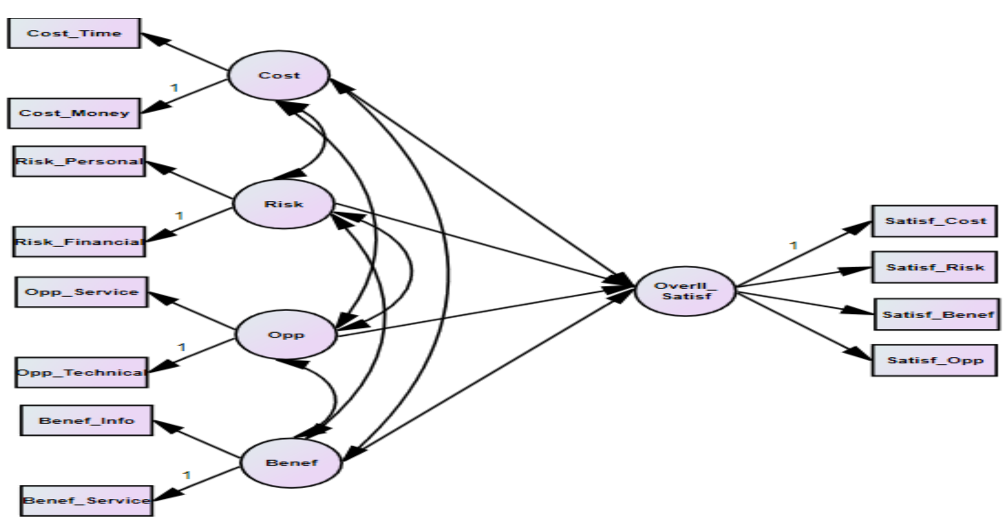

Figure 4: The proposed COBRA relationships among various indicators.

Table 3: Structured Equation Model Fitness Results.

Statistical Test		Values	Accepted Range
CMIN	CMIN/DF= X^2/df	4.39	< 5.00
	GFI	0.91	> 90.0
Baseline Comparisons	NFI	0.94	> 90.0
	RFI	0.91	> 90.0
	IFI	0.96	> 90.0
	TLI	0.93	> 90.0
	CFI	0.96	> 90.0
RMSEA	RMSEA	0.05	< 0.05
	LO 90	0.04	< 0.05
	HI 90	0.05	< 0.05

To validate the proposed COBRA relationships (Figure 5) among the identified variables, factors and sub-categories and the users' satisfaction, a structured equation model was used to test the fitness of the proposed model, (McDonald and Ho, 2002). The results in Table 3 showed that all statistical measure indices were within the acceptable levels with $p < 0.01$. For instance, the value of X^2/df = 4.39; Root Mean Square Error of Approximation, RMSEA= 0.05; Normed Fit Index, NFI = 0.93; Comparative Fit Index, CFI = 0.96. As a result, the SEM results provide a proof that the COBRA proposed model has a satisfactory model fitness and that all of the measured variables can be used to measure the satisfaction of users from the corresponding factors/constructs.

The COBRA model captures the rational behaviour of users - if the cost and risk are lowest and if the benefit and opportunity are highest, then the users would be the most satisfied. This rationality is translated into the DEA modelling process in the following way, if the inputs (cost and risk) are lowest and the outputs (benefits and opportunity) are highest, then the associated decision making unit has the highest DEA score of 1 (equivalent to most satisfied). Moreover, the COBRA validation was based on statistical tests that predict trends but they do not allow the identification of best-practice benchmark for improvements. Those best-practices are always treated as odd points and may be neglected/dropped from the statistical analysis. On the contrary, those odd points may represent the best-practices to guide the improvement process and DEA is more capable at their identifications. They form the set of efficient frontier in DEA terminology. Therefore, we are using the same indicators to generate improvement recommendations as well as DEA scores on users' satisfaction.

In order to generate the satisfaction of users with an e-service, the appropriate DEA model must be selected based on the characteristics of the users and the orientation of desired improvements. Table 4 presents an analysis of the bio-data of the respondents. It can be seen that the users come from heterogeneous groups of different interest usage, annual income and computer skills. These features require the implementation of a data envelopment model with a variable return to scale. Further, since we are interested in measuring the efficiency of utilisation of inputs and the effectiveness of outputs by an e-service, input and output-oriented models must be utilised. Therefore the following two DEA-models are used to analyze the collected data, namely: input-oriented DEA-VRS model – input-oriented DEA with Variable Return to Scale - and output-oriented DEA-VRS model. The DEA results reveal a number of observations. First, the efficiencies of transformation are different across e-services and orientation desired, Table 5. The input-oriented efficiencies of the e-services range from 63.9% to 66.8% with an average of 64.9%, i.e., the current outputs (opportunity, and benefit) can be produced at an average of efficiency of inputs (risk and cost) utilisation of 64.9% than the current level. This indicates more managerial actions are needed to reduce the current resource utilization by 35% to keep the level of outputs (the average of input orientation score is around 65%). In addition, it was found that 86 out 1540 (5.58%) of the respondents were fully satisfied or achieved DEA scores of 1. However, if a reduction of the utilisation is not possible (i.e. keeping the resource utilisation of inputs at the current level) then the management should look at increasing the current level of outputs by an average of 20% since the average of output-oriented efficiency is 80%). Similarly, was found that 211 out 1540 (13.77%) of the respondents were fully satisfied or achieved DEA scores of 1. From the analysis in Table 5, it can be seen that the Driving License e-service is the best among all compared e-services. Its best-practice and operating features can be further documented and analysed to use it as a guiding benchmark for the less efficient e-services.

Table 4: Analysis of the Bio-Data of respondents.

Users' Characteristics	Value	Frequency	Percentage
Internet Usage	Beginner	25	1.62
	Fair	178	11.56
	Good	540	35.06
	Excellent	797	51.75
Annual Income	Less than £10,000	252	16.36
	£10,000- £19,999	357	23.18
	£20,000- £29,999	425	27.6
	£30,000- £39,999	226	14.68
	£40,000- £49,999	114	7.4
	£50,000- £59,999	61	3.96
	£60,000- £69,999	34	2.21
	£70,000- £99,999	48	3.12
	£100,000- £149,999	13	0.84
	£150,000 and above	10	0.65
Use E-service	Everyday	193	12.53
	Several times weekly	278	18.05
	Several times a month	188	12.21
	Once a month	348	22.6
	Several times a year	258	16.75
	Once a year	275	17.86

Second, the different weights given to each input/output variable are different for an e-service in the same country, Table 6. The differences reflect that different importance is assigned to measured variables from the users' perspective. They also vary per orientation and their values would provide management with a guiding tool to what matters to users. This observation highlights a very important weakness in the equal-weight approach that has been used to generated UN e-government indices and invites more research to re-assess the current ranking of countries, since it does not take the relative preference of countries when deriving the ranking scores.

Table 5: DEA input and output oriented results.

	DEA-VRS oriented models	
Name of E-services/Labels	Input	Output

Benefits, Retirement and Financial or Job Seekers support (B)	64.4	79.7
Driving License Queries (D)	66.8	81.9
Healthcare Information (H)	65.3	81.2
Local Government (L)	63.9	79.6
Tax Information (T)	64.1	79.5
All E-service (Overall Average)	64.9	80.4

Table 6: Flexible weights given to users/ indicators from DEA oriented results.

	Weights of DEA-VRS models	
Inputs/Outputs Indicators	Input-oriented	Output-oriented
Cost_Time	0.1	0.15
Cost_Money	0.4	0.25
Risk_Personal	0.25	0.44
Risk_Financial	0.25	0.16
Opportunity_Service	0.23	0.25
Opportunity_Technical	0.18	0.08
Benefit_Info	0.29	0.38
Benefit_Service	0.3	0.29

Finally, both DEA-VRS models generate target improvement expressed in terms of percentage change for a particular e-service or a group of e-services with reference to the set of best-practice frontier, i.e., fully satisfied users. For instance, Table 7 provides such recommended changes on the average for each of the five E-services. Negative values indicate a reduction in the current values of the associated indicators, while positive values indicate increases over the current values reach in order to become efficient or effective from the perspective of the respondents. From table 7, it can be seen that the financial risk, personal risk followed by the cost of time have the highest % of required improvements along with the improvement of the technical opportunity from the input-oriented model. However, looking at the recommended change from the output-oriented model, it can be seen that the financial risk and the cost of time and the technical opportunity must be improved. Both models agree on such recommendations with different degree of change. In this case, the management interested in promoting the provision of e-government service are invited to look at the characteristics of the benchmark and learn new ways to improve the e-service. The importance of the recommendations is coming from the actual observation of an e-service and a group of respondents, who achieved the suggested targets, i.e., we have a set of best practice efficient services that were identified to give the improvement or change process.

Table 7: Recommended targets to improve the e-services.

	% Targets to improve E-services using Input Oriented Model				
Indicators	B	D	H	L	T
Cost Time	-0.39	-0.37	-0.4	-0.4	-0.39
Cost Money	-0.37	-0.34	-0.36	-0.37	-0.37
Risk Personal	-0.36	-0.34	-0.35	-0.37	-0.37
Risk Financial	-0.45	-0.41	-0.42	-0.43	-0.45
Opp Service	0.05	0.05	0.04	0.05	0.05
Opp Technical	0.17	0.19	0.21	0.21	0.18
Opp Technical	0.02	0.03	0.02	0.02	0.02
Benef Service	0.06	0.03	0.04	0.05	0.05
	% Targets to improve E-services using Out-oriented Model				
Indicators	B	D	H	L	T
Cost Time	-0.3	-0.32	-0.35	-0.32	-0.31

Cost Money	-0.09	-0.08	-0.09	-0.09	-0.1
Risk Personal	-0.08	-0.07	-0.08	-0.07	-0.08
Risk Financial	-0.36	-0.33	-0.35	-0.36	-0.39
Opp Service	0.43	0.36	0.37	0.43	0.42
Opp Technical	0.46	0.43	0.45	0.47	0.46
Opp Technical	0.37	0.33	0.34	0.38	0.39
Benef Service	0.44	0.35	0.37	0.43	0.43

CONCLUSIONS

In this paper, a new framework for evaluating e-Government e-services from stakeholders' perspective was introduced. The framework is a mission driven approach with goals that are translated into strategies with objectives and initiatives with desired values. These initiatives would affect the input-resource efficiencies, quality of generated output/outcome effectiveness and business impact of the e-service provisions. The users are one of the key stakeholder and their opinions are often neglected but very important to increase take-up and providers objectives. Moreover, while using an e-service, the e-service may require users' inputs to generate outputs and outcomes that impact users' satisfaction in contrary to the desire of the providers. Therefore, developing a users' questionnaire and validating of prime important for capturing the users' values of e-services. The questionnaire was systematically developed using focused groups with users, providers and academics in Qatar, UK and Lebanon. The generated questionnaire is now validated using collected data from a large sample of UK respondents in this paper. The validation process uses a structured equation modelling to provide a proof of the existence of significant relationships between cost-risk and benefit-opportunity on one hand and users' satisfaction on the other hand. The statistical testing provides the second validation of the COBRA framework in the literature. After the validation process, Data Envelopment Analysis was conducted to determine optimal weights for variables from the relative perspective of users. The results of DEA show that the UK e-services are more effective in terms of output generation and less efficient in terms of input utilization. Hence, the paper provides e-services' providers with a management tool that can identify targets for improvements for specific indicators for an e-service to become either input-efficient or output-effective. It also provides reference to existing best practices that can guide the change in the improvement process. The DEA analysis also showed that the use of fixed weights to aggregate indicators to produce United Nation indices may need re-assessment or revisited. Simply, because, the weights of indicators seem to vary within a country and within the same users' group of e-services let alone use fix weights across nations.

This study is the first of its kind for analysing e-services in the UK from the users' perspective using the proposed quantitative approach. The approach can evaluate a single e-service to establish best-practice among users or evaluate multiple e-services to establish best-practice among e-services. The research team is currently conducting similar studies are currently being conducted to evaluate e-services in Qatar, Lebanon and Turkey from the users and providers perspectives. Future research can also benefit from studying the bio-data and written feedbacks and correlate them to the obtained data development scores using data-mining tool or other descriptive statistics to identify the characteristics of satisfied and distained groups. The various analyses is limited to the use of Likert scale for the users' responses due to the difficulty for users to provide proper estimates for measured variables. But such limitation does not affect the proposed approach, but actual data may give better insights and understanding.

APPENDICES

The user questionnaire is available from authors and not included due to space limitation.

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IMPACT OF COMPETITION ON TOTAL FACTOR PRODUCTIVITY, EFFICIENCY AND TECHNICAL CHANGE: EVIDENCE FROM TUNISIAN MANUFACTURING FIRMS

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ABSTRACT

This paper aims at measuring the impact of competition on productivity growth and on its components i.e. technical change and efficiency change in the Tunisian manufacturing sector at the firm level. We use firm data over the period 1997-2002 and a non-parametric approach to estimate TFP and its components, and we use panel data econometrics, to determine the effects of competition. Our results suggest that the dominant driving force of TFP was technical efficiency. The second source of total factor productivity growth which is technical change plays a negative role in the productivity growth until 2000; a timid technological progress was observed after 2000 in the Tunisian manufacturing.We find that Competition had strongly positive effect on total factor productivity growth, efficiency improvement and technological progress.Likewise, the existence of non-linear effect of the competition on TFP and its factors is verified. At low competition level, more competition raises TFP at the firm level; yet, with high levels of competition, a rise in competition has a negative impact on productivity. The Schumpeterian effect appears and the capacity of firm to innovate decreases. To gain from competition, even at a high level of competition, Tunisian authorities must sustain firms to be more innovative.

***Keywords**: Competition, Total Factor Productivity, Efficiency Change, Technical Change, Manufacturing, Panel Data.*

INTRODUCTION

This paper examines the relationship between competition, and some firm performance measures i.e. technical efficiency, technological change and productivity in Tunisian manufacturing firms. We focus on the role of transmission mechanisms between increased competition and the firm productivity.

In a previous work we have tried to analyse the impact of competition on TFP at the whole in Tunisian manufacturing (Amri and Mouelhi 2012). Now, we try to go deeper by analysing the impact of competition on productivity and its components, that is on firm efficiency and technical change.

The debate on the impact of competition on productivity and its components is still open as regards to developing countries. Our contribution to these debates is essentially an empirical issue. We first try to analyse the degree and the dynamics of product market competition in Tunisian manufacturing sectors. Then, the analysis of a Tunisian firm's data may be viewed as an attempt to apprehend how productivity, efficiency, and technical change in Tunisia, a developing country, is being adjusted to more competition.

The analysis is conducted through the use of a non-parametric approach to estimate the TFP growth[1] and to distinguish between efficiency change and technological progress as sources of total factor productivity growth, the former referring to catching up to the production frontier and the latter, the shifting of the frontier.

To investigate the impact of competition on productivity and its components we use a two step procedure. We first derive Malmquist productivity growth index which we decompose into efficiency change index and technology change index by firm and by year. Then, we use a panel-data econometric analysis to explore the relationship between competition and the estimated TFP change, efficiency change and technical change.

We identify the impact of competition on productivity growth by using both the variation of productivity and competition measures over time and variation across firms from different sectors.

We will control for the role of some other factors in impacting upon productivity and its components, these include: access to export market, foreign participation, ownership structure, openness, … in addition to competition.

The rest of the paper is organized as follows. Section 2 lays down the main models, data and methodology to be used as framework for the econometric analysis. Section 3 presents and discusses the results. Section 4 is made up of the conclusion to this paper.

METHODS

To investigate the impact of competition on productivity and its components we first derive estimates of total factor productivity growth (TFP). The Malmquist TFP index is estimated and decomposed into efficiency change and technical change. In a second stage, we attempt to link competition with changes in TFP and its components using an econometric analysis.

<u>The first step: Malmquist TFP index and its decomposition</u>

we use the method of Fare et al. (1994) to measure Malmquist TFP index.

TFP change= Technical Change x efficiency change

A value greater than 1 for the Malmquist index will indicate a productivity growth between t and t+1, a value lesser than 1 will indicate a productivity decline and a value of 1 will indicate stabilization in productivity.

In this paper we follow the bootstrap methodology of Simar and Wilson (1998) to estimate productivity change, efficiency change and technical change indexes. (See annex)

The data set includes: value added (y) measured in constant prices (deflated by a four digit industry specific price deflator), tangible fixed assets, labour (number of employees L). The number of employees

[1] In our previous work (Amri and Mouelhi 2012) we have used a parametric approach to measure TFP.

is adjusted according to whether it is part or fulltime equivalent employment. Tangible fixed assets were deflated by an industry specific price of FBCF to approximate the capital stock in constant prices.

The second step: Econometric Analysis

In a second stage, we attempt to link competition with changes in TFP and with its components: efficiency change and technical change. We specify the following basic equation, where productivity growth and its components (y) depend on measures of competition (Z), some observable firm's characteristics and unobservable firm's characteristics (ui):

$$y_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 X_{it} + \sum \gamma_t D_t + u_i + v_{it} \qquad (1)$$

Where y= (TFP or eff or tech) is the index of total factor productivity growth (TFP) or efficiency change (eff) or technical change (tech).

X is a vector of control variables susceptible to influence the growth of TFP (or eff, tech).

The equation (1) will also be adjusted to account for relevant time invariant variables. That is, firm's characteristics, like activity and whether or not the firm is an exporting one. By including firm type and activity, we control for possible differences in productivity among firms of different characteristics. We also include time effects to account for macroeconomic shocks (time dummies Dt).

u_i captures the heterogeneity between firms.

v_{it} captures all other shocks to sector productivity.

We have also information about the "ownership", a private or a public firm, the percentage of foreign capital participation, the exporting rate which is the percentage of foreign sales. These variables were included in our regressions to control for some firm's characteristics and some other aspects which may affect individual firm's productivity.

Available data permits us to calculate some competition related variables both at the firm level and at the industry level:

Market share at the firm level: $Marketshare_{it} = \dfrac{sales_{it}}{\sum_i sales_{it}}$

The Price cost margin at the firm level would be a more desirable measure of competition.

$$\text{Price cost margin}_{\text{it}} = \frac{\text{valueadded}_{it} - wages_{it}}{sales_{it}}$$

The Herfindhal index for concentration which is an industry concentration measure is also used. It is the sum of squared market shares:

$$\text{Herfindhal index}_{jt} = \sum_i Marketshare_{it}^2$$

RESULTS AND DISCUSSIONS

The estimation of bootstrapped Malmquist productivity indexes and its components is conducted using the computer program FEAR on R[2] . In this study, 2000 bootstrap iterations were performed (Balcombe, Davidova and Latruffe (2008)). We use firm data over the period 1997-2002 from Tunisian manufacturing sector.

Graph 1 shows the Malmquist TFP index evolution as well as its components: technical change and efficiency change, over the studied period. The productivity stagnated over the studied period. Efficiency change and technical change show evolutions in opposite directions. This graph shows efficiency improvement until 2000 but a decline at the end of the studied period. Technical efficiency was an important contributor in the total factor productivity growth until 2000. The dominant driving force of TFP was technical efficiency. The second source of total factor productivity growth which is technical change plays a negative role in the productivity growth until 2000; a timid technological progress was observed after 2000. Adoption of new technologies and innovations were very limited over the studied period. Technological change should take place more quickly to enhance productivity in Tunisian manufacturing.

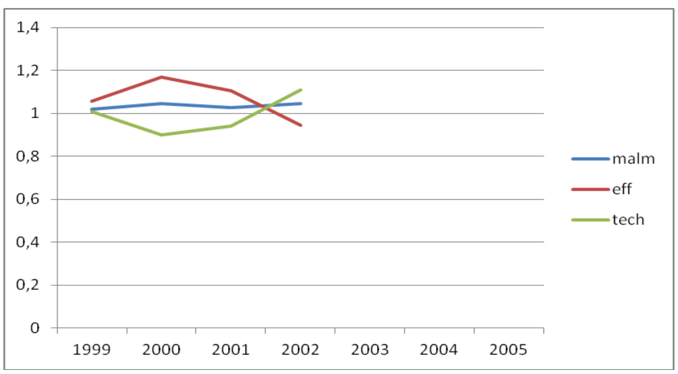

Figure 1: Evolution of TFP change Efficiency change and Technology change

Tunisian's TFP growth in manufacturing sectors mainly comes from efficiency progress rather than from technical improvement until 2000. This suggests that, in order to increase TFP growth, finding ways to improve technical efficiency has also become a pressing concern.

To analyse the impact of competition on firm's productivity, we will use an econometric investigation. Our main specifications from the equation (1) are estimated. Tables 1, 2 and 3 present the empirical results of regressing TFP change, efficiency change and technical change, respectively, on different measures of competition and other control variables using model 1 specified above.

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[2] FEAR is a freely downloadable program to estimate DEA scores and conduct the bootstrap algorithm proposed by Simar and Wilson (1998, 1999)

Table 1: Dependent Variable: Malmquist TFP (Random-effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cte	.735*** (.222)	.697*** (.226)	.737*** (.222)	.734*** (.101)	1.025*** (.194)	.809*** (.124)	.778*** (.128)	.683*** (.104)	-.051*** (.017)
(marketshare)	-.018*** (.006)	-.018*** (.006)	-.019*** (.006)						
(Price cost margin)				-.022*** (.005)		-.025*** (.005)	-.026*** (.005)	-.053*** (.017)	-.053*** (.017)
$(ihh)_{t-1}$					-.001*** (.011)				
(Price cost margin)2								-.004* (.002)	-.003* (.002)
ln(TPE)						-.038** (.016)	-.039** (.016)		
Private						.037*** (.013)	.060** (.026)		.027* (.015)
Petrangere		-.023 (.025)							
Tex			-.025 (.020)						
Inverse mills	.171 (.182)	.208 (.187)	.171 (.182)	.164*** (.1587)	.005 (.172)	.206** (.085)	.215** (.086)	.167* (.088)	.208** (.091)
Observations	4345	4345	4345	2844	4345	2119	2119	2844	2844
R^2	0.0010	0.0012	0.0010	0.0043	0.0000	0.0160	0.0165	0.0049	0.0062

Standard error in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

All computations are done using STATA.

Table 2:Dependent Variable: efficiency change Random-effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cte	.872*** (.246)	.802*** (.251)	.865*** (.109)	1.189*** (.215)	.681*** (.116)	.728*** (.260)	.634*** (.119)	.812*** (.113)
(marketshare)	-.019*** (.007)	-.019*** (.007)				-.016** (.007)		
(Price cost margin)			-.021*** (.005)		-.020*** (.005)		-.049*** (.018)	-.052*** (.018)
(ihh)				-.007*** (.012)				
(Price cost margin)2							-.004* (.002)	-.004* (.002)
(tex)					.037*** (.012)	.060*** (.023)	.038*** (.012)	
Private					.071***	.044*	.071***	

					(.017)	(.027)	(.017)	
petrangere		.039 (.028)						
Inverse mills	.079 (.202)	.147 (.207)	.083 (.095)	-.117 (.190)	.185** (.097)	.170 (.210)	.187 * (.097)	.087 (.095)
Observations	4345	4345	2844	4345	2844	4345	2844	2844
R(2)	0.0013	0.0019	0.0031	0.0002	0.0114	0.0035	0.0120	0.0038

Standard error in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

All computations are done using STATA.

Table 3: Dependent Variable: technology change Random-effects

	(1)	**(2)**	**(2)**		**(3)**	**(4)**	**(5)**	**(6)**
Cte	.780*** (.051)	.822*** (.043)	.851*** (.045)	.875*** (.045)	.893*** (.061)	.946*** (.054)	.852*** (.062)	.737*** (.054)
(marketshare)t-1	-.002** (.001)				-.002** (.001)		-.019*** (.006)	-.017*** (.006)
(Price cost margin)				-.001 (.002)				
(marketshare)2t-1							-.001*** (.0005)	-.001** (.0005)
(ihh)t-1		-.018*** (.002)	-.017*** (.002)			-.018*** (.002)		
Petrangere			.014*** (.005)					
TPE					-.027*** (.007)	-.029*** (.007)	-.029*** (.008)	
Inverse mills	.163 (.041)	.094 (.038)	.069* (.039)	.088** (.039)	.164*** (.041)	.094 ** (.038)	.171*** (.041)	.169*** (.042)
Observations	4345	4345	4345	2844	2844	4345	4345	4345
R(2)	0.0036	0.0180	0.0196	0.0019	0.0062	0.0211	0.0079	0.0049

Standard error in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.

All computations are done using STATA.

The results suggest that there is a positive impact of competition change on productivity growth (table1). The estimation results in table 2 reveal the significant and positive effects of competition measures (market share and price cost margin) on efficiency change. Competition provides incentives for firms to improve their operations. Specifically, competitive pressure is expected to discipline or eliminate inefficient producers.The results in table 3 consistently suggest that competition measures (market share and herifindhel index) is associated with a significant increase in technical change and assimilation of innovation. In response to more competition, firms try to keep up with modern technology in order to maintain or improve their market position. The inverted U specification is supported by the results. This indicates the presence of Schumpeterian effect when the level of competition is higher.

CONCLUSIONS

Our main findings are:

When looking for the productivity and its components evolution we find that productivity stagnated over the studied period. The results show that technical efficiency is an important contributor in the total factor productivity. The second source of total factor productivity growth, i.e. technical change plays a negative role in productivity growth until 2000.

The regression results indicate a positive relationship between competition and productivity and its components. Competition is found to have an overall positive effect on TFP growth, efficiency catch-up and technological innovation; the higher the level of competition in a market, the faster the growth of firms' TFP, efficiency catch-up and technological innovation observed in that market.

On another hand, our results point to the existence of significant and sizable non-linear effects of competition on technological change and then on productivity growth. At higher levels of competition firms' incentives to invest in innovation disappear and firms moderate their productivity growth. Tunisia is far from the world's technological frontier and then an excessive external competition plays a negative role in technological change and then in productivity growth.

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IMPLEMENTING DEA MODELS IN THE R PROGRAM

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ABSTRACT

This paper aims to present an implementation of classical DEA models in R, a free software and open source, highly extensible that offers a variety of functions and graphical routines for data analysis. In this work we show both the CRS and VRS DEA models. The computational implementation is illustrated with real data from the Brazilian electric power distribution utilities.

***Keywords**: Data Envelopment Analysis, classical models, R programming language*

INTRODUCTION

Introduced by Charnes, Cooper and Rhodes in 1978, Data Envelopment Analysis (DEA) is an important branch of the operations research, as well as of economics, as evidenced by numerous publications with practical applications and theoretical developments on little more than three decades (EMROUZNEJAD et al, 2008, COOK & SEIFORD, 2009). In summary, DEA can be described as a nonparametric technique based on linear programming to evaluate the efficiency of organizations working in the same industry.

This paper presents a brief introduction about the implementation of classical DEA models in the R programming language. The models implemented include the CRS (Constant Returns to Scale) and the VRS (Variable Returns to Scale), both in the multiplier form and input oriented. The computational implementation is illustrated by the efficiency evaluation of the 18 biggest Brazilian electric power distribution utilities.

There are several software tools available for DEA (BARR, 2004); however, the possibility of implementing DEA models in other programming languages provides great flexibility in the application of the DEA methodology. The advent of the R project (R DEVELOPMENT CORE TEAM, 2013), a free software and open source, highly extensible, offers a variety of functions and graphical routines (packages) for data analysis. For example, the Frontier Efficiency Analysis with R - FEAR (WILSON, 2008) and Benchmarking (BOGETOFT & OTTO, 2011) are two R packages dedicated to DEA. However, R is more than a library of packages; it allows analysts to build their own programs.

CLASSICAL DEA MODELS

DEA is a widely used technique for evaluating the efficiency of a set with N peer entities called decision making units (DMU) which convert multiples inputs into multiples outputs. In the general case, a DMU uses multiples inputs $X=(x_1,...,x_s)$ to produce multiples outputs $Y=(y_1,...,y_m)$ and its efficiency score is defined by the following quotient:

$$efficiency = (u_1 y_1 + \ldots + u_m y_m)/(v_1 x_1 + \ldots + v_s x_s) = (U \cdot Y)/(V \cdot X) \qquad (1)$$

where $V=(v_1,...,v_s)$ and $U=(u_1,...,u_m)$ denote the weights assigned to the inputs and outputs quantities respectively.

Charnes, Cooper and Rhodes (1978) suggest that the vectors U and V must be determined by the linear programming problem (LPP) (2) at Table 1, called CCR or CRS (Constant Returns to Scale) input oriented in the multiplier form.

Table 1. DEA/CRS input oriented

Multiplier form	Envelopment form
$efficiency = \underset{u,v}{Max} \sum_{i=1}^{m} u_i y_{i,j_0}$ (2)	$efficiency = \underset{\lambda,\theta}{Min} \; \theta$ (3)
s.t.	*s.t.*
$-\sum_{i=1}^{s} v_i x_{ij} + \sum_{i=1}^{m} u_i y_{ij} \leq 0 \;\; \forall j = 1,..., j_0,..., N$	$\theta X_{j_0} \geq \sum_{j=1}^{N} \lambda_j X_j$
$\sum_{i=1}^{s} v_i x_{i,j_0} = 1$	$Y_{j_0} \leq \sum_{j=1}^{N} \lambda_j Y_j$
$u_i \geq 0 \;\; \forall i = 1, m$	$\lambda_j \geq 0 \forall j = 1,..., j_0,..., N$
$v_i \geq 0 \;\; \forall i = 1, s$	

The evaluated DMU (DMU_{j0}) is efficient if the objective function is equal to one and all weights are positive at the optimal solution. Otherwise, the DMU is inefficient. Under the resources conservation approach (input orientation), the measure of technical efficiency θ ($0 \leq \theta \leq 1$) of a DMU is defined as the maximum radial contraction of the input vector X that can produce the same amount of products Y:

$$efficiency = Min \{ \theta \,|\, (\theta X, Y) \in \text{production possibilities set } T(X,Y) \} \qquad (4)$$

Using the duality theory in linear programming (COOPER et al, 2002), one can derive an equivalent model known as DEA model in the envelopment form under input orientation whose mathematical formulation corresponds to the model (3) at Table 1. In this case, the DMU evaluated is efficient if and only if θ=1. Otherwise, the DMU is inefficient. It should be emphasized that the LPP (2) or (3) must be solved for each DMU in order to compute its efficiency score.

Later, Banker, Charnes and Cooper (1984) added the constraint $\lambda_1+\ldots+\lambda_N=1$ in the envelopment form of the CRS model (3). The result is a DEA model called BCC or VRS (Variable Returns to Scale). The VRS model in the multiplier form and input oriented is illustrated below (5), where the unconstrained variable u_0 corresponds to the constraint $\lambda_1+\ldots+\lambda_N=1$ in the dual model.

$$efficiency = \underset{u,v}{Max} \sum_{i=1}^{m} u_i y_{i,j_0} + u_0 \qquad (5)$$

$$s.t.$$

$$-\sum_{i=1}^{s} v_i x_{ij} + \sum_{i=1}^{m} u_i y_{ij} + u_0 \leq 0 \ \ \forall j = 1, \ldots, j_0, \ldots, N$$

$$\sum_{i=1}^{s} v_i x_{i,j_0} = 1$$

$$u_i \geq 0 \ \ \forall i = 1, m \quad v_i \geq 0 \ \ \forall i = 1, s$$

AN R CODE FOR DEA

The R code can organized in three parts: loading input data, processing and output reporting. In order to illustrate the R code for DEA model, consider the dataset with the 18 biggest Brazilian distribution utilities for the year 2009. Each utility is characterized by four variables: the annual operating expenditures in R$ (OPEX), the total length of the distribution network in kilometer (NETWORK), the total electricity consumption (MWH) and the number of consumers supplied by the utility (CONSUMERS). The main outputs of the distribution utilities are the amount of distributed energy and the number of consumers. In addition, the operating expenses are also influenced by non controllable factors, for example, the geographical dispersion of consumers. In order to address this issue, the size of the distribution network can be included as an additional output variable. The outputs variables are the drivers of operating expenditures. For a given level of output, the utility should operate at the lowest cost. Thus, in order to obtain an efficiency score that quantifies the potential reduction of the operating expenditures, we propose an input-oriented DEA model wherein the OPEX is the unique input variable and the outputs are those aforementioned. Consider that the data are stored in a MS Excel file called *data.xls* at directory *c:\example*. The data importing can be done by the following commands (commentaries after #):

```
require(lpSolve) # load lpSolve package previously installed

require(XLConnect) # load XLConnect package previously installed

setwd('c:/example') # set work directory

wb <− loadWorkbook('data.xls') # load the file data.xls

data <− readWorksheet (wb, sheet=1, header=TRUE) # read the first spreadsheet in the data file
```

In the R code above the *loadWorkbook* and *readWorksheet* functions are available in the package XLConnect (http://cran.r-project.org/web/packages/XLConnect/index.html). The *readWorksheet* command create a *data.frame* (VERZANI, 2005) called *data* with all records in the first worksheet into the file data.xls. In the *readWorksheet* command, the *sheet* parameter indicates the index of the worksheet to read from and the *header* parameter set to *TRUE* indicates that the first line contains the variable labels. As illustrated in Fig. 1, the *data* object contains the input and output variables. The input variable is the

OPEX at second column of the data matrix and the output variables are at columns 3 (NETWORK), 4 (MWH) and 5 (CONSUMERS). The selection of inputs and outputs variables can be done by the R code shown in Fig.1.

The DEA model processing consists in solving a LPP for each one of the *N* DMU. The LPP can be solved by the *lp* function available in the package lpSolve (http://cran.r-project.org/web/packages/lpSolve/index.html).

```
> data
            UTILITY       OPEX   NETWORK      MWH CONSUMERS
1       ELETROPAULO 1249143613  45212.99 39922710   5987873
2             CEMIG 1682334644 460219.00 37476802   6832546
3     CPFL - Paulista  497290782  89879.00 25267579   3502793
4             COPEL 1018866491 224817.29 23525040   3628209
5             LIGHT  557206112  58074.00 22902552   3640182
6            CELESC  721455274 144896.32 18105811   2237127
7            COELBA  436436014 215001.47 14286757   4622046
8           ELEKTRO  414602018 107115.75 13398558   2123670
9  CPFL - Piratininga  195789961  22235.63 13013378   1367488
10      BANDEIRANTE  286832273  27496.38 12536237   1482518
11            CELPE  350651684 120427.84 10001560   2994259
12            AMPLA  436532756  51050.29  9506961   2365558
13             CELG  691472253 199494.10  9344291   2213198
14              RGE  186357415  84996.52  7993103   1226079
15           COELCE  316166876 120299.97  7929212   2744830
16          ESCELSA  241433335  56959.90  7897969   1185432
17          AES SUL  206122962  76133.22  7616460   1150518
18             CEEE  385990997  71892.26  7277929   1438072
```

```
namesDMU <- data[1]

inputs <- data[2]

outputs <-  data[c(3,4,5)]

N <- dim(data)[1] # number of DMU

s <- dim(inputs)[2] # number of inputs

m <- dim(outputs)[2] # number of outputs
```

Figure 1. The *data* object in R and the data import code

The LPP (2) can be expressed in the following form:

$$
\begin{array}{llll}
Max & c^T \cdot z & & \\
s.t. & \left[-inputs \quad outputs\right] \cdot z & \leq 0 & \\
 & b^T \cdot z & = 1 & \qquad (6) \\
 & z & \geq 0 &
\end{array}
$$

where *inputs* and *outputs* are the R objects defined in Fig. 1, z^T=[$v\ u_1\ u_2\ u_3$] is the decision variables vector (weights), b^T is the vector of inputs of the evaluated DMU (DMU_{j0}) and c^T is the vector of outputs of the DMU_{j0}.

The efficiency score of each DMU can be evaluated by the R code shown below, where *i* is the index of the evaluated DMU and the vectors *b* and *c* are modified automatically for each DMU:

```
f.rhs <- c(rep(0,N),1)  # RHS constraints
f.dir <- c(rep("<=",N),"=") # directions of the constraints
aux <- cbind(-1*inputs,outputs) # matrix of constraint coefficients in (6)
for (i in 1:N) {
    f.obj <- c(0*rep(1,s),outputs[i,]) # objective function coefficients
```

```
        f.con <- rbind(aux ,c(inputs[i,], rep(0,m))) # add LHS of b^T z=1
        results <-lp("max",f.obj,f.con,f.dir,f.rhs,scale=1,compute.sens=TRUE) # solve LPP
        multipliers <- results$solution # input and output weights
        efficiency <- results$objval # efficiency score
        duals <- results$duals # shadow prices
        if (i==1) {
           weights <- multipliers
           effcrs <- efficiency
           lambdas <- duals [seq(1,N)]
        } else {
           weights <- rbind(weights,multipliers)
           effcrs <- rbind(effcrs , efficiency)
           lambdas <- rbind(lambdas,duals[seq(1,N)])
        }
}
```

Note that in the *lp* function are informed all elements of a LPP: the problem orientation (max or min), the objective function coefficients (f.obj), the matrix of constraint coefficients (f.con), the directions of the constraints <=, = or >= (f.dir) and the right-hand side (f.rhs) of the constraints. In the R code above, the optimal values for the weights (results$solution), shadow prices (results$duals) and efficiency score (results$objval) are stored in the object *results*. Ultimately, the following R code exports the efficiency scores and the input and output weights (U and V) to the spreadsheet illustrated in Fig. 2.

	A	B	C	D	E	F
1	UTILITY	efficiency	OPEX	NETWORK	MWH	CONSUMERS
2	ELETROPAULO	0,5827	8,01E-10	0	6,07E-09	5,68E-08
3	CEMIG	0,5795	5,94E-10	9,74E-07	3,50E-09	0
4	CPFL - Paulista	0,8854	2,01E-09	0	1,53E-08	1,43E-07
5	COPEL	0,5186	9,81E-10	7,95E-07	1,12E-08	2,11E-08
6	LIGHT	0,7755	1,79E-09	0	1,36E-08	1,27E-07
7	CELESC	0,5239	1,39E-09	1,28E-06	1,87E-08	0
8	COELBA	1,0000	2,29E-09	4,65E-06	0	0
9	ELEKTRO	0,6879	2,41E-09	1,95E-06	2,75E-08	5,18E-08
10	CPFL - Piratininga	1,0000	5,11E-09	0	7,68E-08	0
11	BANDEIRANTE	0,6984	3,49E-09	0	2,65E-08	2,47E-07
12	CELPE	0,8225	2,85E-09	0	2,16E-08	2,02E-07
13	AMPLA	0,5498	2,29E-09	0	1,74E-08	1,63E-07
14	CELG	0,5856	1,45E-09	2,94E-06	0	0
15	RGE	1,0000	5,37E-09	4,97E-06	7,22E-08	0
16	COELCE	0,8198	3,16E-09	0	0	2,99E-07
17	ESCELSA	0,6697	4,14E-09	3,36E-06	4,72E-08	8,90E-08
18	AES SUL	0,8406	4,85E-09	3,93E-06	5,53E-08	1,04E-07
19	CEEE	0,4460	2,59E-09	2,10E-06	2,95E-08	5,57E-08

Figure 2. Results from CRS model

```
report <- cbind(effcrs,weights) # output report
colnames(report) <- c('efficiency',names(inputs),
names(outputs)) # header
# create the output file resultscrs.xls
wbout<-loadWorkbook("resultscrs.xls",create = TRUE )
# create the sheet CRS_results within the output file
createSheet(wbout,"CRS_results")
# write DMU names in the first column
writeWorksheet (wbout, namesDMU, startCol = 1, sheet=1,
header = TRUE)
# write the results from the second column onwards
writeWorksheet (wbout, report, sheet=1, startCol=2, header =
TRUE )
# save the output file
saveWorkbook(wbout)
```

The difference between CRS and VRS models resides in the unconstrained variable u_0. This variable can be modeled by the difference of two non negative variables ($u_0 = u^+ - u^-$, $u^+ \geq 0$ and $u^- \geq 0$), as illustrated by the following R code for DEA VRS (5).

```
f.rhs <- c(rep(0,N),1) # RHS constraints
f.dir<-c(rep("<=",N), "=") # directions of the constraints
aux <- cbind(-1*inputs,outputs,1,-1) # matrix of constraint coefficients in (6)
```

```
for (i in 1:N) {
   f.obj<−c(rep(0,s),outputs[i,],1,-1) # 1 and -1 represents u+ and u- respectively
   f.con<− rbind(aux,c(inputs[i,], rep(0,m),0,0)) # add LHS of b^T z=1
   results<−lp("max", f.obj, f.con, f.dir, f.rhs, scale=1, compute.sens=TRUE) # solve LPP
   multipliers <− results$solution # input and output weights
   efficiency <− results$objval # efficiency scores
   duals <−  results$duals # shadow prices
   u0 <−  multipliers[s+m+1]-multipliers[s+m+2]
   if (i==1) {
     weights <− c(multipliers[seq(1,s+m)],u0)
     effvrs <− efficiency
     lambdas <− duals [seq(1,N)]
   } else {
     weights<−rbind(weights,c(multipliers[seq(1,s+m)],u0))
     effvrs <− rbind(effvrs , efficiency)
     lambdas <− rbind(lambdas,duals[seq(1,N)])
   }
}
```

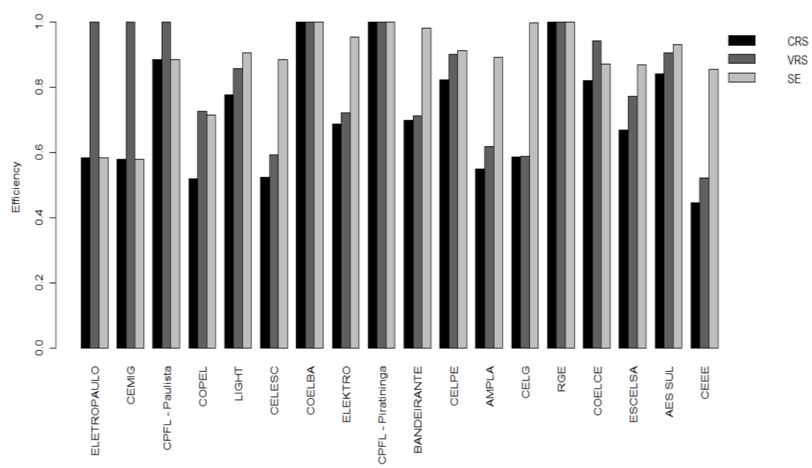

Figure 3. Efficiency decomposition

The efficiency scores from CRS and VRS and the scale efficiency – SE (COOPER et al, 2002) are illustrated in the Fig. 3 generated by the following R code:

```
par(mar=c(10,5,1, 8), xpd=TRUE)  # set plot margins

scale <− effcrs/effvrs # calculate the scale efficiency

spreadsheet <− cbind(effcrs,effvrs,scale) # concatenate the scores

rownames(spreadsheet) <− namesDMU[,1]

colnames(spreadsheet) <− c ("CRS","VRS","SE")
```

```
barplot(t(spreadsheet),col=palette()[c(1,4,7)], ylab="Efficiency",beside=TRUE,las=3)

legend("topright",inset=c(-0.2,0),colnames(spreadsheet),fill=palette()[c(1,4,7)],bty="n")
```

The decomposition illustrated in Fig. 3 depicts if the sources of inefficiency is in the operation, in the scale or both (COOPER et al, 2002).

CONCLUSIONS

The R codes presented in this paper are examples of how to implement DEA models in the R programming language. They can be easily adapted to more sophisticated DEA models, for example, models with restricted multipliers, cross-efficiency evaluation, two-stage DEA model, network DEA and resource allocation based on DEA. The R is free, open source and highly extensible. In addition, it offers a way to integrate the DEA methodology with other quantitative techniques and software, an important issue in decision making process.

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INCORPORATING BOTH UNDESIRABLE OUTPUTS AND NON DISCRETIONARY FACTORS IN DEA

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ABSTRACT

One research issue in the context of Data Envelopment Analysis (DEA) is the problem of nondiscretionary factors and undesirable outputs in production process. Given difficulties in both model construction and data availability, very few published paper simultaneously consider the above two issues. This paper attempts to make a closer look by applying DEA-based performance evaluation models to treat multiple nondiscretionary factors in presence of undesirable outputs.

Keywords: *Data Envelopment Analysis; Non-discretionary inputs; Undesirable outputs; Efficiency.*

INTRODUCTION

Data Envelopment Analysis (DEA) based on the work of Farrell (1957) is currently a popular procedure that measures efficiency and productivity of peer decision-making units (DMUs). Standard DEA models introduced by Charnes, Cooper and Rhodes (1978) and extended by Banker, Charnes and Cooper (1984) assume that the assessed units are performing same tasks with similar objectives operating in similar operational environments. These studies implicitly assume that all of the inefficiencies are caused by bad management while they filter out to describe the differences in the environment in the analysis. A number of different approaches such as Banker and Morey (1986 a,b), Ray(1991), Fried et.al(1993) and Ruggiero(1996, 2004) have been developed to overcome this weakness. On the other hand, these literatures only value the desirable outputs and simply ignore the undesirable. Toward this end, imposing of "weak-disposability" assumption, on the functional form of the underlying technology made a substantial contribution in analyzing undesirable outputs. The traditional approach to modeling weak disposability (reduction of undesirable outputs by decreasing the level of production activity) goes back to Shephard(1970)who applied a single abatement factor for all observed activities in the sample. Kuosmanen(2005) pointed out that applying a uniform abatement factor is not in line with the usual wisdom of concentrating abatement factors on firms with lower abatement costs. Some other treatment of undesirable factors have been critically debated in Hailu and Veeman (2001), Fare and Grosskopf (2003), as well as Hailu (2003) and Kuosmanen (2005). Podinovski and Kuosmanen (2011) developed two further technologies for modeling weak-disposability under relaxed convexity assumption. As far as we know there is little DEA-based work considering both undesirable variables and environmental exogenous factors. In a survey by Yang and Pollit(2009)six DEA- based were set up for a production process which produces both desirable and undesirable along with inclusion of uncontrollable variables. Their article includes various models following the characterization offered in Pastor (2002). This argument attempts to examine the impact of exogenous fixed factors on performance analysis producing undesirable outputs in a one- stage linear model. In order to complete the study, the current paper applies Ruggiero (1996) public sector model for treating environmental factors along with weak disposability assumption as modeled by Kuosmanen(2005). The rest of the paper is unfolded as follows. In the section to follow, a brief review of non discretionary factors and weak disposability will be stated. Section 3 explains the research methodology .Also, the methodology will present variable return to scale (VRS) and demonstrate how to incorporate both factors in a single model. Section 4 illustrates the process through a simple example. Conclusion will end the paper.

2. LITERATURE REVIEW

2.1 NON DISCRETIONARY FACTORS IN DEA

Consider a production unit employing N discretionary inputs $x = (x_1,..., x_N) \in R_+^N$ in the production of M desirable outputs $v = (v_1,..., v_M) \in R_+^M$ given a vector of non-discretionary input $z = (z_1,..., z_L) \in R_+^L$. There are three general approaches that have been developed to control for non discretionary inputs. Banker and Morey (1986a) provided the first model to do so. This model treats non discretionary inputs as normal inputs, but does not require any improvement in them. However, the referent production possibility may not be feasible and leads to improper restriction of the production possibility sets and distorted efficiency measurement. The approach proposed by Ruggiero (1996) fits into the single stage approaches and consists on excluding DMUs with a more favorable environment. The model input-oriented (variable return to scale) has the following formulation:

$$
\begin{aligned}
& Min \quad \theta \\
& \text{s.t} \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \quad r = 1,..., S \qquad (1) \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} \quad i = 1,..., M \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j \geq 0 \quad \forall j \in \{j; z_j \leq z_o\} \\
& \lambda_j = 0 \quad \forall j \in \{j; z_j > z_o\}
\end{aligned}
$$

In fact the Ruggiero (1996) model is an extension of the model of Banker and Morey (1986b), to treat non discretionary categorical variables, to the case where non discretionary factors are continuous. The existing model is unable to properly weight the importance of each nondiscretionary variable in production. As the number of nondiscretionary factors increases, the model will be more likely to overstate efficiency. To address this issue, Ray (1991) developed the third approach for controlling nondiscretionary factor. Ruggiero (1998) developed a hybrid model with three stages to allow for multiple nondiscretionary inputs. As pointed out by Ruggiero (1998) the mentioned multi-stage approaches require the specification of a functional form to the regression model meaning that a missspecification may distort the results. These models are based on different assumptions and they set different requirements for data.

INCLUSION OF UNDESIRABLE OUTPUTS

Modeling undesirable outputs of production activities has attracted considerable attentions among researchers. Hailu and Veeman(2001)have extended a non parametric productivity analysis model to include undesirable outputs. They introduced a non- orthodox mono-tonicity condition on their technology and they claimed "weak disposability" concept in DEA. Consider K DMUs and for DMU_k under evaluation data on the vectors of discretionary inputs, desirable outputs and undesirable outputs are $x=(x_{1k},...,x_{Nk})\geq 0$, $v=(v_{1k},...,v_{Mk})\geq 0$ and $w=(w_{k1},...,w_{Jk})\geq 0$ respectively. Further assume $x_k\neq 0$, $v_k\neq 0$ and $w_k\neq 0$. The production technology can be represented by:

$$P(x)=\{(v,w)\,|\,x \text{ can produce}(v,w),\ x\in R_{+}^{N}\}$$

DEFINITION: Outputs are weakly disposable if and only if

$$(v,w)\in P(x) \quad \text{and} \quad 0\leq\theta\leq 1 \quad \text{implies} \quad (\theta v,\theta w)\in P(x) \ \ ,\ x\in R_{+}^{N}$$

(See, Shephard(1970)).

Fare and Grosskopf (2003) restated the HV model under variable return to scale satisfying weak-disposability. This model can be rewritten as

$$\begin{aligned} T_{FG}=\Big\{(v,w,x)\,|\ & \sum_{k=1}^{K}\theta\ z^{k}v_{m}^{k}\geq v_{m} \quad m=1,...,M \\ & \sum_{k=1}^{K}\theta\ z^{k}w_{j}^{k}=w_{j} \quad j=1,...,J \\ & \sum_{k=1}^{K}z^{k}x_{n}^{k}\leq x_{n} \quad n=1,...,N \qquad (2) \\ & \sum_{k=1}^{K}z^{k}=1 \\ & z^{k}\geq 0\ ,\ 0\leq\theta\leq 1\ ,\ k=1,...,K\Big\} \end{aligned}$$

The contraction parameter θ in the formulation (2) corresponds to Shephard's(1970) definition of weak-disposability. As Kuosmanen(2005)pointed out , this model assumes a uniform abatement factor in the sample. To allow for non- uniform abatement factor of the individual firms, Kuosmanen (2005) proposed the following production technology:

$$T_K = \left\{ (v,w,x) \middle| \begin{array}{ll} \sum_{k=1}^{K} \theta^k z^k v_m^k \geq v_m & m = 1,...,M \\ \sum_{k=1}^{K} \theta^k z^k w_j^k = w_j & j = 1,...,J \\ \sum_{k=1}^{K} z^k x_n^k \leq x_n & n = 1,...,N \\ \sum_{k=1}^{K} z^k = 1 & \\ z^k \geq 0 \ , \ 0 \leq \theta^k \leq 1 \ , \ k = 1,...,K \end{array} \right\} \qquad (3)$$

It should be noted that formulation (2) is a special case of (3) with $\theta^1 = ... = \theta^k$. Variable return to scale is enforced by the restriction that intensity variables z must add up to unity. To linearize formulation (3), the intensity weight of firm k can be partitioned into two components $z^k = \lambda^k + \mu^k$. Using this notation, Kuosmanen (2005) converted the production technology (3) into the following linear form:

$$T_K^{(L)} = \left\{ (v,w,x) \middle| \begin{array}{ll} \sum_{k=1}^{K} \lambda^k v_m^k \geq v_m & m = 1,...,M \\ \sum_{k=1}^{K} \lambda^k w_j^k = w_j & j = 1,...,J \\ \sum_{k=1}^{K} (\lambda^k + \mu^k)\, x_n^k \leq x_n & n = 1,...,N \\ \sum_{k=1}^{K} (\lambda^k + \mu^k) = 1 & \\ \lambda^k \ , \mu^k \geq 0 \ , \ k = 1,...,K \end{array} \right\} \qquad (4)$$

The above formulation (4) is now a linear form and the right hand sides of the envelopment constraints are faced up with scaling variables. In the following section, a model incorporating both non discretionary inputs and undesirable outputs is introduced.

METHODOLOGY

In this section a single-stage model is addressed within which both undesirable outputs and environmental exogenous factors are present. Assume again there are K DMUs and for DMU_k the observed data on the vectors of inputs, desirable outputs and undesirable outputs are $x_k = (x_{1k},...,x_{Nk}) \geq 0$, $v_k = (v_{1k},...,v_{Mk}) \geq 0$ and $w_k = (w_{k1},...,w_{Jk}) \geq 0$ respectively. The environmental exogenous factors are characterized by vector $z_k = (z_{1k},...,z_{Lk})$. Based on the following postulates the production possibility set may be written as:

$$T(z) = \{(v,w,x) | (v,w) \leq f(x|z)\}$$

(A1) Strong disposability of inputs and good outputs, if $(v,w,x) \in T(z)$ and $0 \le v' \le v$, $x' \ge x$ for each component, then $(v',w,x') \in T(z)$.

(A2) Weak disposability of undesirable outputs and good outputs: if $(v,w) \in T(z)$ and $0 \le \theta \le 1$ implies that $(\theta v, \theta w) \in T(z)$.

(A3) Convexity of $T(z)$.

(A4)Inclusion: $\forall$ DMUs $k = 1,...,K$, if DMU_k faces z_k then the observed $(v^k, w^k, x^k) \in T(z)$.

(A5)Environmental effect: $T(z_1) \subset T(z_2)$ for all $z_1 \le z_2$

(A6)Minimum extrapolation: if a production possibility set $T_1(z)$ satisfies postulates (A1)-(A5) then $T_1(z) \subset T(z)$ $\forall z$.

In essence, postulate (A5) allows for a given DMU compared with only to DMUs with an environment that is at least as harsh as the one it faces. This fact is replaced by the following conditions: $\lambda^k \ge 0 \quad z_l^k \le z_l^o \quad \forall l,k$. Under these assumptions, the empirical output technology of $\hat{T}(z)$ can be as follows:

$$
\begin{aligned}
\hat{T}(z) = \{ \quad (v,w,x) | \; & \sum_{k=1}^{K} \lambda^k \theta^k v_m^k \ge v_m \qquad m = 1,...,M \\
& \sum_{k=1}^{K} \lambda^k \theta^k w_j^k = w_j \qquad j = 1,...,J \qquad\qquad (5) \\
& \sum_{k=1}^{K} \lambda^k x_n^k \le x_n \qquad n = 1,...,N \\
& if \quad z_l^k \le z_o^k \quad then \quad \lambda^k \ge 0 \quad l = 1,...,L \;, k = 1,...,K \\
& \sum_{k=1}^{K} \lambda^k = 1 \qquad , k = 1,...,K \\
& 0 \le \theta^k \le 1 \}
\end{aligned}
$$

The last conditional constraints express the meaning of environmental factors according to Ruggiero (1996) public sector model. The model is non linear and includes conditional inequality. As Kuosmanen(2005) pints out the intensity weight can be partitioned as: $\lambda^k = \alpha^k + \beta^k$. Then we have:

$\alpha^k = (1-\theta^k)\lambda^k \quad , \quad \beta^k = \theta^k \lambda^k$ .Using these notations, the activity analysis can be written as:

$$\begin{aligned}\hat{T}(z) = \{ \ (v,w,x) \Big| \ & \sum_{k=1}^{K} \beta^k v_m^k \geq v_m \quad m = 1,...,M \\ & \sum_{k=1}^{K} \beta^k w_j^k = w_j \quad j = 1,...,J \qquad (6) \\ & \sum_{k=1}^{K} (\alpha^k + \beta^k) x_n^k \leq x_n \qquad n = 1,...,N \\ & if \quad z_l^k \leq z_o^k \ \ then \ \ \alpha^k + \beta^k \geq 0 \quad l = 1,...,L \ , k = 1,...,K \\ & \sum_{k=1}^{K} (\alpha^k + \beta^k) = 1 \ \ , \ \ \alpha^k, \beta^k \geq 0 \quad \forall k \}\end{aligned}$$

This technology is linear in terms of unknown variables α^k, β^k. The conditional inequality limits DMU's reference set for peers not with a more favorable environment. To measure the efficiency of firm o in terms of abatement potential in undesirable outputs, we need to solve the following linear programming:

$$\begin{aligned} & Min \quad \varphi \\ & s.t. \\ & \quad \sum_{k=1}^{K} \beta^k v_m^k \geq v_m^o \quad m = 1,...,M \\ & \quad \sum_{k=1}^{K} \beta^k w_j^k = \varphi \ w_j^o \quad j = 1,...,J \qquad (7) \\ & \quad \sum_{k=1}^{K} (\beta^k + \alpha^k) x_n^k \leq x_n^o \qquad n = 1,...,N \\ & if \quad z_l^k \leq z_o^k \quad then \quad \beta^k + \alpha^k \geq 0 \quad l = 1,...,L \ , k = 1,...,K \\ & \quad \sum_{k=1}^{K} (\beta^k + \alpha^k) = 1 \end{aligned}$$

In an effort to be in line with underlying technology following Podinovski and Kuosmanen (2011) a binary variable $\eta^k \in \{0,1\}$ is defined in the following inequality: $\alpha^k + \beta^k \leq \eta^k \quad \forall k$

Rearranging the terms, model (7) can be restated as follows:

$$\begin{aligned} & Min \quad \varphi \\ & s.t. \\ & \quad \sum_{k=1}^{K} \beta^k v_m^k \geq v_m^o \quad m = 1,...,M \\ & \quad \sum_{k=1}^{K} \beta^k w_j^k = \varphi \ w_j^o \quad j = 1,...,J \qquad (8) \\ & \quad \sum_{k=1}^{K} (\beta^k + \alpha^k) x_n^k \leq x_n^o \qquad n = 1,...,N \\ & \quad \eta^k z_l^k \leq z_l^o \quad l = 1,...,L \ , k = 1,...,K \\ & \quad \alpha^k + \beta^k \leq \eta^k \\ & \quad \eta^k \in \{0,1\} \\ & \quad \alpha^k, \beta^k \geq o \end{aligned}$$

In the above formulation, the binary variables η^k serve as indicators that become equal to one if the sum of $\alpha^k + \beta^k$ is positive. If $\alpha^k + \beta^k = 0$ implies that η^k can be equal to zero or one. Indeed if $\alpha^k + \beta^k > 0$ then $\eta^k = 1$ and implies that $z_l^k \leq z_l^o$, so an under evaluation DMU can be compared with the peers presenting only equal or more disadvantageous conditions. Else, $\alpha^k + \beta^k = 0$ leads to η^k

which can be either zero or one. So $\eta^k z_l^k \leq z_l^o$ does not restrict anything as required. In order to reveal the importance of each nondiscretionary input, using potential information and prior specification of data set, every component of multiple non discretionary inputs of the under analysis DMU (z_l^o) is weighted by the culmination of those relevant component of non discretionary factors over all DMUs. Given this fraction, it is possible to obtain a ratio as: $\frac{z_l^o}{\sum_{k=1}^{K} z_l^k}$.To achieve an overall index z of environmental harshness, the proportion above is added over the number of non discretionary variable as $\sum_{l=1}^{L} \frac{z_l^o}{\sum_{k=1}^{K} z_l^k}$.The advantage of this approach is computational. Due to the nature of process, this index provides the means to implicitly weigh the contribution each variable has on the production. In the next section a numerical example will clarify the advantages of the examined methodology discussed above.

NUMERICAL EXAMPLE

To gain further insight, let us illustrate the proposed methodology by a numerical example. The sample consists of twelve DMUs each uses two discretionary inputs for generating two types of output: desirable and undesirable in presence of an exogenous fixed factor. Table 1 summaries the data set.

Table 1: Empirical Data Set

DMU	1	2	3	4	5	6	7	8	9	10	11	12
INPUT1	20	19	25	27	22	55	33	31	30	50	53	38
INPUT2	151	131	160	168	158	255	235	206	244	268	306	284
DESIRABLE OUTPUTS	100	150	160	180	94	230	220	152	190	250	260	250
UNDESIRABLE OUTPUTS	90	50	55	72	66	90	88	80	100	100	147	120
ENVIRONMENTAL VARIABLES	2	1	2	2	1	2	1	1	1	2	1	2

To see how the weak disposability works in presence of environmental variables, model (8) will be employed o the data set of Table (1). The optimal value of abatement undesirable factor acts as objective function. The binary variable η^k will range between two different values zero and one. Table (2) summarizes the results.

Table2: Efficiency measurement (model8)

DMU	1	2	3	4	5	6	7	8	9	10	11	12
efficiency measure	0.37	1	0.97	0.84	0.47	0.86	0.89	0.64	0.66	0.84	0.64	0.70

As Table (2) illustrates the efficiency score are confined in the interval $[0,1]$. The linear model is also capable of accommodating both undesirable and non-controllable variables. Of note, if the number of environmental variables increases, the number of efficient units will be increased inherently. Applying the aggregating technique of multiple non discretionary factors through the proposed approach, the number of efficient units will be decreased. The results are reported in Table 3.

Table3: Results for Aggregating Environmental Factors in Model (8)

DMU	1	2	3	4	5	6	7	8	9	10	11	12
Environmental factors	2	1	2	2	1	2	1	1	1	2	1	2
	2	9	5	2	2	3	2	1	3	1	2	5
efficiency measure-without aggregating	0.44	1	1	1	0.57	1	1	1	0.76	1	0.74	0.75
Unified efficiency measure	0.44	1	1	1	0.57	1	1	0.63	0.76	1	0.75	0.75

As Table (3) records when the number of environmental variables increase model (8) tends to overstate efficiency. Given the aforementioned reasons, aggregating environmental factors is actually able to decrease efficient units as estimated before. Back to Table (3), it can be seen unit 8 acts as an efficient unit in linear model with multiple environmental factors, while the aggregation makes it inefficient. However, the number of efficient unit decrease slightly, but it can support the idea of collapsing multiple environmental variables in presence of undesirable output production.

CONCLUSION

There are very few published papers on performance analysis which simultaneously incorporate both undesirable outputs and uncontrollable factors. This article has focused to examine the impact of non discretionary variables and undesirable outputs in production process and in the programming models used to efficiency measurement. The model developed herein is derived from existing literatures and is able to consider both issues in one-stage linear programming. Despite being simple, an alternative aggregation method has been implied to underestimate the influence of multiple non discretionary factors producing undesirable outputs.

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INDIAN POWER DISTRIBUTION SECTOR: PERFORMANCE ANALYSIS AND WAY AHEAD

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ABSTRACT

Power sector development is central to India's growth. This study assesses the performance of Electricity Distribution Companies (DISCOMs) in the 20 major Indian states over the years 2006-2010 – deploying Input minimising Data Envelopment Analysis in cross-sectional and time-varying data. Since, standard DEA models may identify more than one state utility as efficient – approach used in this paper uses factor weights which are obtained from unbounded runs of DEA, to set upper and lower limits on weights in the "bounded" formulation. The results indicate that performance of several Discoms is sub-optimal, leaving a potential for cost reduction and possible reduction in energy losses. This model developed herein is envisioned to be instrumental to policy makers and managers to improve the efficiency of inefficient Discoms and thereby increase competitiveness. However, as Indian states are economically and politically diverse from each other, there is scope to vary the organizational structure across states. This paper provides a means to do so. The agenda for policymakers is to identify the situation in their respective states and choose a reorganization path that is the best compromise. The study also serves as a guiding tool for financing institutions by facilitating identification of credit worthiness of different State Discoms.

Keywords*: Data Envelopment Analysis, Bounded Weights, Distribution Utilities, Efficiency*

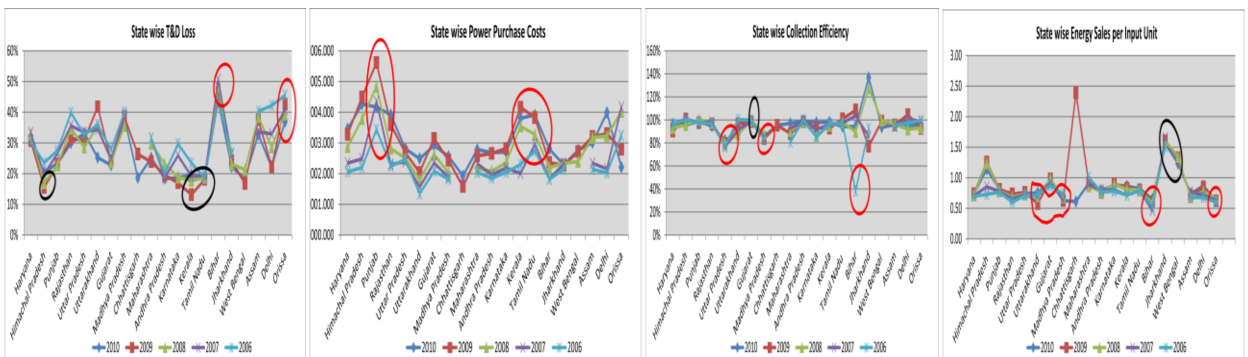
INTRODUCTION

As a developing country, India seeks to improve its economic prospects; power sector development has been the central part of this effort. Series of reform initiatives over the past two decades, covering investments, regulatory reforms, market reforms, efficiency, access and related issues gave way to better energy governance in India. The Distribution segment in the country, has grown in an unplanned and haphazard manner to meet the immediate objectives of meeting the growing demand on an urgent basis. This approach, over years has resulted in sub optimal performance of the distribution system. It has also affected the financial performance of utilities. Lack of sufficient capacity to make timely and adequate investments give way to higher losses. Because the Discoms have been loss makers, the generation companies do not recover their dues from their biggest buyers (Discoms). All these impact the banking system as well. The borrowing requirements of the utilities are fairly huge but for most banks the sectoral caps for the power sector have been reached and the prospect of bad debts leads to automatic aversion to fresh lending. For the limited funds, there is a need for channelizing the resources so that the states with "potential" for improvement can be pushed up first. Therefore, in this study, our focus is to identify the drivers of inefficiency in the distribution segment at individual state level and on the basis of efficiency ranking of different state Discoms, to devise strategies and identify measures for progress towards attainment of efficiency gains. We employ the bounded formulation of Data Envelopment Analysis

(DEA) to construct an index on the basis of past trends of a few critical input and output variables, to establish concrete and reliable baselines and benchmark the utility performance vis-a-vis that.

METHODS

Sources of inefficiency in the distribution system vary across States. On detailing the sector evolution at the State level according to various indicators of operational and financial performance, we find that the overall efficiency of a State cannot be determined on the basis of its performance in terms of only a few favorable factors. Hence, it is vital to analyze and understand the complex interrelated factors affecting the efficacy and stability of distribution segment in any State. The graphs below provide useful insights regarding the power distribution segment:



Uttar Pradesh (UP), Bihar and Madhya Pradesh (MP) appear to be amongst the worst performers in terms of most of the parameters depicted above. One may observe that the power purchase costs in these States are moderately reasonable but solely on the basis of this, it would be wrong to construe that the States can figure amongst the better performers. Although power purchase costs are the single largest determinant of financial performance of distribution utilities, financial aspect is also related to the power sales and trends in Collection efficiency which reflects the extent of cash flow stress. Transmission and Distribution (T&D) losses, on the operational aspect is another vital determinant of utility performance. Similarly, Gujarat appears to be amongst the better performers. However, for the States like Punjab, which has historically sustained losses despite good operational performance or Maharashtra, with reasonable financial performance but relatively poor operational performance, it becomes difficult to evaluate a State as good or bad by mere inspection of various parameters.

In order to identify a State which corresponds to one whose investments are economically adapted to demand and operates under an optimal operational plan and which can be used as comparison benchmark for other States, we consider the application of DEA methodology, proposed by Charnes et al. (Ref). We evaluate relative efficiency of 20 major State Discoms in India, in presence of multiple inputs and outputs. The analysis is performed for the period 2006 to 2010. Inefficiencies in the distribution system are primarily on account of huge T&D losses, largely due to outright theft and unmetered supply, ever-growing burden of power purchase costs, skewed tariff structure leading to unsustainable cross subsidies by the State Government, systemic failure to ensure proper revenue collection along the value chain, mounting subsidies and lackadaisical financial management. Thus, various performance parameters that are considered in our analysis are: T&D losses (x_1), Power Purchase Cost per unit (x_2), Collection Efficiency (x_3), Debtor Days (x_4), Creditor Days (x_5). Other major components that captures utility performances are Financial Gap (x_6), Accumulated losses (sum of financial loss and the amount by which subsidy received is less than subsidy booked) (x_7) and Energy Deficit (x_8).While the gap between the average cost of supply and the average revenue earned per unit is an important measure of profitability, accumulated Losses shows how many times the current revenue are the historical utility losses. Energy Deficit (%) reflects the quality and reliability of power supply to consumers. All the above parameters are treated as "inputs" to the system. Energy sold per unit of Input (y_1) is considered to be an output – because higher it is, the better. Since higher values of Collection efficiency indicate better performance, we have used the inverse of Collection efficiency in our computations. The Input Minimization model of Data Envelopment Analysis is adopted to create efficiency index for various state Discoms. Since, we are considering the Input Minimization model, our objective function is the weighted sum of inputs that has to be minimized. We consider the following fractional programming problem (1) for each State:

$$\min z_m = \frac{\sum_{i=1}^{I} u_{im} x_{im}}{\sum_{j=1}^{J} v_{jm} y_{jm}}$$

$$Subject\ to,$$

$$1 \leq \frac{\sum_{i=1}^{I} u_{im} x_{in}}{\sum_{j=1}^{J} v_{jm} y_{jn}} \leq 0, \qquad \forall\, n = 1(1)N$$

$$u_{im}, v_{jm} \geq 0, \qquad \forall\, i = 1\ (1)\ I; j = 1\ (1) J$$

Where, z_m is the efficiency measure of the *m*th DMU/State, x_{im} is the *i*th input of the *m*th State, u_{im} is the weight of the *i*th input of the *m*th State, y_{jm} is the *j*th output of the *m*th State, v_{jm} is the weight of the *j*th output of the *m*th State, $x_{in} and\ y_{jn}$ are the *i*th input and *j*th output respectively of the *n*th State. Here n includes m.

The above fractional program (1) is converted into the linear programming (LP) by normalizing the denominator of the program, which estimates the efficiency of *mth* DMU. We solve the following LP for each State:

$$\min z_m = \sum_{i=1}^{I} u_{im} x_{im}$$

$$Subject\ to,$$

$$\sum_{j=1}^{J} v_{jm} y_{jm} = 1$$

$$\sum_{j=1}^{J} v_{jm} y_{jn} - \sum_{i=1}^{I} u_{im} x_{in} \leq 0 \qquad \forall\, n = 1(1)N$$

$$u_{im}, v_{jm} \geq 0, \quad \forall\, i = 1\ (1)\ I; j = 1\ (1) J$$

The above LP model is solved *n* times to determine relative efficiencies of all *N=20* States for each year. Since the above problem is a minimization problem, a relative efficiency score of 1 indicates that the State is efficient, whereas a score of more than 1 indicates that it is inefficient. The above model, which allows for unrestricted factor weights (u_i*'s* and v_j*'s*), may generate efficiency scores, identifying a State, weighing heavily on few favorable inputs/outputs while completely ignoring the others to be efficient. Such States would be those not indulging in overall good practices. Also, the model might result in screening out the States performing well w.r.t many inputs and outputs due to it being outperformed by few other States in different attribute values, but not by much. Although this State is not efficient by the above model, it may be optimal if restrictions on the weights of various inputs/outputs are attached. To overcome this problem, some control over factor weights is important. In order to limit the range within which the factor weights are allowed to vary, we enter additional information into our analysis in form of bounds on weights that reflect the relative importance of different inputs/outputs. The following weight constraints are represented in form of linear inequalities and appended to the DEA model (2):

$\alpha_i \leq u_i \leq \beta_i \qquad i = 1\ (1) I \qquad a_j \leq v_j \leq b_j \qquad j = 1\ (1) J$, α, β, a, b are non negative scalars.

Factor weights which are obtained from the unbounded runs of DEA (2) are used to set lower and upper limits on weights in the *bounded* formulation. This allows selection of states which one would want all other states to emulate. The states selected were Gujarat, Kerala and West Bengal. Based on judgment (based on discussions with the Banks that actually lend to state utilities in India) and comparison of these states, weight restrictions were imposed on the models for other states. Weight restrictions and rationale for the same is provided below:

Weight on Financial Gap and Accumulated Losses were constrained to be greater than 5. This was because in the base model without weight restrictions, model had assigned weights of 5.79 and 5.4 to Financial Gap and Accumulated Losses respectively. All other states, including Gujarat and West Bengal had a zero weight on Financial Gap primarily because Kerala was better than these states in terms of Financial Gap. Similarly Kerala had lower accumulated losses in 2010 as compared to other states. These are two important variables and need to be given higher weights. Inverse of Collection Efficiency received close to zero weights for all the efficient utilities in the base model. However, the Bankers do give some weight to collection efficiency, therefore the weight on collection efficiency in the model is constrained to be greater than 0.001. Almost all efficient states in the base model had assigned some weight to both the debtor days and creditor days. Therefore, based on judgment and weights assigned in the base model to these parameters in the case of efficient states, the weights on debtor days and creditor days were constrained to be greater than 0.008.

Transmission and Distribution Loss is definitely an important consideration. In the case of Kerala – the weight assigned to T and D loss parameter is 15.34. Therefore, in the model, the weight on T and D loss was constrained to be greater than 10. Energy deficit (in %) had a weight of 0.082 in the base model for Kerala. Based on comparison with other states, the weight on Energy Deficit was restricted to 0.01. Power Purchase Cost is normally non-discretionary. In the base model, model assigned zero weight to power purchase cost in the cases of Gujarat, Kerala and West Bengal. In the DEA approach used in this paper, the weights on power purchase cost were restricted to be greater than 0.001.

RESULTS AND DISCUSSIONS

The efficiency scores for 2010 and optimal weights on inputs for each State, within the specified weight restrictions obtained from solving the bounded DEA problem are given below:

States	Financial Gap	Collection Efficiency	Debtor Days	Creditor days	T&DLoss (%)	Accumulated Losses	Energy Deficit (%)	Power Purchase Cost/Input	Efficiency Score	Rankings
Kerala	10.9	0.001	0.008	0.008	10	10.9	0.9496	0.001	1	1
Gujarat	9.91	0.001	0.008	0.0433	10	10.9	0.01	0.001	2.4	2
West Bengal	7.42	0.001	0.008	0.008	10	5	0.0365	0.001	2.91	3
Andhra Pradesh	5	0.001	0.008	0.0084	10	5	0.036	0.001	3.58	4
Chhattisgarh	5	0.001	0.009	0.0178	10	5	0.01	0.001	3.68	5
Delhi	10.9	0.001	0.008	0.018	10	5	0.0545	0.001	3.69	6
Karnataka	5	0.001	0.008	0.008	10	5	0.01	0.0547	4.45	7
Himachal Pradesh	5	0.001	0.008	0.008	10	5	0.011	0.001	4.78	8
Maharashtra	5	0.001	0.008	0.008	10	5	0.01	0.0477	5.45	9
Rajasthan	5	0.001	0.008	0.0094	10	5	0.0376	0.001	6.25	10
Punjab	5	0.001	0.008	0.0133	10	5	0.01	0.001	8.71	11
Haryana	5	0.001	0.008	0.0095	10	5	0.0378	0.001	9.14	12
Orissa	5	0.001	0.008	0.008	10	5	0.1702	0.001	10.25	13
Assam	5	0.001	0.008	0.008	10	5	0.0337	0.0302	10.49	14
Uttarakhand	5	0.001	0.008	0.008	10	5	0.034	0.0248	13.84	15
Madhya Pradesh	5	0.001	0.008	0.008	10	5	0.01	0.1482	15.98	16
Tamil Nadu	5	0.001	0.008	0.008	10	5	0.0352	0.001	17.2	17
Jharkhand	5	0.001	0.008	0.008	10	5	0.01	0.001	21.05	18
Uttar Pradesh	5	0.001	0.008	0.008	10	5	0.01	0.0975	22.25	19
Bihar	5	0.001	0.008	0.008	10	5	0.01	0.1336	27.02	20

Various input parameters for the DEA were determined in discussion with the key lending banks to power sector in India. When faced with multiple input parameters, DEA methodology gives high weights to parameters on which the state utility (DMU) is better than others. A comparison of the weights achieved by each state indicates that the differences in efficiency levels of the states exists on account of: Financial Gap, Creditor Days, Accumulated Losses, Energy Deficit and Power Purchase Cost per unit of input. For all other parameters, the weights are the same across states. In other words, when normalized for output, all the states are similar in terms of all the other inputs and therefore, only the parameters that have varying weights are the key determinants of efficiency. Guajarat is the only state where the Distribution Companies have consistently been in positive profits for last eight years. This is corroborated by some recent studies undertaken by the Minsitry of Power, Government of India. West Bengal is another state, where even the operational performance has improved over years. In terms of Creditor Days, Gujarat achieves the highest weight essentially because, it is a utility which makes prompt payments and maintain good relations with its vendors. Accumulated losses are the lowest in Kerala and Gujarat. All other states (except West Bengal, which has recently turned profitable) have been in persistent losses over years. High weights on power purchase cost could reflect either a very efficienct portfolio management or a a preference for load shedding instead of having to purchase costly power in short term markets. None of the states in India have a reliable estimate of their Long Term, Medium Term and Short Term Power Purchase requirements – indeed, none of the states have a portfolio optimization model. The states, like Bihar, Uttar Pradesh, Madhya Pradesh and Uttarakhand have a high weights on power purchase cost because these states donot purchase power in the short term markets (where prices are usually higher than in the long run markets). Here, we analyze this variable along with the weights assigned to energy deficit. The weights observed in the above results not only enable evaluation of Discom performance but also facilitate identifying the improvement needs in terms of the above five indentified parameters of Discom operation. Apart from Kerala, Gujarat, West Bengal and Delhi, all the States should consider cutting down on their Financial Gap. Regular tariff revisions will play key role in reducing financial gap for most of these States. Weights on power purchase costs doesn't enable us to directly identify States that need improvement on this front beacause the actual picture of load shedding should also be considered here, in absence of which, these weights are studied in connection to the weights on Financial Gap. States with a weight of 5 on Gap and 0.001 on power purchase costs, like Chhattisgarh, Himachal Pradesh, Jharkhand, Tamil Nadu, Punjab, Haryana, Rajasthan and Orissa are those that are underperforming in terms of financial gap and face high input costs. Sound Regulatory framework giving way to regular tariff revisions can cater to the problems of high power purchase costs and cash gaps in these States. All such States are those that also exhibit dependence on loans, as explained by the weights on their creditor days. Debt restructuring is an essential way forward for these. Weights on power purchase costs, when studied in conjunction with the weights on energy deficit highlight that all those States that have a weight on power purchase costs greater than its lower bound with the weight on deficits being at its minimum are those that shed load and manage with lower power purchase costs but compromise with the quality and reliability of power supply to consumers. These are amongst the most inefficient States, as they not only need to contain financial inefficiencies but also maintain quality services to customers. They also have to rely on borrowings due to lack of enough resources.

CONCLUSIONS

Despite wide disparities among the States, monitoring the performance of the states in a complex market framework require a core set of indicators. These indicators for distribution utilities are derived from the factors identified in this paper. An important conclusion that can be drawn from the analysis is that Tariff adjustments to tame power purchase costs and financial gap and sustaining quality service are the vital areas of improvement across most states and this can be accomplished only through substantial investments and truly integrated and consistent energy policies guiding and directing India's power sector. At the same time debt restructuring of those utilities that exhibit historical interest burden and poor financial performance should be considered to avoid exposure of the banks. Thus, the above analysis also serves as a guiding tool for financing institutions by facilitating identification of financial health, credit worthiness and overall quality of power supply of different State Discoms and lending and disbursal can accordingly be made contingent on passing diligence tests based on identified parameters. Identify the states that urgently need financial restructuring and choose a reorganization path that is the best compromise otherwise the worsening finances indicate imminent drag on social and economic development and on the financial system in the country. One of the limitations of the study is that it uses the inputs and output weights of the States identified efficient from the unbounded runs of DEA. The weights computed through this methodology have an element of users' subjectivity. As an extension to this study, it will be interesting to use the formulations proposed by Doyle and Green that computes weights by not only maximizing the efficiency of the target DMU but simultaneously minimizing the efficiency of the composite DMU. We can further construct cross efficiency matrix using these weights to identify an overall good performer. However, this paper illustrates its importance as a decision making tool in the area of Power Sector Development.

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INVESTIGATION OF ELECTRICAL ENERGY EFFICIENCY OF TURKEY BY THE DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Turkey electric power system which consists of three stages such as Production-Transmission-Distribution goes through the period of change and transformation. Liberalization process which speeds from 1990 to 2000 takes its effects on power area. Especially it seems in electric power system as well. In this context, this study based on the effects of Distribution Companies in the Electric Distribution stage and efficiency scores of 21 electric distribution companies were calculated by testing with Data Envelopment Analysis (DEA). Activity ranking of the companies were created and interpreted according to the results.

Keywords*: Data Envelopment Analysis, goal programming, OECD countries.*

INTROUDCTION: WHAT IS ENERGY EFFICIENCY?

Energy efficiency is to minimize regardless of the energy amount consumed, amounts in production and quality by not preventing economic development and social welfare. More specifically energy efficiency is set of efficiency improver measures such as energy recovery, developed industrial process, more effective energy resources to decrease the energy request by not preventing energy production and to prevent the energy loses in gas, vapor, air and electric.

Energy saving is the most important factor in the electric efficiency. The use of less energy generally is perceived as energy saving by turning off the one of the light bulbs. Bur energy saving is to minimize the energy amount consumed, its quality and performance by preventing energy loses and energy wastes. Energy saving is carried out in two ways. First is to use the latest Technologies such as home, car which save on energy and to regulate the behaviors and habits. Second is to minimize the new goods production by providing the use of available goods and to regulate the settlements of energy consumption and to use the technology which has less energy consumed and to direct to the activities have not material consumption.

As a result of technological advances, some problems in many businesses have been overcome and efficiency and productivity have come to the forefront. The competition has forced businesses to use resources in the correct way. Businesses need to evaluate their performance in the sector. In this context, analysis methods of efficiency and productivity have been developed in order to measure the performance by analyzing the inputs and outputs of the production process in firms or industries.

Electric industry which is one of the natural monopoly sectors had operated for many years as in the form of vertically integrated monopolies. During this period, high costs and high qualities with low qualities and low efficient have become the main problems of the sector. Restructuring and privatization process have started because large-scale investments cannot be meet by scarce public resources. In particular, privatization process has the thought that private sectors have been operated more effective than public sectors. Thus, the idea that a vertically integrated monopoly can be separated the parts with a good organization and these parts can be transmitted to the private sectors in a competitive environment has become widespread. In the case of realization of such a decomposition, the idea that investments will be saved from burden of financing and social welfare will increase with private sector dynamics has started to adopt. Also in this process, many models have attempted in order to encourage private sector participation but desired results haven't been achieved because applications are away from the economic activity.

Electricity distribution is to deliver the electricity to the end user. The network of distribution system delivers the electricity from distribution system to consumers. For instance the network includes substations, medium tension lines, distribution sites, distribution transformers, low tension line and measure terms.

Equipment failures, unsuitable spare parts and inefficient supply process can cause the infrastructure facilities losses. Today, considering the demands and service expectations of the people, managers need to adopt a management plan which has more efficient, cost-effective.

Electricity distribution companies are responsible for providing the electricity to the consumers. For this reason, it is available to compare all TEDAS with each other in terms of their abilities on the lowest input amount and finance.

LITERATUR REVIEW

In the first study in Turkey, Bağdadioğlu et al. (1996) have tried to demonstrate the possible effects of privatization by benchmarking public electricity distribution institutions and private technical events. The results have indicated that distribution companies have high performance in private institutions and also there are many public institutions which transmit the electricity like private institutions. Interesting finding of this study is that public institutions which have high performance have been separated and privatized. This has created suspicion for privatization candidates that the government thinks there will be positive effect on performance. Some of the studies in this field are as follows in terms of country, application are and year;

Authors	YEAR	COUNTRY	Number of Company
Weyman-Jones	1991	Great Britain	12 Company
Miliotis	1992	Greece	45 Company
Hougaard	1994	Denmark	82 Company
Bağdadioğlu, et al.	1996	Turkish	21 Company
Forsund ve Kittelsen	1998	Norway	150 Company
Korhonen et al.	2003	Finland	102 Company
Pahwa et al.	2003	US	50 Company
Jamasb et al.	2003	6 Europe Country	63 Company
Edvartsen et al.	2003	Northern Europe	38 Company

Estache et al.	2004	South America	84 Company
Giaanakis et al.	2005	Great Britain	34 Company
Hattori et al.	2005	Great Britain	21 Company
Bağdadioğlu	2005	Turkish	63 Company
Ghaderi et al.	2006	İran	38 Company
Von Hirschhausen et al.	2006	Germany	307 Company
Cullman et al.	2006	Germany	84 Company
Hess et al.	2007	Germany	304 Company
Bağdadioğlu et al.	2007	Turkish	80 Company
Cullman et al.	2008	Poland	32 Company
Bağdadioğlu	2009	Turkish	21 Company
Düzgün	2011	Turkish	21 Company

DATA ENVELOPMENT ANALYSIS

Data Envelopment Analysis (DEA) is a fractional mathematical programming technique that has been developed by Charnes et al. (1978). It is used to measure the productive efficiency of decision making units (DMUs) and evaluate their relative efficiency. This analysis determines the productivities of DMUs, specified as the ratio of the weighted sum of outputs to the weighted sum of inputs, compares them to each other and determines the most efficient DMU(s). DEA obtains the optimal weights for all inputs and outputs of each unit without imposing any constraints on these weights.

Assuming that there are n DMUs each with m inputs and s outputs the relative efficiency of a particular DMU_0 is obtained by solving the following fractional programming problem:

$$\begin{aligned} & w_o = \mathrm{Max} \ \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \\ & \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \quad j = 1, 2, \ . \ . \ . \ , n \\ & u_r \ge 0, \quad r = 1, 2, \ . \ . \ . \ , s \\ & v_i \ge 0, \quad i = 1, 2, \ . \ . \ . \ , m \end{aligned} \tag{1}$$

where j is the DMU index, $j = 1, \ . \ . \ . \ , n$; r is the output index, $r = 1, \ . \ . \ . \ , s$; i is the input index, $i = 1, \ . \ . \ . \ , m$; y_{rj} is the value of the r^{th} output for the j^{th} DMU, x_{ij} is the value of the i^{th} input for the j^{th} DMU, u_r is the weight given to the r^{th} output; v_i is the weight given to the i^{th} input, and w_o is the relative efficiency of DMU_0, the DMU under evaluation. In this model, DMU_0 is efficient if and only if $w_o = 1$.

A DMU is considered individually in determining its relative efficiency. This DMU is referred to as the target DMU. The target DMU effectively selects weights that maximize its output to input ratio, subject to the constraints that the output to input ratios of all the n DMUs with these weights are ≤ 1. A relative efficiency score of 1 indicates that the DMU under consideration is efficient whereas a score less than 1 implies that it is inefficient.

This fractional program, well known as CCR model, can be converted into a linear programming problem where the optimal value of the objective function indicates the relative efficiency of DMU_0. Hence the reformulated linear programming problem is as follows:

$$
\begin{aligned}
w_o = \ & \mathrm{Max} \ \sum_{r=1}^{s} u_r y_{ro} \\
& \sum_{i=1}^{m} v_i x_{io} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \qquad j = 1, \ 2, \ \ldots, n \\
& u_r \geq 0, \quad r = 1, 2, \ \ldots, s \\
& v_i \geq 0, \quad i = 1, 2, \ \ldots, m
\end{aligned}
\tag{2}
$$

In this model, the weighted sum of the inputs for the DMU_0 is forced to 1, thus allowing for the conversion of the fractional programming problem into a linear programming problem which can be solved by using any linear programming software. Similarly, the model of returns to scale for the DEA, namely BCC, can be given as follows:

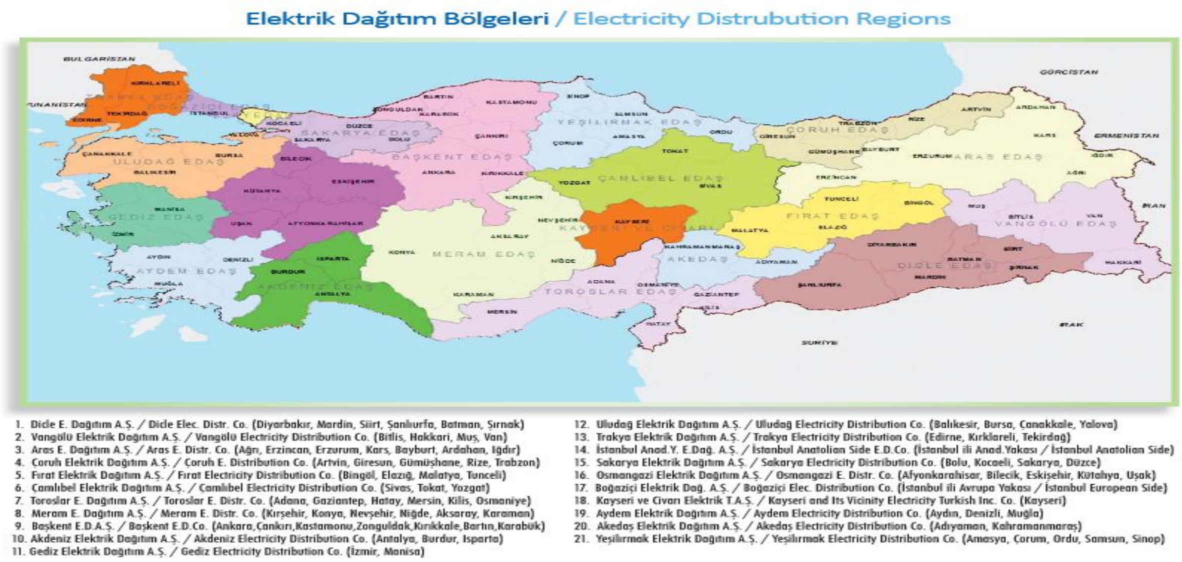
$$
\begin{aligned}
w_o = \ & \mathrm{Max} \ \sum_{r=1}^{s} u_r y_{ro} + c_o \\
& \sum_{i=1}^{m} v_i x_{io} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + c_o \leq 0 \qquad j = 1, \ 2, \ \ldots, n \\
& u_r \geq 0, \quad r = 1, 2, \ \ldots, s \\
& v_i \geq 0, \quad i = 1, 2, \ \ldots, m \\
& c_o \ \text{free in sign}
\end{aligned}
\tag{3}
$$

where c_o indicates returns to scale. w_o, u_r $(r = 1, 2, \ \ldots, s)$ and v_i $(i = 1, 2, \ \ldots, m)$ are defined as in the CCR model.

The solution to these models assigns the value 1 to all efficient DMUs. The super efficiency concept is proposed for all efficient DMUs when there are more than one efficient DMUs. One of the super efficiency models for ranking efficient DMUs in DEA was introduced by Andersen et al(1993). This method enables an extreme efficient unit o to achieve an efficiency score greater than one by removing the o^{th} constraint in the envelopment linear programming formulation.

RESEARCH METHOD

The effects of 21 companies which are responsible for Turkey Electricity Distribution in 2011/12 have been evaluated and searched which company is more active than the others in the study.



During this period, 21 companies data to TEDAS have been assumed and some analyzes have been made in order to increase the effectiveness of companies' activities, to change o variables and to make inactive companies effectively in our study. CCR model and VZA model have been used to measure the performance of the companies and to control the output of the companies about services for each costumer. All of these analyzes have been made by EMS computer program.

Input and output variables in addition to 21 decision-making units are as follows:

Inputs

- Energy Supplied
- Number of Staff
- Number of Transformer
- Installed Capacity Transformer
- Line Length

Outputs

- Loss and Illegal Electricity Usage

- Number of Subscribers
- Number of Annual Failure and Downtime
- Explanation of these variables;

Energy Supplied: Distribution of the amount of energy provided by various organizations (KWh)

Number of Staff: The number of people working in Electricity Distribution Companies

Number of Transformer: Number of transformers of the distribution company (#)

Installed Capacity Transformer: Maximum running current and voltage values of a transformer can transfer the maximum amount of power. (MW)

Line Length: length of the electricity lines which transmits electricity below 36 kv to the end users.(km)

Loss and Illegal Electricity Usage : Distribution Company in the amount of energy obtained from a portion of the amount illegally during deployment

Number of Subscribers: Number of persons served by the distribution company.(#)

Number of Annual Failure and Downtime : The number of subscribers connected to the distribution company faced failure and downtime.(#)

Transformer: A device which is used to transmit electricity efficiently and at a low cost, and performing this task with increasing and decreasing the voltage.

AN APPLICATION

2011/2012 period; Efficiency scores of all companies have been calculated with EMS and the observed values are summarized in Table 1. It is shown that which scores company has and which companies take an example from other companies in order to be active in Table 1. In this context, we can see that which company can be effective while taking reference from the branches in the following Table.

DMU	Score	Energy Supplied	Number of Staff	Number of Transformer	Installed Capacity Transformer	Line Length	Loss and Illegal Electricity Usage	Number of Subscribers	Number of Annual Failure and Downtime	Benchmarks
EDAŞ 21	45,09%	0	0,27	0	0,6	0,13	0	0,45	0	4 (0,32) 14 (0,20) 17 (0,09)
EDAŞ 20	65,41%	0	0	0	0,87	0,13	0	0,5	0,16	14 (0,02) 20 (0,20) 21 (0,18)
EDAŞ 17	86,09%	0,2	0	0	0,8	0	0	0,76	0,1	4 (0,45) 5 (0,16) 21 (0,11)
EDAŞ 5	122,09%	0,72	0,28	0	0	0	0,16	1,06	0	9
EDAŞ 6	120,25%	0	1	0	0	0	0,75	0,26	0,2	2
EDAŞ 11	99,52%	0	0,07	0	0,93	0	0,17	0,68	0,14	4 (0,11) 5 (0,27) 18 (0,42) 21 (0,09)
EDAŞ 18	77,51%	0	0,27	0	0,56	0,17	0	0,74	0,03	4 (0,89) 14 (0,31) 17 (0,27) 20 (0,03)
EDAŞ 16	86,56%	0,17	0,64	0	0	0,18	0	0,87	0	4 (0,95) 17 (0,06) 19 (0,25)
EDAŞ 12	97,80%	0,55	0,19	0	0	0,26	0	0,98	0	4 (1,77) 14 (0,19) 17 (0,25)
EDAŞ 8	109,81%	0,57	0,16	0	0	0,27	0	0,85	0,25	3
EDAŞ 15	91,57%	0	0,9	0	0	0,1	0	0,84	0,08	13 (0,81) 17 (0,33) 19 (0,27)
EDAŞ 13	97,65%	0,57	0,22	0	0	0,21	0	0,95	0,03	4 (0,75) 10 (0,10) 14 (0,22) 17 (0,22)
EDAŞ 7	112,49%	0	0,75	0	0	0,25	0,29	0,72	0,12	1
EDAŞ 4	151,79%	0	0	1	0	0	0,05	1,17	0,31	6
EDAŞ 19	75,64%	0,54	0,21	0	0	0,25	0,02	0,7	0,04	4 (0,36) 10 (0,19) 14 (0,03) 17 (0,15) 18 (0,02)
EDAŞ 14	95,59%	0,36	0,37	0	0	0,27	0,07	0,76	0,13	4 (0,27) 10 (0,30) 17 (0,10) 18 (0,15) 20 (0,09)
EDAŞ 3	164,96%	0	0,72	0,17	0	0,1	0	1,65	0	8
EDAŞ 1	318,68%	0	0	0,47	0	0,53	3,19	0	0	3
EDAŞ 9	109,31%	0	1	0	0	0	0	1,09	0	2
EDAŞ 2	288,10%	0	0,38	0	0,16	0,45	0	0	2,88	3
EDAŞ 10	106,28%	0	0	0	1	0	0	1,06	0	3

If we interpret the results of EDAS 20 in Table; the transformer installed power must be 87%, the length of the line must be 13%, but the number of subscribers must be decreased 50%, annual failure and number of breakdowns must be decreased 16% in order to enable EDAS 20 to be active. EDAS 20 needs to take references from EDAS 1 as 2%, EDAS 2 as 20% and EDAS as 10-18%.

CONCLUSIONS

Performance concept is defined as the quantitative and qualitative results related to goals, results and resources of business, business processes and personnel performing this business. When it is evaluated inside the organization, it means the capability of the organization to attain its goals using the resources effectively. Therefore, in today's world performance, profitability and effectiveness became the key success factor for the future of private and public organizations.

In this study, effects of 21 electricity distribution companies were assessed. In total 9 variables are used, including 5 inputs and 4 outputs. Throughout the process, variables analyzed with EMS computer program. Here, as an input: obtaining energy, which is important in performance criteria, number of stuff, number of transformer, Installed Capacity Transformer and line length have been used. On the other hand, as an output: amount of Loss and Illegal Electricity Usage, number of subscriber and number of disconnection (annually) have been used. In order to not to come across unwanted consequences, amount of Loss and illegal Electricity Usage and annual disconnection number have been rotated through output. According to Table 1, 10 electricity distribution companies have efficient in 21 companies. Rests of them are showed with reference companies and it indicates, in which amount of ratio, companies whether increase or decrease the variables to be more efficient. Especially there are some companies, which have low efficiency score, in specific provinces. In these areas, the ratio of Loss and illegal Electricity Usage exceeded 50% and the figure points out that this is a crucial indicator while evaluating process.

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MEASURING EFFICIENCIES OF HIGH SCHOOLS USING DEA

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ABSTRACT

Relative efficiencies of twelve high schools in Gaziantep by Data Envelopment Analysis (DEA) are examined. Inverse of average of 11th grade students in a class, inverse of average of weekly course hour of each 11th grade teacher, number of students taking OSS exam (University Entrance Exam in Turkey), and average of attending OSS exam preparation courses are taken as inputs. Outputs of the study are several OSS results. The scores showed that any high school can determine potential increase and decrease by values. Thus DEA is powerful tool to measure relative efficiency.

***Keywords**: Efficiencies, Data Envelopment Analysis (DEA)*

INTRODUCTION

The meaning of the word "efficiency" differs from one to another. However it seems like efficiency should be a universally agreed upon concept. The most valuable definition of efficiency is that something that raises revenues rather than reducing expenses. From this point of view the efficiency of organization can be defined as raising quality of education rather than reducing loss in education or industries.

Why is efficiency important for a school? The efficiency concept has become a core objective of policymakers within most public services. Particularly, measurement and comparison of the relative efficiency of organizations can gain powerful insights into best performance and where performance improvements might be made. However, the analysis and measurement of efficiency is complicated process. To stress this complicated phenomenon there has many researches developed. There will be defined the organization efficiency in two types ; technical efficiency and allocative efficiency. The technical defined as the maximization of output for a given set of inputs. The allocative described as the use of inputs in optimal proportions given their respective prices (Smith & Street, 2006).

METHODS

Data Envelopment Analysis (DEA) is a linear programming based technique for measuring the relative performance of organizational units where the presence of multiple inputs and outputs makes comparisons difficult. Also it is defined as methodology that has been used to evaluate the efficiency of entities (e.g., programs, organizations etc.) which are responsible for utilizing resources to obtain outputs of interest. Efficiency or relative performance is crucial in DEA that is productivity of an organization. There is an increasing concern with measuring and comparing the efficiency of organizational units such as local authority departments, schools, hospitals surgical units, shops, public schools, business companies, banks, tourism sector, and real- property maintenance for the U.S.

Data about schools was collected with the help of Administration of Gaziantep School Districts of Ministry of Education. Purpose of this thesis is to measure relative performance of twelve high schools in Gaziantep with respect to OSS exams. Twelve schools in Gaziantep were chosen: Atatürk High School, Gaziantep High School, Mimar Sinan High School, 19 Mayıs High School, Gaziantep Anatolian High School, Akınal Anatolian High School, Tekerekoglu Anatolian High School, Bayraktar High School, Private Seçkin High School, Private Mutafoğlu High School, Private Sanko High School, Private Kolej Vakfı High School. These 12 schools have almost equal level of education and they land same localities having equal socio-economic-status. Schools were determined with idea that "equality" of school circumstances like teachers experience years, students' socio-economic status, facilities of schools. Different types of schools were taken since sample space may reflect well Gaziantep's educational media. Three Anatolian High Schools, Eight High Schools Educating In Foreign Languages (Three of them are Private Schools) and one Normal High School. One might think that Private Schools' facilities are so high then this disrupts equality of opportunity, but according to 2005 OSYM In the study (Atan, Gaye, & Aykut, 2002) twenty-two Anatolian High Schools in Ankara number of students, number of teachers, number of classes and grades, and number of labs were inputs. Number of graduated students, number of students passing classes, number registering university and percentage of OSS success were outputs. First number of labs and number of students have little meaning in OSS i.e. small weight. And number students passing class has also small weight since every student graduate easily from a high school in Turkey.

Table 1: Inputs

	TYPE	NAME OF SCHOOLS	S T O	1/SIC	POPC	1/WCHET
1	EFLHS	ATATÜRK HS	46	4,3	80,4	4,5
2	EFLHS	GAZIANTEP HS	105	3,8	84,8	4,8
3	EFLHS	MIMAR SINAN HS	50	4,0	54,0	2,7
4	EFLHS	19 MAYIS HS	59	5,1	76,3	5,0
5	AHS	GAZIANTEP ANA. HS (GAL)	114	4,4	100,0	5,0
6	AHS	AKINAL ANA. HS	110	3,6	100,0	4,8
7	AHS	TEKEREKOGLU ANA. HS	82	4,9	100,0	4,0
8	EFLHS	BAYRAKTAR HS	45	5,3	77,8	4,5
9	EFLHS	PRIVATE SECKIN HS	18	5,6	88,9	5,0
10	HS	PRIVATE MUTAFOGLU HS	97	5,2	99,0	4,0
11	EFLHS	PRIVATE SANKO HS	61	8,2	93,4	5,0
12	EFLHS	PRIVATE KOLEJ VAKFI HS	98	6,1	100,0	3,3

Table 1 shows the inputs which abbreviated as follows that 1-STO: Number of students taking OSS exam. Besides most of students graduated from high schools take OSS exam, I took STO as input since there is big correlation with outputs i.e. the weight is much more than the other inputs. 2- 1/SIC: Inverse of average of number of students in each class. Since negative influence of efficiency caused to take the input how many classes are needed to accommodate 100 students. Crowded classes are the first shortcoming problem to our mind for Turkish education. Actually it has real impact on problems. 3- POPC: Percentage of students attending OSS preparation courses. Another extraordinary special aspect of our educational system. There is no any other alternative way for a high school students to have a ob (to go to university) and this way pass on OSS preparation courses, unfortunately POPC positively influence number attending university. 4-1/WCHET: Like in SIC inverse of average of weekly course hour of each 11th class teachers is taken. How many teachers in 100 hours courses. That is the input shows number of teachers needed for 100 hours courses. The school type was abbreviated as; EFLHS : Educates In Foreign Languages, AHS : Anatolian High Schools, HS: High School.

Table 2 Outputs

	TYPE	NAME OF SCHOOLS	S A Y	EA	PSRU
1	EFLHS	ATATÜRK HS	184,654	199,241	19,57
2	EFLHS	GAZIANTEP HS	205,842	219,814	45,71
3	EFLHS	MIMAR SINAN HS	200,173	207,969	30,00
4	EFLHS	19 MAYIS HS	181,843	200,747	27,12
5	AHS	GAZIANTEP ANA. HS (GAL)	245,3	243,386	68,42
6	AHS	AKINAL ANA. HS	228,103	232,561	63,64
7	AHS	TEKEREKOGLU ANA. HS	226,753	233,892	56,10
8	EFLHS	BAYRAKTAR HS	193,803	212,184	57,78
9	EFLHS	PRIVATE SECKIN HS	208,076	216,017	77,78
10	HS	PRIVATE MUTAFOGLU HS	183,939	205,135	42,27
11	EFLHS	PRIVATE SANKO HS	195,41	215,6	80,33
12	EFLHS	PRIVATE KOLEJ VAKFI HS	176,44	192,848	48,98

Table 2 shows the outputs abbreviated as 1-SAY: Average of students' SAY marks in OSS exam. Three outputs show exact result for achievement. Marks from OSYM pages. 2-EA Average of students' EA marks in OSS exam. 3-PSRU: Percentage of students registering university. It is the single indicator for any school in OSS success. Especially some private schools choose a few brilliant students and grow them well so these few take great marks in OSS. They make great advertisements. But they do not have extended success. PSRU will be sufficient indicator for success.

RESULTS AND DISCUSSIONS

Two type efficiency scores were calculated, former is basic, the latter is advanced. In basic type, the problem is solved by the models inputs-oriented and constant-returns-to scale (CCR). Since the inputs of problem would be changed. According to results relative efficiencies of twelve high schools in Gaziantep, 5 out of 12 are inefficient. The value for 19 Mayıs HS means that its inputs can simultaneously be reduced by a factor of 1-0,7772, i.e. 22,28%. This corresponds to moving this unit to the efficient frontier radially, that is without altering the proportion of its inputs. The value for Atatürk HS tells us that the inputs must be decreased by a factor of 1-0,9382, i.e 6,18 %. Gaziantep HS does not need much more change its inputs to get efficiency 1, just 3,22%.Bayraktar HS needs approximately 5% increase to catch the greatest efficiency score and las tly Mutafoglu HS needs nearly 20 % percent increase to reach efficiency score 1.

As mentioned earlier inefficient DMU must approach to efficient frontier. So we form a virtual DMU as a weighted combination of some efficient DMU's. These are equivalent ways to express improvement. For inefficient DMU, the set of suitable efficient units is called its reference set, or simply the of its efficient peers. In a efficient peers of inefficient schools are shown. Gaziantep HS is to become 35.24 % of Mimar Sinan HS and 63.01% of Akınal HS. This means that Gaziantep HS has to adopt methods and practices from Mimar Sinan and Akınal HS's. Atatürk HS has to become 81,28 % of Mimar Sinan HS and 13,98 % of Private Seçkin HS. Thus Atatürk HS has to adopt technics from these two schools. The least efficiency score belonged to 19 Mayıs HS, so the schools needs 89,15 % change to adopt Mimar Sinan HS and 7% to Private Seçkin HS. Private Mutafoglu HS needs 34,89 % change to adopt Mimar Sinan HS, 00,4 % to adopt Akınal HS and 56,65 % Tekerekoglu HS. Ataturk HS has Mimar Sinan HS and Private Seckin HS peer Gaziantep HS has peers (Mimar Sinan HS and Akınal HS) so the virtual inputs for Gaziantep HS are: -STO: 0,3524(Input-1 for Mimar Sinan HS) + 0,6301 (Input-1 for Akınal) = 86,93, i.e. 0,3524x50 + 0,6301x110 = 86,93. This means that Gaziantep HS has to decrease its number of students from 105 to 87 by 17,21 % as shown in next column of STO column.

CONCLUSIONS

The relative efficiency of some high schools in Gaziantep is measured by Data Envelopment Analysis. Twelve schools chosen for the study reflect all high schools in Gaziantep since percent of registration to universities for the schools is almost the same for all high schools in Gaziantep (www.osym.gov.tr). The first type of calculation is basic type. The basic type gives the scores as seven out of twelve schools are efficient where as the rest is inefficient. Four of inefficient schools are public schools which are Atatürk HS, Gaziantep HS, 19 Mayıs HS, Bayraktar HS. There may be many reasons causing lack of performance of these four schools. Some of them are; (a) insufficient education reasoned by crowdedness of schools, (b) educational background of students, (c) motivation of students, teachers and parent. For many parents, educators and policymakers, smaller classes are apparently not liable to failure direction for improving student performance (Resnick, 2003). The ideal number of students in a class must be 22 to 25 for high schools. We are far from these numbers, there is one never heard that there nearly 60-80 students in classes in Turkey.   Therefore it will become impossible to manage and educate in the classroom. There are much more disciplinary events and lack of administrative authority in crowded schools, thus resulting less educational attempts. Bayraktar HS unfortunately has the most number of violence events in the city according to official data. Students in these schools were graduated with low marks from secondary schools. Educators cite persistently that having incompetent training results less achievement. The fifth inefficient school (Private Mutafoglu HS) is a newly founded school, thus the school can not build educational system and students having high capacity from secondary school might not prefer the school.

The efficient peers of schools explain that how much an inefficient school should resemble its reference school(s). And which school must be taken as reference point in this resembling. Ataturk HS has two reference schools (peers) which are Mimar Sinan HS and Private Seckin HS. In fact Ataturk HS and Mimar Sinan have almost equal inputs but Mimar Sinan HS yielded more efficiently by same inputs than Atatürk HS. Mimar Sinan HS has much more effect than Private Seckin HS that is, weight of Mimar Sinan Hs is 0,8532 but Seckin's 0,1468. The reason is that Mimar Sinan HS yielded efficiently with restricted conditions. The rest of data can be analyzed by the same manner. It also can be said that the efficient schools can be classified by this analysis.

ACKNOWLEDGEMENTS

An Excel based program XLDEA is used for calculations. Inputs and outputs are read by program. (“http://www.prodtools.com/,” 2013). DEA models; input-oriented, output-oriented and constant returns to scale, variable returns to scale are chosen by menu.

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MEASURİNG THE EFFİCİENCY OF PRİMARY HEALTHCARE ORGANİZATİONS İN THE CAPPADOCİA REGİON USİNG DATA ENVELOPMENT ANALYSİS

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ABSTRACT

Healthcare is an important sector that serves people of all ages. There are different steps and facilities used for providing health care services in Turkey. Mainly these facilities are primary, secondary and tertiary healthcare organizations. In the first step the primary healthcare organizations (PHOs) do exist. The PHOs give preventive healthcare services and this kind of services are among the main pillars of the primary healthcare. In this study the relative efficiency of PHOs that serve in the Cappadocia region was evaluated. The most appropriate inputs and outputs that reflect the sector were used for comparing the PHOs, namely DMUs. Efficiency measures were computed using the Data Envelopment Analysis (DEA) method; efficient and inefficient PHOs were found. Finally, constraints of this study and the research areas were pointed out for the future research on this subject.

***Keywords**: Efficiency Measurement, Data Envelopment Analysis, Healthcare Sector, Primary Healthcare Organizations.*

INTRODUCTİON

Healthcare is an important sector that serves people of all ages. There are different steps and facilities used for providing health care services in Turkey. Mainly these facilities are primary, secondary and tertiary healthcare organizations. In the first step the primary healthcare organizations (PHOs) do exist. The PHOs give preventive healthcare services and this kind of services are among the main pillars of the primary healthcare.

Generally, the main function of the health system is to provide health services to the whole population. In detail, primary goals of health care services are raising the quality of health care services offered, providing all groups and individuals within society with equal, fair, effective and qualified health care services, increase patient’s satisfaction, and improving the efficiency and effectiveness of health care services (Özkara, 2002).

According to Arslan and Semin (2006) less than 1% of health expenditure is allocated for preventive health services in Turkey but more than half of this is used for pharmaceutical expenditure. Primary healthcare centers are the initial step organizations in Turkey and their main responsibilities are preventing and treating diseases, immunization, family planning, public health education and collecting statistical data.

Turkey has gradually established social health insurance since the 1940s and introduced a comprehensive health transformation program in 2003. Multiple actors have been involved since the 1940s but the state remained the main actor in healthcare governance (Wendt et al 2013).

Ministry of Health of Turkish Republic initiated the Health Transformation Program (HTP) in 2003 with the aim of improving the standards and quality in both primary and secondary health care services. The Family Medicine implementation in Turkey was started with a pilot implementation in Düzce Province in 2005 and in the end of 2010 it was expanded to the whole country. The main aims of this implementation were to roll out primary health care services and to offer these services in an efficient and equal manner.

The HTP was developed by the Turkish Ministry of Health (MoH) with an overall objective to improve governance, efficiency, user and provider satisfaction, and long-term fiscal sustainability of the health care system in Turkey. Akinci et al. (2012) have mentioned that like some other countries Turkey has some problems/obstacles in providing primary healthcare such as inefficiency, lack of true "family physicians", maximizing the community coverage of primary care and minimizing the unnecessary referrals to secondary health care institutions.

There are many studies conducted to assess the efficiency of healthcare organizations using DEA. Some of them are listed below.

Ozcan et al (2000) searched the resource utilization between primary care physicians and specialists in the treatment of sinusitis patients in Virginia. The efficiency frontier, representing the best achievable performance was identified using DEA.

Giokas (2001) assessed the relative efficiency of the Greek hospitals by DEA, using the "total cost" as the only input and the "number of inpatient days in medical care", "number of inpatient days in surgical care", "number of outpatient visits", and "number of ancillary services" as the four outputs. In this study 72 general and 19 teaching hospitals were assessed for the year 1992. According to the results obtained 37% of teaching hospitals and 15% of general hospitals were found to be efficient. The average efficiency rating was 84.7% for the teaching hospitals and 75.1% for the general hospitals. By using DEA some useful information were provided to decision-makers about improving a hospital's operating efficiency and cutting costs.

Chang et al (2004) assessed the operating efficiency of Taiwan hospitals using annual cross-sectional data over the period 1996-1997. DEA was used for obtaining the relative efficiency scores and public and private hospitals were compared. Four inputs and three outputs were used for the estimation of the DEA model. "Number of patient beds", "number of physicians", "number of nurses", and "number of supporting medical personel" were the inputs and "number of patient days", "number of clinic or outpatient visits", and "number of patients receiving surgery" were the putputs. Public hospitals were found to be less efficient than private hospitals.

Martinussen and Midttun (2004) evaluated the technical efficiency of Norwegian hospitals for the 1999-2001 period in terms of day surgery. They used DEA for the efficiency measurement and they took "number of discharges" and "number of outpatient visits" as the outputs, and "number of full-time equivalents per year of physicians", "number of full-time equivalents per year of other staff", and "medical expenses" as the inputs. They found that the average technical efficiency lied between 82.71 and 84.08% for all 3 years.

Linna et al (2006) compared the cost efficiency of Finnish and Norwegian hospitals using the cross-sectional data on 47 Finnish and 51 Norwegian public hospitals in 1999. Calculation of cost efficiency scores are obtained using DEA and “net hospital operating costs” was used as input variable and the “number of discharges”, “number of outpatient visits”, “number of day care cases”, and “number of inpatient days” were the used as output variables. According to results there was more variation in cost efficiency among Finnish hospitals, and the average level of cost efficiency was 17-25% lower in Norwegian hospitals.

Katharaki (2008) assessed the relative technical efficiency of 32 Greek Obstetrical and Gynaecological (O&G) hospital units via DEA. The inputs they used were “number of O&G beds”, “number of O&G medical personnel”, and “total expenditure for the provision of care” and the outputs were “number of O&G hospitalization days/bed-days”, “number of female patients treated”, “number of O&G examinations in outpatient clinics”, and “number of O&G lab tests”.

Amado and Santos (2009) compared the geographical equity of access to services, technical efficiency and quality of services of the health centers in Portuguese. They used DEA for measuring technical efficiency and data of 2004 and 2005. They concluded that there was evidence of large variation in equity of access to services, in technical efficiency and quality of services across district health authorities. Their findings suggested that a better use of resources could lead to more and improved services. The “number of doctors”, “number of nurses”, and “number of administrative, technical and other support professionals” were the inputs and “number of family planning consultations”, “number of maternity health consultations”, “number of junior health consultations”, “number of adult health consultations”, “number of elderly health consultations”, “number of home visits by the doctor”, “number of other consultations by the doctor”, “number of consultations by the nurse”, “number of home visits by the nurse”, “number of curatives and other treatments”, “number of injections”, and “number of vaccinations” were the outputs used in this study.

Caballer-Tarazona et al (2010) measured the efficiency of 22 hospitals in the Valencian part of Spain in terms of three units; general surgery, ophthalmology, traumatology_orthopaedic surgery. They used the data for the year 2005. CCR was used as the DEA model. The input variables were “number of doctors” and “number of beds” and the outputs variables were “weighted admissions”, “first consultations”, “successive consultations”, and “number of surgical interventions”. Eight efficient units and 14 inefficient units were identified for the general surgery hospital unit, while 9 efficient and 12 inefficient units were found for ophthalmology. Finally, only 6 efficient but 16 inefficient units were identified for traumatology_orthopaedic surgery.

Özata and Sevinç (2010) measured the efficiency levels of the primary healthcare organizations in Konya using DEA.

Ng (2011) measured the technical efficiency of 463 hospitals in China using five years (2004-2008) data. They took the number of doctors, number of nurses, number of pharmacists, number of other staff and number of beds as the inputs and the number of outpatients treated and the number of inpatients treated as the outputs.

Tiemann et al (2012) also reviewed the efficiency of hospital based on their ownerships. They focused on the recent studies comparing the efficiency of German public, private non-profit and private for-profit hospitals using stochastic frontier analysis (SFA) or DEA. The results of the studies showed that private ownership was not necessarily associated with higher efficiency compared to public ownership.

Ben-Arieh and Gullipalli (2012) showed the usage of DEA with fuzzy clustering concepts when the missing data exist in input and/or output variables. They demonstrated this approach on a real and complete dataset of 22 rural clinics in the State of Kansas, assuming varying levels of missing data.

As can be seen above, there are many studies exist in the literature about the usage of DEA, specifically in healthcare. The aim of this study is to measure the relative efficiency of the primary healthcare organizations that are placed in the important stage of health care delivery in Turkey. The family medicine units (FMUs) were taken as the representatives of the PHOs and became the DMUs. The efficient and inefficient FMUs were determined and in order to reach the efficiency frontier, some suggestions were made to inefficient ones.

METHODS

The DMUs compared in this study were the Family Medicine Units (FMUs). A FMU is composed of a family physician and a nurse (or a midwife). A center that includes more than one FMU is called Family Health Center (FHC). Finally at the top of the hierarchy Society Health Centers (SHCs) exist. The SHCs are composed of FHCs. As a result the FMUs were taken as the representatives of the PHOs. Since it was the most current and reliable data, the data set of 2011 was used. The data were obtained from the Public Health Directorate of Cappadocia region.

Three inputs and four outputs were used.

Inputs are:

- Number of Physicians
- Number of Nurses or Midwives
- Registered Population

Outputs are:

- Number of Pregnant Women Monitored (Annual)
- Number of Babies Monitored (Annual)
- Number of Doses of Vaccine Made (Annual)
- Number of Patient Visits (Annual)

Researchers often employ two different methodologies to evaluate the efficiency of healthcare organizations: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). In general, SFA measures technical or cost efficiency while DEA mainly measures technical efficiency. In particular, technical efficiency is a measure of how well an hospital produces output from a given amount of input, or alternatively produces a given amount of output with minimum quantities of inputs. (Tiemann et al, 2012).

DEA has been used in many fields since its development and its wide usage still continues. Liu et al (2013) recently have conducted a detailed literature survey of DEA applications from 1978 through 2010. They found that banking, health care, agriculture and farm, transportation, and education were the top-five industries addressed among the various application areas. In addition, the applications that had the highest growth momentum recently were energy and environment as well as finance.

In this study, the output oriented Charnes, Cooper, and Rhodes (CCR) model is used. The output oriented CCR model is given below with Model (1) and Model (2). (1) is the multiplier model and (2) is the dual of (1), also known as the envelopment model (Cooper et al, 2004).

$$\begin{aligned} \min \quad & q = \sum_{i=1}^{m} v_i x_{i0} \\ st. \quad & \\ & \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0 \qquad \textbf{(1)} \\ & \sum_{r=1}^{s} \mu_r y_{r0} = 1 \\ & \mu_r, v_i \geq \varepsilon \geq 0 \ , \quad \forall r, i \end{aligned}$$

$$\begin{aligned} \max \quad & \phi + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\ st. \quad & \\ & \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{i0}, \quad i = 1,2,\ldots,m; \qquad \textbf{(2)} \\ & \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \phi y_{r0}, \quad r = 1,2,\ldots,s; \\ & \lambda_j \geq 0, \quad j = 1,2,\ldots,n. \end{aligned}$$

DMU_0 is efficient if and only if $\phi^* = 1$ *and* $s_i^{-*} = s_r^{+*} = 0$ for all *i* and *r*.

RESULTS AND DİSCUSSİONS

The model was run in the Efficiency Measurement System (EMS) software which is developed by Holger Scheel. The efficiency scores of the FMUs are shown in Table-1.

According to the efficiency scores obtained, only four of the FMUs (5%) were found as efficent: FMU3, FMU6, FMU42 and FMU66.

Some of the FMUs are very close to the efficiency frontier. These are FMU17, FMU18, FMU19 and FMU54.

Some of the FMUs are far from the efficiency frontier: FMU12, FMU24, FMU31, FMU33, FMU75 and FMU81.

Table-1. Efficiency scores of the FMUs

DMU	Score
FMU1	111,86%
FMU2	131,49%
FMU3	**100,00%**
FMU4	108,60%
FMU5	120,23%
FMU6	**100,00%**
FMU7	135,76%
FMU8	143,33%
FMU9	138,40%
FMU10	125,03%
FMU11	186,39%
FMU12	265,87%
FMU13	154,03%
FMU14	142,39%
FMU15	136,41%
FMU16	138,90%
FMU17	105,06%
FMU18	107,58%
FMU19	107,92%
FMU20	135,72%
FMU21	122,43%
FMU22	123,54%
FMU23	160,54%
FMU24	223,71%
FMU25	126,33%
FMU26	178,59%
FMU27	135,03%
FMU28	152,32%

DMU	Score
FMU29	154,35%
FMU30	212,96%
FMU31	265,93%
FMU32	157,85%
FMU33	234,49%
FMU34	127,70%
FMU35	164,61%
FMU36	199,00%
FMU37	197,93%
FMU38	131,32%
FMU39	177,18%
FMU40	132,10%
FMU41	117,02%
FMU42	**100,00%**
FMU43	114,53%
FMU44	149,84%
FMU45	151,97%
FMU46	151,40%
FMU47	127,47%
FMU48	141,65%
FMU49	135,19%
FMU50	120,47%
FMU51	113,48%
FMU52	123,19%
FMU53	108,19%
FMU54	102,44%
FMU55	111,11%
FMU56	112,81%

DMU	Score
FMU57	134,47%
FMU58	139,01%
FMU59	130,55%
FMU60	130,63%
FMU61	156,94%
FMU62	138,35%
FMU63	136,58%
FMU64	161,75%
FMU65	122,18%
FMU66	**100,00%**
FMU67	176,84%
FMU68	139,88%
FMU69	117,44%
FMU70	127,65%
FMU71	128,67%
FMU72	178,95%
FMU73	127,18%
FMU74	181,85%
FMU75	248,58%
FMU76	197,38%
FMU77	155,80%
FMU78	190,69%
FMU79	170,07%
FMU80	179,75%
FMU81	272,16%
FMU82	205,43%
FMU83	187,23%

CONCLUSİONS

In this study we evaluated the relative efficiency of the PHOs and took the FMUs as their representatives. The efficiency of the FMUs in the Cappadocia region has not been studied before, this study tried to close this gap.

Only 5% of the FMUs were classified as efficient. The efficient FMUs must maintain their situations and the inefficient ones must compare themselves with the efficient FMUs and try to reach to the efficiency frontier. The results of this study could give information to the healthcare directors and policy makers about the current state of the primary healthcare implementation.

Last but not least, the situation of the inefficient FMUs must be investigated whether there is a relation between the number of patients treated in their units and the number of referrals made to secondary level healthcare organizations from their registered population.

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MEASURING THE PRODUCTIVITY OF TELECOMMUNICATION: A COMPARISON FOR COUNTRIES OF EU AND TURKEY

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ABSTRACT

With advanced technology, Telecommunication has become an important part of world economy. By taking the base years 2007, 2008, 2009, 2010, 2011, efiiciency and total factor productivity of member states of EU and Turkey and their performances by using Data Envelopment Analysis and Method of Malmquist total factor productivity index are indicated in this study. To be determinate the input and output, literature research is used. Also, there is 1 dummy variable and 4 output variable which are determinated. The former is equalized to 1 for all countries. The latter is made from fixed (wired) broadband subscriptions, fixed telephone subscriptions, percentage of individuals using internet and mobile cellular telephone subscriptions. For 28 countries which are choosen as decision- making units, the model of CCR is solved as the output-oriented. In addition to this, with the Malmquist Index, countries' total productivity is calculated.

***Keywords**: Data Envelopment Analysis, Malmquist Index, Telecommunication*

INTRODUCTION

In this study, the data from 2007, 2008, 2009 2010 2011 are based and for the changes in the technical efficiency and total factor productivity are used. This study is done for comparing the Turkey and the performance of the EU's countries sector of telecommunication which is important sector for today. As an input variable; dummy variable (virtual input is equalized to the 1 for all countries) and as an output variables; fixed (wired) broadband subscriptions,fixed telephone subscriptions, percentage of individuals using internet and mobile cellular telephone subscriptions are chosen.

METHOD

In this study, output-oriented CCR model which is from VZA models is going to analyze. This model is improved by Charnes, Cooper and Rhodes (1978). Output-oriented CCR models below;

$$\max Z_o = \phi$$

$$\sum_{j=1}^{n} \lambda_j X_{ij} \leq X_o$$

$$\phi y_o - \sum_{j=1}^{n} \lambda_j y_{rj} \leq 0$$

$$\lambda_j \geq 0; j = 1, \ldots, n; \; r = 1, \ldots, s;$$

$i = 1, \ldots, m$

The other method used in this study is Malmquist total factor index which shows the changes during the time in the efficiency. According to output, distance function with x, the sets of possible y which can be produced are demonstrated with d. As the distance function is shown like d (x_t, y_t) = min{d: (x_t, y_t / d) ϵ *S*}. İf the vector of y is higher than the limit of S which is producing limit, the value of the distance function *d* (x_t, y_t) is equal to 1. İf the vector of y defines a point which is not efficiency in the limit of S, the value of the distance function d (x_t, y_t) is bigger than 1.0 and İf the vector of y defines a point which s not possible fo rthe S, the value of the distance function d (x_t, y_t) is less than 1.0(Çıngı ve Tarım 2000). According to the output which is etween the term of t and the following term of t+1, Malmquist total factor productivity changing index is calculated around the distance function.

$$MI_0(x_t, y_t, x_{t+1}, y_{t+1}) = \sqrt{\frac{d_t^0(x_{t+1}, y_{t+1})}{d_t^0(x_t, y_t)} \times \frac{d_{t+1}^0(x_{t+1}, y_{t+1})}{d_{t+1}^0(x_t, y_t)}}$$

That the value of MI in this function is bigger than 1 shows that there is a growing in the total factor productivity from t term to t+1 (Coelli, 1996).Furthermore, in this study, the other scales which is analyzed;

effch: Shows that the changing in the base year to the previous for the aspect of CCR efficiency.

techch: Shows the rate of ‘tfpch’ to the ‘effch’.

pech: Shows that the changing in the base year to the previous for the in terms of BBC.

sech: Shows that the changing according to the base year which is previous for the in terms of scale efficiency.

tfpch: is the scale of the productivity changing which takes into account all factors.

RESULTS AND DISCUSSIONS

The efficiency scores of Countries which are in EU and Turkey which is member to the EU are calculated by using the output-oriented CCR model

Image 1: The result of output-oriented CCR for 2007

DMU	Score	Reference
Avusturia	123,71%	19(1,00)
Belgium	133,18%	19(1,00)
Bulgaria	252,75%	10(0,07) 19(0,93)
Cyprus	210,50%	19(1,00)
Czech Republic	164,60%	10(0,03) 19(0,97)
Denmark	100,93%	19(1,00)
Estonia	129,66%	19(1,00)
Finland	106,24%	19(1,00)
France	115,44%	10(0,89) 19(0,11)
Germany	100,00%	11

Greece	235,45%	10(0,13) 19(0,87)
Hungary	161,01%	19(1,00)
İreland	141,73%	19(1,00)
İtaly	107,16%	10(1,00)
Latvia	145,04%	19(1,00)
Lithuanian	171,98%	19(1,00)
Luksemburg	108,74%	19(1,00)
Malta	182,99%	19(1,00)
Netherlands	100,00%	24
Poland	162,87%	10(0,63) 19(0,37)
Portugal	213,30%	10(0,12) 19(0,88)
Romania	284,30%	10(0,50) 19(0,50)
Slovak Republic	138,87%	19(1,00)
Slovenia	151,25%	19(1,00)
Spain	143,15	10(0,65) 19(0,35)
Sweden	104,65%	19(1,00)
Turkey	155,27%	10(1,00)
United Kingdom	103,61%	10(0,75) 19(0,25)

For 2007, Germany and Netherlands were effective by using their source in an actively. Turkey had the 155, 27% the score of efficiency was in the other countries which were not effective. The value of reference for the effective countries shows how much they give a reference to ineffective. Netherleands gave a reference to 24 countries and Germany gave a reference to 11 countries. The reference values for ineffective countries show which rate they should take reference from effective countries. If Romania takes a reference in rate of 0,50 from Germany, also Netherlands with the same rate , it can be effective country.If Turkey takes a reference to Germany, it can be effective country.

Image 2: The result of output-oriented CCR for 2008

DMU	Score	Reference
Avusturia	122,94%	10(0,03) 26(0,97)
Belgium	135,34%	10(0,06) 26(0,94)
Bulgaria	222,69%	10(0,14) 26(0,86)
Cyprus	212,72%	26(1,00)
Czech Republic	141,05%	10(0,10) 26(0,90)
Denmark	105,86%	26(1,00)
Estonia	127,51%	26(1,00)
Finland	107,57%	26(1,00)
France	112,57%	10(0,87) 26(0,13)
Germany	100,00%	15
Greece	228,52%	10(0,23) 26(0,77)
Hungary	158,61%	10(0,10) 26(0,90)
İreland	137,74%	26(1,00)
İtaly	116,81%	10(1,00)
Latvia	141,93%	26(1,00)
Lithuanian	162,98%	26(1,00)
Luksemburg	109,45%	26(1,00)
Malta	179,71%	26(1,00)
Netherlands	100,89%	10(0,15) 26(0,85)
Poland	155,60%	10(0,61) 26(0,39)

Portugal	209,00%	10(0,20) 26(0,80)
Romania	257,11%	10(0,55) 26(0,45)
Slovak Republic	136,26%	26(1,00)
Slovenia	155,17%	26(1,00)
Spain	138,62%	10(0,62) 26(0,38)
Sweden	100,00%	24
Turkey	160,31%	10(1,00)
United Kingdom	103,23%	10(0,76) 26(0,24)

For 2008, Germany and Sweden were effective by using their source in an actively. Turkey had the 160,31% the score of efficiency was in the other countries which were not effective. Sweden gave a reference to 24 countries and Germany gave a reference to 15 countries.

Image 3: The result of output-oriented CCR for 2009

DMU	Score	Reference
Avusturia	123,26%	10(0,04) 26(0,96)
Belgium	129,14%	10(0,05) 26(0,95)
Bulgaria	199,29%	10(0,11) 26(0,89)
Cyprus	182,69%	26(1,00)
Czech Republic	139,38%	10(0,10) 26(0,90)
Denmark	104,79%	26(1,00)
Estonia	125,52%	26(1,00)
Finland	110,32%	26(1,00)
France	112,37%	10(0,87) 19(0,13)
Germany	100,00%	14
Greece	209,41%	10(0,18) 26(0,82)
Hungary	186,53%	10(0,12) 26(0,88)
İreland	135,05%	26(1,00)
İtaly	119,29%	10(1,00)
Latvia	136,15%	26(1,00)
Lithuanian	152,28%	26(1,00)
Luksemburg	104,23%	26(1,00)
Malta	154,60%	26(1,00)
Netherlands	100,00%	1
Poland	142,79%	10(0,57) 26(0,43)
Portugal	192,36%	10(0,13) 26(0,87)
Romania	232,06%	10(0,51) 26(0,49)
Slovak Republic	130,00%	26(1,00)
Slovenia	142,19%	26(1,00)
Spain	134,03%	10(0,61) 26(0,39)
Sweden	100,00%	22
Turkey	167,25%	10(1,00)
United	104,69%	10(0,78) 26(0,22)

For 2009, Germany, Netherlands and Sweden were effective by using their source in an actively. Turkey had the 167,25 % the score of efficiency was in the other countries which were not effective.

For 2010, Germany and Netherlands were effective. Turkey had the 169,27 % the score of efficiency was in the other countries which were not effective. Netherlands gave a reference to 24 countries and Germany gave a reference to 11 countries.

For 2011, Germany and Netherlands were effective. Turkey had the 166, 41 % the score of efficiency was in the other countries which were not effective. Netherlands gave a reference to 24 countries and Germany gave a reference to 9 countries.

Table 4: Malmquist index annual average abstract table

Year	Effch	Techch	Pech	Sech	tfpch
2008	1,019	1,047	1,019	1,000	1,067
2009	1,034	1,012	1,034	1,000	1,047
2010	1,040	1,006	1,040	1,000	1,046
2011	1,032	1,018	1,032	1,000	1,051
MEAN	1,031	1,021	1,031	1,000	1,053

Between 2007-2011 there was an increasing in total factor productivity. However, from 2008 to 2009 and from 2009 to 2010, total factor productivity increased at a decreasing rate. Between 2007-2011, the scale efficiency was stabile. When the five-year-average of countries are analyzed, the changing in total factor productivity of the all countries has the positive direction.

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MODIFIED CROSS EFFICIENCY AND ITS APPLICATION IN STOCK EXCHANGE

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ABSTRACT

This paper firstly revisits the cross efficiency evaluation method which is an extension tool of Data Envelopment Analysis. In this paper, we consider the DMUs as the players (institutions) in a cooperative game, where the characteristic function values of institutions are defined to compute the Shapley value of each DMU (institution), and the common weights associate with the imputation of the Shapley values are used to determine the ultimate cross efficiency scores for institution of Stock Exchange of Tehran. In models some weight may happen to be zero for all optimal solutions. This means that the corresponding criterion is not accounted for in the solution of the game at all. The zero weight issue can thus be solved in this way. This paper introduces the models for computing benefit for each institution. Using shapely value we obtain the effect of each institution, and through determining common weight for each company we find out the ultimate weight which shows how much the existence or not existence of that institution affects the interesting competence.

***Keywords**: Data Envelopment Analysis (DEA), Cross efficiency, Cooperative game, Shapley value, stock exchange.*

INTRODUCTION

As a non-parametric programming efficiency -rating technique for a set of decision making units (DMUs) with multiple inputs and multiple outputs, Data Envelopment Analysis (DEA) is receiving more and more importance for evaluating and improving the performance of manufacturing and service operations. In the game, each DMU will be a player, and the solution of Shapley value is computed to determine the ultimate cross efficiency of each DMU [4].

TECHNICAL WORK PREPARATION

Assume that there are n DMUs that are to be evaluated in terms of m inputs and s outputs. We denote the ith input and rth output for $DMUj(j=1,2,...,n)$ $j(j=1,2,...n)$ as $X_{ij}(i=1,2,...,m)$ and $Y_{rd}(r=1,2,...,s)$, respectively. The efficiency rating for any given DMU_d can be computed using the following CCR model in the form of linear programming (LP):

$$\begin{aligned}
&\text{Max } \sum_{r=1}^{s} \mu_r y_{rd} = \theta_d \\
&s.t. \quad \sum_{i=1}^{m} w_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0, j = 1,2,\ldots,n \\
&\qquad \sum_{i=1}^{m} w_i x_{id} = 1, \quad w_i \geq 0, i = 1,2,\ldots,m \\
&\qquad \mu_r \geq 0, r = 1,2,\ldots,s
\end{aligned} \tag{1}$$

DETERMINATION OF ULTIMATE CROSS EFFICIENCY USING DEA GAME MODEL

In this section, we will use the DEA game model and Shapley value in [5], for determine the ultimate cross efficiency of each DMU.

DETERMINATION OF COMMON WEIGHTS

Now we introduce [5] and solve this problem for determining *w*

$$\begin{aligned}
&\text{Min} \quad p \\
&s.t \quad wE_j' + s_j^+ - s_j^- = z_j, (j = 1,2,\ldots,n) \\
&\qquad w_1 + w_2 + w_3 + ..w_m = 1 \\
&\qquad s_j^+ \leq p, \; s_j^- \leq p, (j = 1,2,\ldots,n) \\
&\qquad w_i \geq 0, (i = 1,2,\ldots,m), \; s_j^+ \geq 0, s_j^- \geq 0, (j = 1,2,\ldots,n)
\end{aligned} \tag{2}$$

Where E_j' denote the *j*th column vector of E_j.

Let an optimal solution of this program be $(p^*, w^*, s^{+*}, s^{-*})$ then we have two cases [3].

The common weights, i.e. the optimal value of w in model (2), can be used to determine the ultimate cross efficiency, and the ultimate cross efficiency of each DMU is expressed as follows:

$$E_j^{cross} = \sum_{d=1}^{n} w_d^* E_{dj}, j = 1,\ldots n \tag{3}$$

AVOIDING OCCURRENCE OF ZERO WEIGHTS

Some weight may happen to be zero for all optimal solutions. Let us suppose that all players agree to put preference on certain criteria. The zero weight issue can thus be solved in this way. If all players agree to incorporate preference regarding criteria, we can apply the following "assurance region method"[1]. For example, we set constraints on the ratio w_1, w_i $(i = 2,\ldots,m)$ as:

$$L_i \leq \frac{w_i}{w_1} \leq U_i \quad , i = 2,\ldots,m$$

The program (1) is now modified as:

$$\begin{aligned}
&\text{Max} \ \sum_{r=1}^{s} \mu_r y_{rd} = \theta_d \\
&s.t. \quad \sum_{i=1}^{m} w_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0, \ j = 1, 2, \ldots, n \\
&\qquad \sum_{i=1}^{m} w_i x_{id} = 1, \quad w_i \geq 0, i = 1, 2, \ldots, m \\
&\qquad L_i \leq \frac{w_i}{w_1} \leq U_i \ \ , \ i = 2, \ldots, m \\
&\qquad \mu_r \geq 0, r = 1, 2, \ldots, s \qquad (4)
\end{aligned}$$

Similarly we can avoid occurrence of zero weight in program (2).

CROSS EFFICIENCY IN STOCK EXCHANGE OF TEHRAN

We now apply this approach to some institution in stock exchange of Tehran. There are 4 capital institutions in this district. Clearly, using new programs shows the better (successful) institution. Table 1 shows specifications of companies. Our sample covers the period from 1 March 2010 to 1 September 2010. The data were obtained from the stock exchange of Tehran. Now we compute the inferiority and superiority criteria for institution. Each institution uses 2 inferiority and 2 superiority criteria. In Tables 2 and 3 inferiority and superiority for these institutions (players) are given, respectively. Also in Table 5, the results of approach are presented.

Table 1: Specifications of companies

Company	First price	Stocks	Remaining capacity	Purchase price	Change rate	Selling capacity	Selling price
1	7000	4780617160	466334	6900	2.66	466334	7000
2	1428	2924848280	10606	1450	4	10606	1482
3	2406	62871272	210306	2406	3.97	1100	2441
4	1300	1271112850	5208061	1300	4	4000	1388

Table 2: Inferiority criteria for the 4 institutions of stock exchange

Player j	x1j= First price× Stocks	$x_{2j} = \text{selling capacity} / \text{selling price}$
1	3.346432012×1013	67.5846

2	4.33461703×1011	7.314482759
3	1.5112682804×1011	87.40897756
4	1.652446705×1012	4006.200769

Player j	y1j= Change rate	$y_{2j} = \text{remaining capacity} \big/ \text{purchase price}$
1	2.66	66.619143
2	4	7.156545209
3	3.97	0.450634985
4	4	2.88184438

Table 3: Superiority criteria for the 4 institutions of stock exchange

Table 4: Cross Efficiency

DMU	Dmu1	Dmu2	Dmu3	Dmu4
Dmu1	1.000	1.000	0.0526	0.0007
Dmu2	1.000	1.000	0.0053	0.0007
Dmu3	0.7759	1.000	0.7379	0.0646
Dmu4	1.000	1.000	1.000	0.0349

DMU	Shapley value	Common weight	Ultimate Cross Efficiency
DMU1	0.0758	0.0000	0.2675
DMU2	0.2464	0.4638	1.000
DMU3	0.1212	0.0000	0.6384
DMU4	0.1336	0.5362	0.7034

Table 5: Results

In this paper, we have studied the common weight issues that connect the game solution with arbitrary weight selection behaviour of the players. Regarding this subject, we have proposed a method for compute cross efficiency using shapley value. Using shapely value we obtain the effect of each player (institution). Table 5 shows second company is the efficient institution.

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OECD COUNTRIES SOCIO-ECONOMIC PERFORMANCES BY THE GOAL PROGRAMMING DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Data Envelopment Analysis (DEA) has been a very popular method for measuring and benchmarking relative efficiency of peer decision making units (DMUs) with multiple input and outputs. Beside of its popularity, classical DEA models (CCR and BCC) have some drawbacks such as unrealistic input-output weights and lack of a discrimination among efficient DMUs. Goal programming Data Envelopment Analysis model, GPDEA, proposed by Bal et al. (2010), also improve the discrimination power. In this study, primarily GPDEA model is presented, then the OECD countries, using data for year 2010-2011 socio-economical performance measurement, are evaluated using classical CCR and goal programming Data Envelopment Analysis (GPDEA) model.

***Keywords**: Data Envelopment Analysis, goal programming, OECD countries.*

INTRODUCTION

DEA is a very popular mathematical programming technique developed by Charnes et al. (1978) and has been widely applied and studied all over the scientific world. It is used to measure the productive efficiency of DMUs and rate their relative efficiencies. It designates the productivities of DMUs, specified as the ratio of the weighted sum of outputs to the weighted sum of inputs, compares them to each other and aims to indicate the most efficient DMU. DEA obtains the optimal weights for all inputs and outputs of each unit without imposing any constraint on these weights. While it is an advantage of DEA that these weights are free, the assigned weights are sometimes unrealistic. The issue of unrealistic weights has been investigated by the techniques of weight restriction. However, these techniques sometimes may give infeasible solutions for weights. Because many of the methods incorporate additional constraints to the model they make harder to solve the problem and may cause to infeasibility. Another disadvantage of DEA is the problem of discrimination power; that is, the problem of inability to discriminate the efficient DMUs. For the betterment of this problem of DEA, the models of super efficency, cross efficiency and multiple objective approaches are developed. However, in some cases it is also possible to meet the infeasibility problem and complexity of multiple objectives for these models (Li and Revees, 1999; Meza and Lins, 2002).

The cross efficiency method is a useful technique developed by Sexton et al. (1986) so as to rate the DMUs by using the cross evaluation scores computed as related to all DMUs and hence identify the best DMUs (Anderson et al. (2002). The basic idea of cross evaluation is to use DEA as machinery in peer evaluation instead of self evaluation. Peer evaluation refers to the assigned score for each DMU that obtained by using the optimal weights of other DMUs. The advantages of cross efficiency method are the ability of rating DMUs and being a useful tool without feeling the need of any expert opinion or prerequisites to work out the unenviable cases such as multiple solutions, solutions with extreme or zero values for the weights in DEA.

Bal et al. (2010) proposed a goal programming Data Envelopment Analysis model, GPDEA, to improve the discrimination power.

In this study, in order to show the improvement of the dispersal of input-output weights and the increasing discrimination power for GPDEA model, we have used an OECD countries data.

DATA ENVELOPMENT ANALYSIS

Assuming that there are n DMUs each with m inputs and s outputs the relative efficiency of a particular DMU_0 is obtained by solving the following linear programming problem (Charnes et al., 1978):

$$\mathrm{Max}\ \sum_{r=1}^{s} u_r y_{ro}$$

st.

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

(1)

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0\,, \qquad j = 1,\ 2,\ \ldots,\ n$$

$$u_r \ge 0\,, \qquad r = 1, 2,\ \ldots, s$$

$$v_i \ge 0\,, \qquad i = 1, 2,\ \ldots, m$$

where j is the DMU index, $j = 1, \ldots, n$; r is the output index, $r = 1, \ldots, s$; i is the input index, $i = 1, \ldots, m$; y_{rj} is the value of the r^{th} output for the j^{th} DMU, x_{ij} is the value of the i^{th} input for the j^{th} DMU, u_r is the weight given to the r^{th} output; v_i is the weight given to the i^{th} input, and w_o is the relative efficiency of DMU_0, the DMU under evaluation. In this model, DMU_0 is efficient if and only if objective function value $= 1$.

A DMU is considered individually in determining its relative efficiency. This DMU is referred to as the target DMU. The target DMU effectively selects weights that maximize its output to input ratio, subject to the constraints that the output to input ratios of all the n DMUs with these weights are ≤ 1. A relative efficiency score of 1 indicates that the DMU under consideration is efficient whereas a score less than 1 implies that it is inefficient.

MULTIPLE CRITERIA DEA MODEL

Model (1) can be expressed equivalently in the form given by Li and Revees (1999).

$$\min d_o \quad \left(\text{or } \max \sum_{r=1}^{s} u_r y_{ro}\right)$$

s.t.

$$\sum_{i=1}^{m} v_i x_{io} = 1 \qquad \textbf{(2)}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0 \qquad j = 1,\ 2,\ \ldots,\ n$$

$$u_r \geq 0, \quad r = 1, 2,\ \ldots, s$$

$$v_i \geq 0, \quad i = 1, 2,\ \ldots, m$$

$$d_j \geq 0, \quad j = 1,\ 2,\ \ldots,\ n$$

where d_o is the deviation variable for DMU_0 and d_j is the deviation variable of DMU_j. The quantity d_o, which is bounded by the interval $(0,1]$, can be regarded as a measure of inefficiency. Under this model, DMU_0 is efficient if and only if $d_o = 0$ or $\sum_{r=1}^{s} u_r y_{r_o} = 1$. If DMU_0 is not efficient, its efficiency score is $1 - d_o$. The smaller the value of d_o, the lesser inefficient (thus the more efficient) DMU_0 is. We shall call model (2) the basic DEA model. We say that the basic DEA method minimizes DMU_o's inefficiency, as measured by d_o, under the constraint that the weighted sum of the outputs is less than or equal to weighted sum of the inputs for each DMU.

The lack of discriminating power of the basic DEA, i.e., DEA's frequent inability to differentiate efficient DMU's, using a single objective function can overcome by using multiple and more discriminating objective functions, as proposed by Li and Revees (1999). A multiple criteria Data Envelopment Analysis (MCDEA) model formulation with the minmax and minsum criteria, which minimizes a deviation variable, d_o, rather than maximizing the efficiency score, $\max \sum_{r=1}^{s} u_r y_{ro}$, is shown below (Bal et al. (2010).):

$$\min\ d_o \quad \left(\text{or } \max \sum_{r=1}^{s} u_r y_{ro}\right)$$

$$\min\ M$$

$$\min\ \sum_{j=1}^{n} d_j$$

s.t.

$$\sum_{i=1}^{m} v_i x_{io} = 1 \qquad \textbf{(3)}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0 \ , \ j = 1, \ 2, \ \ldots, n$$

$$M - d_j \geq 0 \ , \ j = 1, \ 2, \ \ldots, n$$

$$u_r \geq 0, \quad r = 1, 2, \ \ldots, s$$

$$v_i \geq 0, \quad i = 1, 2, \ \ldots, m$$

$$d_j \geq 0, \quad j = 1, \ 2, \ \ldots, n$$

where d_j is a deviation variable for DMU_j, M is a maximum deviation variable ($\max\{d_j\}$). The larger the deviation variable, which is also bounded by interval [0,1], the lesser efficient is DMU_0. The efficiency score is equal to $1 - d_o$. The first objective function, $\min \ d_o$, is the classical DEA objective. Under objective $\min \ d_o$, a DMU is efficient if and only if the value of d_o is zero. The second objective function, $\min \ M$, is a minmax function minimizing the maximum deviation variable. The third objective function, $\min \ \sum_{j=1}^{n} d_j$, is a minsum function minimizing the sum of the deviation variables. The constraints $M - d_j \geq 0$, $j = 1, \ 2, \ldots n$ that define the maximum deviation M do not change the decision feasible region of decision variables as discussed in by Li and Revees (1999).

GOAL PROGRAMMING DEA MODEL: GPDEA

If the decision maker is more interested in direct comparisons of the objectives, then weighted or non pre-emptive goal programming should be used. In this case all the unwanted deviations are multiplied by weights, reflecting their relative importance, and added together as a single sum to form the achievement function. Weighted Goal Programming simultaneously considers all goals in a composite objective function minimizing the deviations between goals and aspiration levels (Bal et al, 2010). The objective function of a model is meaningless when it aggregates incommensurable deviational variables. After prioritizing the objective functions in model (4), a non pre-emptive goal programming (MCDEA) model can be used to solve the Multiple Criteria DEA Model (MCDEA). Here, the above MCDEA model (4) can also be easily adapted to the weighted goal programming as follows:

$$\min \ a = \left\{ d_1^- + d_1^+ + d_2^+ + \ \sum_j d_{3j}^- + \sum_j d_j \right\}$$

s.t.

$$\sum_{i=1}^{m} v_i x_{io} + d_1^- - d_1^+ = 1$$

$$\sum_{r=1}^{s} u_r y_{ro} + d_2^- - d_2^+ = 1 \qquad \textbf{(4)}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0\ ,\ \ j = 1,\ 2,\ \ldots,\ n$$

$$M - d_j + d_{3j}^- - d_{3j}^+ = 0\ \ ,\ \ j = 1,\ 2,\ \ldots,\ n$$

$$u_r \geq 0,\quad r = 1, 2,\ \ldots, s$$

$$v_i \geq 0,\quad i = 1, 2,\ \ldots, m$$

$$d_j \geq 0,\quad j = 1,\ 2,\ \ldots,\ n$$

$$d_1^-, d_1^+, d_2^-, d_2^+ \geq 0$$

$$d_{3j}^-, d_{3j}^+ \geq 0,\ j = 1,\ \ldots, n$$

where for the DMU under evaluation, d_1^- and d_1^+ are the unwanted deviation variables for the goal which constraints the weighted sum of inputs to unity, d_2^- is the wanted deviation variable for the goal which makes the weighted sum of outputs less than or equal to unity, d_2^+ is the unwanted deviation variable for the goal which makes the weighted sum of outputs less than or equal to unity. d_{3j}^-'s are the unwanted deviation variables for the goal (i.e., $M - d_j \geq 0\ \ ,\ j = 1,\ 2,\ \ldots,\ n$) which realizes M as the maximum deviation, and d_{3j}^+'s are the wanted deviation variables for the same goal (i.e., $M - d_j \geq 0\ \ ,\ \ j = 1,\ 2,\ \ldots,\ n$), where all d_j deviation variables are also unwanted.

Achievement objective function $\left\{ d_1^- + d_1^+ + d_2^+ + \sum_j d_{3j}^- + \sum_j d_j \right\}$ implies that all deviations are given equal weight.

Whereof our aim, given equal weight to the unvanted deviations, is to minimize the sum of unwanted deviations d_1^-, d_1^+ (i.e, $\sum_{i=1}^{m} v_i x_{io} = 1$), d_2^+ (equivalently minimizing d_o or maximizing $\sum_{r=1}^{s} u_r y_{ro}$), $\sum_j d_{3j}^-$ and the sum of deviations (i.e, $\sum_j d_j$).

EFFICEINCY EVALUATION OF OECD COUNTRIES

For this reason, for thirty OECD countries having three input and five output variables are used (*www.oecd.org*). y_1: national income per capita (USA dollars, 2010), y_2: human development index: life expectancy in birth (2010), y_3: human development index: education index (2010), y_4: contribution rate to labor force of woman population (2010), y_5: health expenditure per capita (USA dollars, 2010), x_1: unemployment ratio (2011), x_2: rate of inflation (2011), x_3: baby death rate (2011).

The basic CCR model rates Iceland, Luxembourg, Norway, Sweden, Switzerland, England and USA as efficient, but the GPDEA model determines only the countries Switzerland and USA as efficient. Hence it can be concluded that the GPDEA model has a good discrimination power than the basic CCR model, that is, it discriminates the countries better than the basic CCR model. Furthermore, it can be affirmed that the GPDEA model assigns efficiency score values consistent with the CCR model beside it discriminates the units well.

Table 1: Results of the basic CCR and GPDEA for the OECD data sets

	CCR			*GPDEA*		
DMU	*Eff.*	*Super Eff.*	*Rank*	*Eff.*	*Super Eff.*	*Rank*
Australia	0.742	0.742	17	0.512	0.512	17
Austria	0.605	0.605	18	0.505	0.505	18
Belgium	0.542	0.542	21	0.561	0.561	15
Canada	0.541	0.541	22	0.498	0.498	19
Chec. Rep.	0.601	0.601	19	0.547	0.547	16
Denmark	0.796	0.796	13	0.701	0.701	11
Finland	0.795	0.795	15	0.698	0.698	13
France	0.799	0.799	12	0.701	0.701	10
Germany	0.801	0.801	11	0.714	0.714	9
Greece	0.445	0.445	28	0.348	0.348	23
Hungary	0.421	0.421	29	0.301	0.301	25
Iceland	1	1.847	2	0.847	0.847	7
Ireland	0.512	0.512	24	0.487	0.487	20
Italy	0.555	0.555	20	0.501	0.501	19
Japan	0.958	0.958	8	0.912	0.912	4
S. Korea	0.807	0.807	10	0.796	0.796	8
Luxembourg	1	1.258	4	0.898	0.898	5
Mexico	0.514	0.514	23	0.501	0.501	19
Netherland	0.788	0.788	16	0.701	0.701	11
N.Zealand	0.808	0.808	9	0.699	0.699	12
Norway	1	1.156	5	0.878	0.878	6
Poland	0.496	0.496	25	0.303	0.303	24
Portugal	0.451	0.451	27	0.404	0.404	22
Slovak. Rep.	0.398	0.398	30	0.247	0.247	26
Spain	0.495	0.495	26	0.408	0.408	21
Sweden	1	1.027	7	0.941	0.941	3
Switzerland	1	1.501	3	1	1.678	2
Turkey	0.796	0.796	14	0.687	0.687	14
England	1	1.140	6	0.847	0.847	7
USA	1	1.994	1	1	2.478	1

CONCLUSINS

In many instances, the basic DEA models yield non-homogeneous weight dispersal of inputs and outputs, and yield many numbers of efficient DMUs. This paper corrects this problem by using weighted goal programming Data Envelopment Analysis. The GPDEA model can be confidently used to improve discriminating power of the DEA and also yields more reasonable input and output weights. If the number of DMUs is smaller in comparison with the total number of inputs and outputs, the proposed models give fewer efficient units than the basic DEA models. For this reason, in the case in which we study with the proposed models, it seems true that the efficient DMUs are well discriminated from each others.

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ON THE USE OF MODIFIED DATA ENVELOPMENT ANALYSIS MODELS FOR PRODUCT LINE SELECTION

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ABSTRACT

Product line selection problem is defined as selecting a subset of potential product variants that can simultaneously minimize product proliferation and maintain market coverage. Selecting the most efficient product mix is a complex problem, which requires analyses of multi-criteria. This paper proposes a method based on Data Envelopment Analysis (DEA) for product line selection. Data Envelopment Analysis (DEA) is a linear programming based technique, used for measuring the relative performance of a group of decision making units with multiple inputs and outputs. Although DEA has been proved as an effective project evaluation tool, it has not been applied to solve the product line selection problem. In this study, Modified Data Envelopment Analysis method that systematically adopts DEA to solve a product line selection problem, is used. Afterward the proposed method is applied to an existing line of staplers to provide quantitative evidence for managers to generate desirable decisions to maximize the company profits while fulfilling market demands.

Keyword: *Product line selection, Data Envelopment Analysis, Linear Programing, Modified Data Envelopment Analysis*

INTRODUCTION

There are two main issues which every financial institute is faced in representing a new product to the market. The product should satisfy all the customers' needs, in one hand (Customers have variety of tastes as well as different needs), and the producing procedure on another hand are the issues. Financial problems and lack of resources in each part could be the reasons which a financial institute is not able to acquire several production lines for each specific product. Even if the facilities are sufficient, it won't be financially feasible. So the question here is, how far a firm could go to cover these varieties.

MAUT is the model which has been developed recently by Thevenot, et al. (2006, 2007) based on multi-attribute theory, in product line selection. MAUT selects the best optimum among the varieties of tastes on the basis of two or more choose able variables. It has to be mentioned that in producing a variety of products by the mentioned model, the firm faces number of difficulties such as variety of inputs, technology of product, human resources, variety of output. Obviously, complexity and being time consuming to overcome the issues, is another state of problem.

Hence to choose wisely and get the best results by avoiding the mentioned issues, there is a demand for another and of course better solution. DEA Is considered to be a better solution to choose the best optimum and to reach the maximum net profit. This study tries to utilize modified DEA to choose the best optimum and to reach the maximum net profit and to reduce the complexity of manufacturing a product and achieve the needed competitive advantage in the industry.

The future of each company relies on the decisions which are made in different situations. To estimate the economic growth of a firm, all the decisions should be evaluated periodically. Among a number of tools which are available, DEA is one of the best non parametric tools to evaluate the Decision making unit's performance. DEA derives of Data Envelopment Analysis which is used to evaluate the Decision making unit's performance. It contains several inputs and outputs.

METHODS

Data Envelopment Analysis (DEA), developed by Charnes et al. (1978), is a linear programming based technique. DEA is commonly used to measure the relative productivity efficiency among a group of decision making units (DMUs) by forming an efficient frontier. Since the model is developed by Charls cooper and Roodrez is called CCR and has been published in 1987 in an article entitled “measuring the Decision making units”. In fact DEA optimizes linear programming which is also called NON-Parametric model.

DEA Models:

DEA models includes CCR and BCC. The CCR model was introduced as a model that has constant return to scale. Then in input-output space all hyper planes of efficient frontier passed through the origin and also efficient DMUs are located on them. Consider a CCR-efficient DMU as for optimal solution of model we have:

$$\sum_{r=1}^{s} u *_r y_{rj} = 1 = \sum_{i=1}^{m} v *_i x_{i0}$$

$$\sum_{r=1}^{s} u *_r y_{rj} - \sum_{i=1}^{m} v *_i x_{i0} = 0$$

Modify:

The CCR- impressive DMUs, in which the optimum avail of over problem is nonzero, are those that can be situated on the connection of the impressive boundary and the feeble impressive boundary hyper planes. Let the set of these DMUs be called β. (see Figure 1)

For the DMUs depending to β say(X_0,Y_0) solve the subsequent problems:

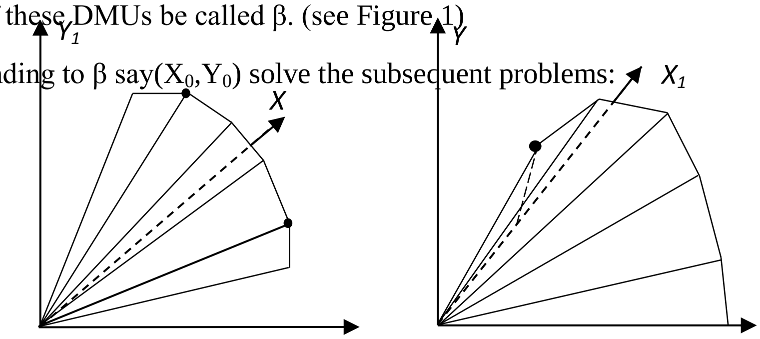

Figure 1. Elements of set β for T_C in two cases

$$Max\ v_i$$

$$st. \sum_{i=1}^{m} v_i x_{i0} = 1 \quad (1)$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0\ j = 1,2 \ldots n$$

$$v_i \geq 0 \ \ u_i \geq 0$$

And

$$Max\ u_i$$

$$st. \sum_{i=1}^{m} v_i x_{i0} = 1 \quad (2)$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0\ j = 1,2 \ldots n$$

$$v_i \geq 0 \ \ u_i \geq 0$$

Imagine that the optimum avail for (1) and (2) are it has been shown by v_i^+ and u_r^+severally. To decrease the number of problems, it is advised that the problems (1) and (2) just to be Resolved for v_is and v_is with identical indices when $Si^- > 0$ and $S_r^+ > 0$, in optimum solution of problem. Even so for each r = 1,., s and i=1,…,m, imagine that:

$$\epsilon_r = min\{u_r^+ | DMU \ \in B\}\ \forall r = 1,2 \ldots s \quad (3)$$

$$\epsilon_i = min\{v_i^+ | DMU \ \in B\}\ \forall i = 1,2 \ldots m \quad (4)$$

Now according to (3) and (4) the CCR method, modified as below:

$$Max\ u_r$$

$$st. \sum_{i=1}^{m} v_i x_{i0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \; j = 1,2 \ldots n$$

$$v_i \geq \varepsilon_i \;\; u_r \geq \varepsilon_r$$

With acknowledgment to explanation of ϵ, r = 1,…, s and ϵ, i = 1,…, s, using them as a lower bound of each factor weights in CCR model, produces passable hyper planes. These hyper planes are replaced by hyper planes of weak boundary. This substitution preserves the possibility of modified CCR model in multiple side and unboundedness, in envelopment side.

PROBLEM DEFINITION

We exploit data relevant to a product family formerly lead into in (Thevenot et al., 2006) (see Table 1). The problem presented was the succulent: a company produces three different cases of staplers (numbered 1, 2, 3and 4). Corporation rectors in the company would like to add a new model to their product line to augmentation to the market coverage (numbered 5 in the Product Mix column in Table 1). However, presenting a new product is a twisted resolve as it shock many usable issues and their consequences .The goal in this problem is to decide which product mix would usable conclusion in high benefits while minimizing product propagation and sustain competitive market coverage. Note that this case study is based on real data from the company, but the strategy analyzed is only an illustrative example for proof our methodology and will not be perform.

Table 1

Product Mix	PCI (%)	Profit ($)	Market Coverage (%)
1 2 3 4 5	36.5	$45,543,018	80
1 2 3 4	40.7	$36,280,518	70
1 3 4 5	40.7	$26,389,514	60
1 5 4 2	43.1	$48,793,824	80
2 1 3 4	43.1	$39,817,768	80
2 1 3 5	59.2	$17,127,014	50
2 1 4 5	42.9	$30,555,268	70
2 3 4 5	42.9	$20,664,264	60
3 1 2	42.9	$39,531,324	70
3 1 4	42.9	$29,640,320	0.6
3 1 5	63.3	$28,416,004	0.3
3 2 4	51.7	$65,997,295	97
3 2 5	51.3	$65,486,678	83
3 4 5	29.4	$33,283,961	88
4 1	30.5	$31,479,280	91

Normalizing Data:

One of the best ways of making sure there is not much imbalance in the data sets is to have them at the same or similar magnitude. A way of making sure the data is of the same or similar magnitude across and within data sets is to *mean normalize* the data. The process to mean normalize is taken in two simple steps. First step is to find the mean of the data set for each input and output. The second step is to divide each input or output by the mean for that specific factor (Table 2).

Table 2

DMU	PCI	Profit	Market Coverage
1	1	0.96985	0.7825
2	1	0.692875	0.613929
3	1	0.503979	0.076429
4	1	0.879961	0.662857
5	1	0.718084	0.662857
6	1	0.224872	0.301429
7	1	0.553611	0.5825
8	1	0.374402	0.499286
9	1	0.716242	0.5825
10	1	0.537033	0.004643
11	1	0.348927	0.001429
12	1	1	0.478571
13	1	1	0.371429
14	1	0.802233	1
15	1	0.724506	1

We want to use the DEA technique as an approach to assist the company in selecting the most efficient product family given two inconsistent points of view, the existing data set includes 15 various combinations of product families along with their corresponding product line commonality values (PCI), market coverage (MC), and profit information. The data set is provided in Table 1. The PCI, introduced by Kota et al. (2000), measures the product line commonality from several dimensions. It evaluates if component size/shapes, materials/manufacturing processes, and assembly processes are identical for the non-unique components across the products of a family. PCI values range from 0 to 100. A higher PCI value display more commonality among the non-unique components of the product family. The profit and market coverage represent the possible results that the choice of the certain product family alternative could bring.

From a manufacturing point of view, along with the high profit and wide market coverage, the company might prefer to produce a product family with high product commonality. High commonality in products would reduce the complexity in manufacturing processes, and also reduce the production costs.

By applying DEA and Modified DEA method for set of data and evaluating the amount of Ɛ it is possible to compare the result.

Ɛi 1= 0.07244 Ɛi 2= 0.03714 Ɛr =0.0238

Table 3

DMU	θ*	θ* (modified)
1	1	1
2	0.7419	0.7412

3	0.5039	0.5009
4	0.9028	0.9028
5	0.7813	0.7813
6	0.3014	0.3010
7	0.6373	0.6373
8	0.4992	0.4983
9	0.7407	0.7407
10	0.5370	0.5320
11	0.3489	0.3467
12	1	1
13	1	0.9960
14	1	1
15	1	0.9924

CONCLUSIONS

In the paper, a decision making method, which involves DEA, is proposed for product line selection problems. The application presented above shows these advantages. However, upon a close review of the application one can also observe that the way decision variables are introduced to the model impacts the recommended product mix for varying market conditions. In the paper, while we propose a way to achieve this solution, we recommend further research in the area to incorporate the dynamic nature of such decisions.

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OPERATIONAL EFFICIENCY AND PRODUCTIVITY GROWTH OF INDONESIAN AIRPORTS

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ABSTRACT

This paper reports operating efficiency and productivity growth of 23 Indonesian airports for the periods of 2006 – 2010. Using the proposed Data Envelopment Analysis approach, we assume that the airports are operating at variable returns to scale, and aim to maximize their outputs. We employ the DEA method to measure the trend of airports' operating efficiency. Second, the measurement of airports' productivity and its decomposition is administered using the DEA-Malmquist productivity approach. The results show although there was a slight reduction in productivity growth, there is an increasing trend of the airports' efficiency during the observation periods and all the airports were operating at the increasing return to scale.

Keywords: *Airports, Indonesia, Data Envelopment Analysis, Malmquist productivity*

INTRODUCTION

The Indonesian airline industry has experienced a significant growth since 2001 due to the deregulation in the industry that caused by the issuance of The Decree of Minister of Transportation Number 11 Year 2001. The decree rules an easier way for airline establishment that caused the significant growth in the number of airlines, including low cost carriers (LCCs). Since 2001, there had been at least five LCCs operating in the Indonesian sky. As a result, every carrier is urged to operate efficiently in order to get more passenger and buyer of the service provided.

In the case of Indonesian air transport industry, the existence of LCC is suspected to have influence on the growth of its revenue, as it grew by 14.37% from 2002 to 2006 (Angkasa Pura 1 (2010), and Angkasa Pura II (2010)). The increasing of operating revenues is suspected to be caused by the increasing of aircraft and passenger movements, as well as the amount of cargo handled by the airports (See Table 1). However, although airports are naturally operated as local monopoly, due to increasing competitiveness in the industry they need to enhance their ability to operate efficiently.

Airports in Indonesia are operated by two state-owned companies, namely: PT. Angkasa Pura I (AP I) and PT. Angkasa Pura II (AP II). AP I is operating airports in the eastern part of Indonesia whereas AP II is operating airports in the western part of Indonesia.

Table 1: The Growth of Service Provided by the Indonesian Air Transport Industry, 2006-2010

Year	Aircraft Movement	Passenger Movement	Cargo Handled

2006			
2007	1.74%	6.94%	17.17%
2008	2.18%	2.64%	4.46%
2009	2.98%	6.76%	-2.34%
2010	15.85%	26.59%	12.52%
Average growth	**5.69%**	**10.73%**	**7.95%**
2006-2010	**24.03%**	**48.35%**	**34.49%**

Source: Angkasa Pura I (2010) and Angkasa Pura II (2010)

Gillen and Hall (1997) advice that airports activities may produce two types of services, i.e: terminal services which include number of passenger movements and amount of cargo handle, and movements, which comprise of air carrier movement and commuter movements. Furthermore, Doganis (1992) suggests that airport activities will produce three services, such as operational services, handling services, and commercial services. The operational services are related to every aeronautical activity that allow for aircraft movement such as runway services, flight control duties, as well as aircraft parking. On the other hand, handling services associate with all ground activities, such as processing of the passengers and freights in the terminal areas. In addition, all activities that are not related to the previous activities are known as commercial services. This comprises business activities such as concession of spaces for shops, restaurants, etc.

The issue of airport efficiency received more attention and widely studied by scholars and policy makers. This due to a complex activities involve in operating the airports and its effects on the nation economy (Button and Taylor, 2000).

Numerous studies on airport operational efficiency had been conducted by applying various frontier methodologies. In general, Data Envelopment Analysis (DEA), total factor productivity (TFP), and stochastic frontier approach (SFA) were used to measure and evaluate the efficiency of airports. Studies that used various DEA models to assess the airport efficiency for instance were done by Gillen and Lall (1997), Sarkis (2000), Chi-Lok and Zhang (2009), Yu (2010), and Lozano and Gutierrez (2011).

Studies that used TFP approach for instance were done by Oum et al. (2003) and Oum et al. (2006). Lastly, studies that used SFA and other parametric approach were done by Barros (2008), Abrate and Erbetta (2010), and Tovar and Martin-Cejas (2010). Other researchers, such as Yoshida and Fujimoto (2004) used both DEA and TFP to assess the efficiency of airports in Japan while Vasigh and Haririan (2003) used Ratios analysis and regression analysis to compare the efficiency of seven privatized airports in UK to eight government owned airports in the US.

Most studies used resources, such as airport infrastructure (apron area, runway area, terminal area), labor (number of employees and labor cost), and operational costs as measures of input, whereas aircraft movements, passenger volume and cargo volume are motsly used as mesures of output. Lozano and Gutierrez (2011) also included undesireble output, namely delayed flight in their study, while Tovar and Martin-Cejas (2010) also considered aircraft size and share of non-aeronautical revenue as output. several studies such as Sarkis (200) and Oum et al. (2006), Abrate and Erbetta (2010) included revenues as measure of output.

To the best of our knowledge there has been no published study on Indonesian airport efficiency. Considering the increasing growth of revenues, passenger movements, aircraft movements and amount of cargo handled by the Indonesian airports in the last five years, this study investigates whether the performance is due to the operational efficiency or the policy imposed by the government. Furthermore, we also explore the productivity changes of the Indonesian airports. The operational data was gathered from PT. Angkasa Pura I and PT. Angkasa Pura II.

METHODS

This study employs two types of the DEA approach. First, it applies the standard DEA approach especially the efficiency measures as results of allocative and technical efficiency. Secondly, it applies the Malmquist total productivity measures to determine the efficiency gains.

In this paper, an output-oriented measures and variable return to scale (VRS) is assumed because the DMUs want to maximize their outputs given inputs used related to the production function (Banker, Charnes and Cooper, 1984).

In the second stage, the Malmquist factor productivity measure is used to identify efficiency gains/loss. In this case, we use the model proposed for the first time by Fare, et al. (1994), and the Malmquist index of total factor productivity change (TFPCH) over period t and t+1 is the product of technical efficiency change (EFFCH) and technological change (TECHCH). The technical efficiency change measures the change in efficiency between period t and t+1, while the technological change captures the shift in the technology applied over time. A value greater than one in both cases indicates growth in productivity: that is positive factor values.

Our analysis of Indonesian airports uses annually observed data of 23 out of 25 airports located in 22 cities during the period of 2006 to 2010. The airports are selected based on the data availability of each airport. This article uses non-parametric linear programming technique of DEA to calculate the airports' operating efficiency and productivity using selected inputs and outputs. The data is run using DEAP software.

We measure inputs and outputs of the airport that are related to parts of its infrastructure, i.e: terminal services and movements. Outputs are represented by aircraft movements (MOV), passenger movements (PASR), and cargo movements (CRG) while inputs are runway area (RWA), apron area (APR), and terminal area (TMA). Since the number of sample airports greater than three times numbers of inputs and outputs, it satisfies the requirement of the discriminatory power (Avkiran, 2002).

RESULTS AND DISCUSSIONS

The mean score of overall efficiency, technical efficiency and allocative efficiency in 2006 are 0.692, 0.769, and 0.909 respectively. These figures is supported by the fact that 13 airports (56.52%) are operated at *increasing returns to scale* (IRS), and only 3 airports (13.04%) are operated at *decreasing returns to scale* (DRS). Furthermore, results in Table 2 also reveal that in 2006 only 5 out of 23 airports operating in the frontier, i.e: airports in Jakarta, Yogyakarta, Palembang, Surabaya and Makassar. Since these airports appear in the frontier in all observation periods, these airports therefore act as peers of inefficient airports. Results of the efficiency estimation in 2007 to 2010 also draw the same conclusion. This indicates that the mean value of allocative efficiency (AE) is higher that of technical efficiency (TE). It implies that most of these airports operated in the condition of *increasing returns to scale*. This also implies that those airports need to increase their output produce and change the scale of production to be able to improve their overall efficiency performances.

Table 2: Airports' Overall Efficiency, Technical efficiency and Allocative Efficiency, 2006

Airport's Location	OE	TE	AE	
Mataram	0.848	0.949	0.893	Irs
Ambon	0.266	0.266	1.00	-
Banjarmasin	0.610	0.618	0.987	Irs
Bandung	0.397	0.428	0.928	Irs
Biak	0.522	0.575	0.907	Drs
Balikpapan	0.941	0.942	0.998	Irs
Banda Aceh	0.701	0.782	0.896	Irs
Jakarta – Soetta	1.00	1.00	1.00	-
Denpasar	0.688	0.736	0.934	Irs
Jakarta - Halim	0.416	0.530	0.785	Drs
Yogyakarta	1.00	1.00	1.00	-
Kupang	0.370	0.370	1.00	-
Manado	0.388	0.417	0.932	Irs
Medan	0.848	0.909	0.934	Drs
Padang	0.594	0.684	0.869	Irs
Pekanbaru	0.833	1.00	0.833	Irs
Palembang	1.00	1.00	1.00	-
Pontianak	0.796	1.00	0.796	Irs
Solo	0.478	0.478	0.999	Irs
Semarang	0.919	1.00	0.919	Irs
Surabaya	1.00	1.00	1.00	-
Tanjung Pura	0.306	1.00	0.306	Irs
Makassar	1.00	1.00	1.00	-
Average	0.692	0.769	0.909	

Source: Airports data, processed

Table 3: Malmquist Index of Annual Means

YEAR	EFFCH	TECHCH	TFPCH
2006/2007	1.053	0.985	1.037
2007/2008	1.015	1.00	1.015
2008/2009	0.816	1.034	0.844
2009/2010	0.966	1.159	1.119

Average	0.958	1.042	0.999

Source: Airports data, processed

Result in Table 3 shows that the average score of TFP change is 0.999, which is almost close to 1.00. This indicates that all airports in the sample experienced productivity declined of 0.1%, during the period of 2006 to 2010. The scores in period of 2008/2009 suggest that there is loss in productivity whereas the gain in productivity in the next period has led to an overall 0.1% loss of efficiency. The results are given by negative catch-up to the frontier in two periods which most affected by the most recent period prior to the onset of the world financial crisis in 2008/2009. This indicates that TFP decline as being entirely due to negative efficiency change although there is a positive shift of the frontier. This means that the decline in productivity may be due to inefficiency in managing firms' operation.

Regarding the Malmquist productivity index and its decomposition, the results show that based on its total factor productivity index, Denpasar's airport (in Bali) experienced as the most productive airport over the test period. This airport was able to increase its productivity by 13.9%, which resulting from increasing in innovation (technological change) and managerial efficiency (catching-up) by 7.2% and 6% respectively. In addition, in terms of managerial efficiency, Kupang's airport experienced the highest growth (12.2%), while Ambon's airport is the one that is able to get benefit from the use of technology in order to increase its productivity. Ambon, Denpasar and Kupang are among famous tourist destination areas in Eastern part of Indonesia. This condition therefore, leads us to seek answers to a question of whether the different city's characteristics, such as tourist or business destination (See Chi-Lok and Zhang, 2009) may affect the airport's efficiency performance. Unfortunately, due to the limited data availability we cannot conduct further analysis.

CONCLUSIONS

This study aims to investigate the operational efficiency, and productivity changes of the Indonesian airports in 22 cities. In general, we found that on average, the operational efficiency of the airports range between 0.266 to the efficient score of 1.00. Furthermore, all airports were operated in the condition of increasing returns to scale during the period of 2006 to 2010. This condition may result from the increasing number of passengers after the air transport deregulation policy in 2001.

Results from the estimation of the firms' TFP (using DEA-Malmquist index) show that the sample airports experienced a slight decrease in average total factor productivity, which due to the decrease in managerial efficiency. In contrast, there is improvement in the use of advanced technology (technological change) during the observation period.

The Act of Minister of Transportation Number 11 Year 2010 has made it possible for private companies to operate airports in Indonesia. Therefore, in the future, there may be more than one airport in a certain city that run by different operators. To be able to compete and provide excellent service to the increasing number of customers, airports in Indonesia should increase their efficiency.

Due to the data limitation, we are only able to analyze 23 out of 25 airports during the period of 2006-2010, which may not correctly depict the condition of the Indonesian airports. Furhermore, we cannot further analyze factors that affecting the Indonesian airport efficiency in our study. We hope to correct these limitations in our future research, by disaggregating efficiency changes and technological changes to inspect input factors that affect changes in airports' productivity. In addition, when possible this study needs to be extended by investigating factors affecting the efficiency using second-stage DEA.

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PERFORMANCE ASSESSMENT AND QUALITY OF CARDIAC PROCEDURES IN RIO DE JANEIRO THROUGH DEA

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ABSTARCT

This work resulted from research developed in the context of CT-Saúde, a project supported by the Ministry of Health, which also keeps the DATASUS, a database that provides data on procedures and death of inpatients. A two-stage modeling is proposed to assess two processes: the first aims at providing services to cardiac inpatients, the second focuses on the inpatient outcomes. The methodology uses geometrical and graphical analysis to support weight restrictions formulation. Analysis of results comprises both primal and dual variables and their contribution to build performance indices, thus allowing confrontation with experts' judgments regarding large hospitals assessment in the state of Rio de Janeiro.

Keywords: *Data Envelopment Analysis; Health Services Assessment; Cardiac Procedures.*

INTRODUCTION

Cardiovascular diseases (CVDs) are the leading causes of death and disability in the world. In 2008, an estimated 17.3 million people died from CVDs, over 80% in low- and middle-income countries and, by 2030, almost 23.6 million people are expected to die from CVDs**.** In Brazil, CVD is the leading cause of mortality, 30% of all deaths, and it is estimated that nowadays up to 6.4 million Brazilians suffer from this group of diseases. Although a large proportion of CVDs is preventable, by means of controlling tobacco use and promoting a healthy diet and physical activity, they continue to rise mainly because preventive measures have been ineffective. Albeit prevention is cheap, treatment is costly and requires allocation of the scarce family and public resources to medical care (1).

Among the universe of cardiovascular diseases, the coronary artery disease (CAD), that generates coronary heart disease (CHD), as angina (stable or unstable) and myocardial infarction (MI), has the highest lethality rate, comprising 25 to 35% of all cardiovascular deaths. The treatment of coronary heart disease (CHD) has evolved significantly due in part to improvements in both medical therapy and surgical and percutaneous revascularization techniques. The majority of patients with chronic stable angina are treated with medical therapy, but there are a variety of indications for high complexity interventional treatments as coronary artery bypass graft surgery (CABG) or percutaneous transluminal coronary angioplasty (PTCA). In a large sense, the subgroups that primarily benefit from CABG are those with triple vessel disease and left ventricular dysfunction, those with significant left main coronary disease and those with diabetes mellitus. Coronary angioplasty, along with intracoronary stents and atherectomy devices, has multiple indications, including unstable angina, acute myocardial infarction (AMI) and multivessel CAD, serving viable myocardium (2).

Simultaneously, there is increasing interest in deploying and publicly reporting a risk-adjusted measure of mortality as a quality indicator of hospital system-level performance. Among these indicators, the Agency for Healthcare Research and Quality (AHRQ) has proposed, as inpatient quality indicators, the PTCA and CABG mortality rates to reflect quality of care inside hospitals. In 2002, in the United States of America, for instance, the mean rate was 3.42 per 100 discharges at risk for CABG and 1.37 per 100 discharges at risk for PTCA (3). These indicators are usually evaluated along with volume because, as noted in the literature, higher volumes of PTCA and CABG have been associated with fewer deaths (4).

The objective of this study is to develop a model to assess performance of the habilitated hospitals in Rio de Janeiro, Brazil, considering not only the efficiency to perform the quantity of procedures (volume of CABG and PTCA), but also the quality of care (by means of mortality rates per procedure).

METHODS

Many performance and benchmark reviews approach the issue of practical use of health care assessment from the efficiency perspective. Ozcan, O'Neill *et al.*, Lins *et al.*, Lobo *et al.* (5,6,7,8) health care efficiency studies collectively provided comprehensive overview of the theme, pointing out the general advantages, concerns and limitations of applying these methods in hospital settings. One issue of concern was pointed by Hollingsworth (9), who argued that the pressure to be efficient can lead to low cost, low quality system, and there may be also a trade-off between these aspects and the one of equity.

The most common used technique, Data Envelopment Analysis (DEA) based on linear programming, draws a frontier of best practices, shows which health organizations are efficient, gives the magnitude of inefficiency and indicates the means of improving efficiency by giving targets/projections for each of the inputs and/or outputs individually (10). The units of analysis (DMUs- Decision Making Units) in our case are hospitals in Rio de Janeiro habilitated to perform CABG and PTCA. The ones over the frontier, therefore, efficient, have an efficiency measure that equals to 1.00 or 100%, while the DMUs located under the frontier are inefficient (scores between 0 and 1.00, or 100%). The production models used in this work consider variable returns to scale (VRS) and are oriented to the increase of outputs to the projection in the frontier (maximization). The VRS model allows an inefficient unit to be compared only with others efficient units of similar size or operate in similar scale and is the choice to cope with hospitals that have differing sizes. The orientation choice (output) admits the maximum success of the results (procedures and survival rates), given a fixed amount of resources.

To assess both quantity and quality, a two-stage model was designed. The first model, or the Quantitative Efficiency Model, considered efficiency as the quantity of procedures executed (as the number of CABG and PTCA are the outputs) given the resources spent to perform them. The inputs were: a) number of beds, summing up the cardiologic and the cardiac intensive care ones; b) equipment, multiplying the number of cardiologic equipment in the hospital units by the mean price for each one in Brazil´s medical market.

The outputs of the first model (number of CABG and PTCA) were then made inputs for the second Model, or the Qualitative Efficiency Model, which had the inpatient survival numbers for each procedure as outputs.

In order to enhance the models, weight restrictions were inserted in both of them. In the Quantitative Model, the Assurance-Ratio Global (ARG) model was used to guarantee that all virtual inputs (outputs) would contribute at least with 10 percent relative to the total virtual inputs (outputs). In this way, no unit could allocate a zero weight to any variable. In the second Qualitative Model, the inception of weight restrictions should consider the difference in the risk of dying after being submitted to each output procedure (higher for CABG). Given that the weights or multipliers are responsible for the equations that assume the inclination of the frontier, the mechanism of choice was based on its geometrical appearance. To reach the bound values, a VRS output model was run with both survival rates as outputs and the ratio of the respective output weights of the efficient units, hence, that were on the frontier, was calculated. As the calculated values ranged from 1.8 to 9.7, the bounds chosen for the AR Qualitative Model ranged from 2 to 9.

The data sources used are publicized from the Ministry of Health/ DATASUS: Hospital Information System (SIH) and National Dataset on Health Facilities (CNES), for the year 2005. The software used was the DEA-Solver PRO.

RESULTS AND DISCUSSIONS

In 2005, eleven hospitals were allowed to perform both procedures in Rio de Janeiro; 06 of them are located in the capital; 04 of them are public (02 are teaching hospitals/TH), 02 are private for-profit and 05 are private non-for-profit (philanthropic, 01 is TH). The number of cardiologic beds varied from 07 to 131 (mean 52). The number of CABG ranged from 30 to 171 (mean 95), with mean survival rate of 92, 8 %. The number of PTCA varied from 19 to 464 (mean 171), with mean inpatient survival rate of 98, 9 %.

Table 1 presents the rank for the Quantitative Model, the benchmarks for each hospital and the projection of all the units so that each one could reach the best practice frontier. 04 hospitals were considered efficient: Santa Helena Clinic (CSH - for-profit, outside the capital), FUNDACOR (FC- public and specialized, from the Ministry of Health, in the capital), São Lucas Hospital (HSL - for-profit, at the capital), Hospital Escola Alvaro Alvim (HEAA - not-for-profit, outside the capital). The average efficiency was 59.8% and the lowest value was 0.2 % (Hospital Universitário Clementino Fraga Filho - HUCFF). CSH and FC were considered benchmarks for 08 and 06 hospitals, respectively. Except for the CSSJ, all hospitals attributed a higher (nearly 90%) virtual weight to the CABG volume. To reach he frontier, the inefficient units should raise the CABG numbers by 62.0% and the PTCA numbers by 69.7% (except HUCFF, as outlier). It is noteworthy that almost all targets are above 120 procedures per year, exactly the minimum number recommended by the Brazilian Ministry of Health.

Table 1 : Rank, Score, Benchmarks and CABG and PTCA Projections for the Hospitals, Rio de Janeiro, 2005

DMU	Score	Benchmarks		Projection CABG	Projection PCTA
HOSPITAL SAO LUCAS - HSL	100,00%	HOSPITAL SAO LUCAS		150	155
HOSPITAL ESCOLA ALVARO ALVIM - HEAA	100,00%	HOSPITAL ESCOLA ALVARO ALVIM		75	94
CLINICA SANTA HELENA - HSH	100,00%	CLINICA SANTA HELENA		152	464
FUNDACOR - FC	100,00%	FUNDACOR		171	426
HOSPITAL SAO JOSE DO AVAI - HSJA	93,91%	CLINICA SANTA HELENA	FUNDACOR	158	452
HOSPITAL SANTA TERESA - HST	41,31%	CLINICA SANTA HELENA	FUNDACOR	169	245
SANTA CASA DE MISERICORDIA DE CAMPOS - SCMC	35,84%	CLINICA SANTA HELENA	FUNDACOR	173	243
CASA DE SAUDE SAO JOSE - CSSJ	31,03%	CLINICA SANTA HELENA		152	464
FALMED - FM	30,87%	CLINICA SANTA HELENA	FUNDACOR	156	455
HOSPITAL UNIVERSITARIO PEDRO ERNESTO - HUPE	24,16%	CLINICA SANTA HELENA	FUNDACOR	335	79
HOSPITAL UNIVERSITARIO CLEMENTINO FRAGA FILHO - HUCFF	0,21%	CLINICA SANTA HELENA		14.057	47

Table 2 presents the scores for the Qualitative Model, along with the mortality rates encountered for these hospitals. Only one hospital was considered efficient: Hospital Universitário Clementino Fraga Filho - HUCFF, a federal university hospital inside the capital, a benchmark for all others, and the hospital with the lowest score in the Quantitative Model. Just beneath, two other private hospitals (not-for-profit) that were not remarkable in the Quantitative Model, Hospital São Jose do Avaí (HSJA) and Santa Casa da Misericórdia de Campos (SCMC), appear with a 99% score. The average efficiency was 96.3% and the lowest value was 91.1 % (FALMED). In this model, there was an equitable distribution of virtual weights to both outputs. The mean observed Mortality Rate for PTCA was 1.1%, with two hospitals surpassing the vales recommended by AHRQ (Hospital Santa Teresa and FALMED). For CABG, the average Mortality Rate was 7.2, doubling the AHRQ preconized value.

Table 2: Qualitative Model Score and Mortality Rate (MR%) for PTCA and CABG

DMU	Score	MR PTCA	MR CABG
HOSPITAL UNIVERSITARIO CLEMENTINO FRAGA FILHO	100,00%	NP	3,33
HOSPITAL SAO JOSE DO AVAI	98,64%	1,87	1,89
SANTA CASA DE MISERICORDIA DE CAMPOS	98,56%	1,15	3,23
HOSPITAL SANTA TERESA	98,20%	3,96	2,86
CLINICA SANTA HELENA	97,26%	0,22	7,24
CASA DE SAUDE SAO JOSE	97,20%	0,00	12,50
FUNDACOR	96,15%	1,03	7,60
HOSPITAL ESCOLA ALVARO ALVIM	95,04%	0,00	9,33
HOSPITAL SAO LUCAS	94,48%	0,65	8,67
HOSPITAL UNIVERSITARIO PEDRO ERNESTO	92,18%	0,00	9,88
FALMED	91,12%	2,13	12,90

Although it is not easy to establish a cut-off point or a trade-off between quantity and quality, a DEA model with both scores was run, to get a final score, given that each previous model should have a virtual weight of at least 20% (by Assurance Ratio Global). The results of all models are found in Figure 1 (the final score outside the parenthesis; quantitative and qualitative scores inside them). Clinica Santa Helena (CSH) is in the top of the rank, followed by Hospital São Jose do Avai, Fundacor, Hospital Escola Alvaro Alvim and Hospital São Lucas, pointing towards a balance between quantity and quality. As a limitation of the study, a risk adjustment for CABG survival rates should be important here as the only hospital with rates beneath the recommended parameter by AHRQ was seen in Hospital São Jose do Avai.

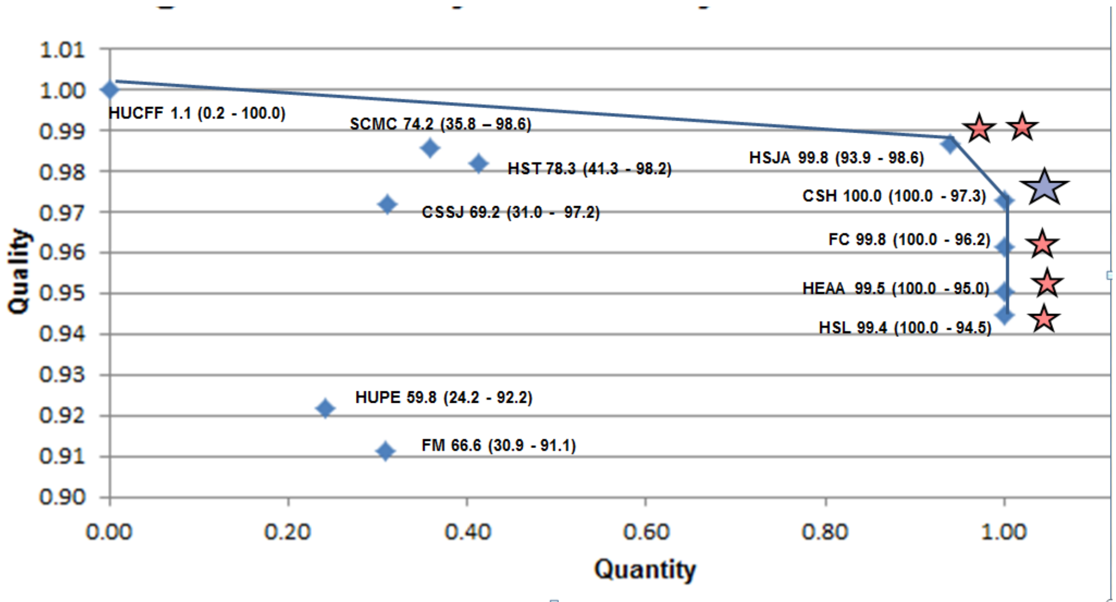

Figure 1: Quantitative and Qualitative DEA Scores (Trade-off final model)

CONCLUSIONS

DEA model is a potential tool to assess the hospital efficiency for cardiologic procedures in both, the quantitative and qualitative perspectives, and should be explored to aid decision making in public policy. As a multi-input multi-output index, it allows the comparison of hospitals that have diverse sizes and resources and also establishes differing goals to each one, based on their real capabilities.

From a methodological point of view, it is really important to incorporate quality variables inside the production models that deal with health scenarios, and flee from the sole quantitative logic. Also, the systematic dialogue between the OR analyst and the health specialist enhances the models, as any result can be discussed according to its impact on the clinical setting and on the health system. In this case, clinical information could ameliorate the model by means of pointing out the need and values for the weight restrictions.

Although the expected correlation between volume and survival was not observed, face validity of this conclusion is weak because there was no risk-adjustment for severity of disease (11). Besides this necessary correction, in the future, the Quantitative and Qualitative Models could be unified in one sole Network Dynamic Model (12), so that a quality output (survival) could be indirectly influenced by an input resource (bed or equipment), now presented in a distinctive quantitative model.

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PUBLIC SPENDING EFFICIENCY AND PERFORMANCE PARADOX

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ABSTRACT

The paper focuses on public sector efficiency (expenditure efficiency) and the performance paradox. The study assumes that there is close relation between efficiency of the public spending, sound public finance and general macroeconomic condition of the state. The efficiency of public spending has been analyzed for the 12 OECD countries over the period 2000-2011. The paper is organised as follows: theoretical background, empirical evidence, and findings. The theoretical part presents literature review, the main thesis, and the goals of the study. Conventional wisdom has been discussed and the major factors which might cause differing efficiency scores have been separated. In the last part of the discussion, efficiency scores and findings are presented.

Keywords*: public expenditure, efficiency, DEA, OECD countries, performance paradox*

INTRODUCTION

Efficiency is one of the crucial economic issues which, is the subject of numerous research and analyses. Efficiency, as a category is not homogenous, that's why there are many approaches to study this problem. Providing efficiency is especially important for public entities which are exposed to the phenomenon of decreasing efficiency of public spending (market failure and negative externalities) inter alia problems of: free rider, common pool, fiscal illusion, fly paper effect, and bankruptcy skills. On the contrary, the private bodies are usually efficient in nature which is the result of the market mechanism adjustment (the unsound entities that are going to be restructured or bankrupt).

After the economic crisis of 2007, the importance of public spending efficiency has increased because of the excessive deficits and debts that are encountered by many states across the globe. However, the reforms of public finance, based on New Public Management in many countries, had been undertaken before the crisis of 2007. The reforms had been focused on public sector performance and upon performance budgeting (T. Curristine, 2007).

The purpose of this article is to analyze the efficiency of the public expenditures for the 12 OECD countries from 2000 to 2011, considering their contributions to the economic affairs.

RELATED WORK

There are two mainstreams that are carrying on research in regards to the economic efficiency: the first one is defining efficiency and the second one is in how one measures it. The main one works on efficiency which has caused impacts incurrent understanding – which has occurred since 1951. In that time, T.C. Koopmans (who defined technical efficiency) and G. Debreu had carried research on the efficiency of production units interacted one to each other. In 1957, M.J. Farell modified Koopman's definition and G. Debreu extended it for independent productions units. M. J. Farell divided the new kind of efficiency which he called allocation efficiency. In 1966 (and after Farell's work) H. Lebenstein used X-efficiency and tried to confirm relation between rationalization and efficiency in a decision making process. In 1984, R.D. Banker, A. Charnes, and W. Cooper developed the efficiency model in which variables return to scale (VRS).

The public sector analysis is usually conducted in two ways: as the general efficiency analysis (A. Afonso, L. Schuknecht, V. Tanzi 2005) or as the analysis of the certain category of public expenditures (inter alia health, education) according to the purpose of spending (S. Gupta at al. 1997, H.Gravelle at al. 2003, S. Herrera, G. Pang 2005, A. Afonso, M. St. Aubyn 2006, D. Sutherland 2007). The findings that were presented by A. Afonso, L.Schuknecht, and V.Tanzi showed that the public sector efficiency across the countries differs and that they are determined by such factors as: per capita income, public competence, education level, and security of property rights (A. Afonso, L. Schuknecht, V. Tanzi 2005). The determinants impacting the certain category of public spending according to the studies included: the public expenditures (S. Herrera, G. Pang 2005), per capita GDP (A. Afonso, M. St. Aubyn 2006), ability of planning adjustment (H. Gravelle at al. 2003), the motivational strategies for public employees (A. Dixit 2002).

There are also a lot of papers that have examined the efficiency of public spending at a regional and local tier (A. Afonso, Fernandes 2003, Widmer, Zweifel 2008, Borge at al. 2008). General results of the studies that were carried on self-government entities showed that the efficiency of these units was impacted by the type of entity and its revenue level; (A. Afonso, S. Fernandes 2003) small, rural units are less efficient and the mechanism of redistribution (P.Widmer, P. Zweifel 2008) entities supported by subsidies are less efficient, political factors (the scale of fragmentation of political authority the more fragmented, the less efficient entity is).

There are many constraints in the process of measuring of efficiency of public entities. It is worth to mention that the economic aspect is not leading one in the decision making process regarding public spending. The easiest way of efficiency assessment of the public expenditure is to compare costs and benefits of certain action. The problem is that the costs and benefits of public entities are not only financial but also socio-economic kind. The other obstacle is that costs and results of public spending do not occur at the same time. The historical, geographical, and cultural factors have a great impact on the disparity of efficiency among the public units. The other problem is that in order to understand the way this works more, one must define results of public tasks and to quantify them.

It is equally important to bear in mind that the most difficult thing is to compare efficiency level among the units and across the countries because of the homogeneity requirements. In that context quality of inputs and outputs and the quality adjustment is one of the most pressing challenges (U. Mandl, A. Dierx, F. Ilzkovitz 2008). Furthermore, M.W. Meyer, K. O'Shaughnessy point out the problem of so called performance paradox which means "a weak correlation between performance indicators and performance itself"(F.L. Leeuw 2003). This phenomenon is due to run over the time of the indicators (S. von Thiel, F. L. Leeuw 2002). All of the factors mentioned above should be taken into account in the measuring efficiency of public spending.

METHODS

There are two groups of efficiency assessment methods that are divided into parametric and nonparametric. One of the nonparametric methods is Data Envelopment Analysis (DEA) which allows one to identify an efficiency frontier for the examined sample of the objects. The DEA method was developed in 1978 by A.Charnes and is one of the most common used methods in efficiency assessment (over 4015 papers using DEA method written by 2500 authors from 50 countries; Ch.Bamtasou, G. Hadjiconstatniou 2009).

Objects whose efficiency is evaluated using the DEA method shall be determined for the purposes as DMU (called Decision Making Units). Number DMU is limited and efficiency assessment for each unit regards to the solving of the linear programming task, which depending on the DEA model is to minimize expenditures at a given level of inputs (inputs oriented efficiency) or maximizing outcomes for a given level of outcomes (outcomes oriented efficiency; M. Al-Shammari 1999).

The analysis of a set of objects (DMU) is defined for each of these optimization tasks and setting the maximum technical efficiency of each DMU. The next step is the classification of the objects efficient DMU (forming limit production capacity) and inefficient units, below the effective unit designated by the efficiency curve. The level of inefficiency finds the distance of the object from the efficiency frontier.

DATA AND VARIABLES

The main assumption of the research was to verify the efficiency of public expenditures as an important instrument of fiscal stimulus (A.Greiner, P.Flaschel, 2009). For the purpose of the study, the DEA method has been used to diagnose the efficiency of public spending in 12 OECD countries (DMU) over the period 2000-2011. These countries are: Austria, Finland, France, Germany, Hungary, Ireland, Italy, Luxemburg, Poland, Portugal, Spain, United Kingdom. For these DMUs the data set (OECD and World Bank) was completed and is comparable.

The government expenditure (% of GDP) and public spending on economic affairs (% of GDP) were the input variable. The aim of the paper was to evaluate general performance of public spending that's way the main macroeconomics indicators (outputs) such as: 1) unemployment rate (%), 2) GDP growth rate (%), 3) GDP per capita (US$), 4) inflation rate (CPI%) were taking into considerations as the outputs variables. The statistics for inputs and outputs are presented in Table 1.

All of the outputs are strictly connected with fiscal policy (especially public expenditures policy), which has a great influence on every single output. The selection of inputs and outputs mentioned above might be explained in the light of the Keynesian approach and D.A. Aschauer findings which claim that public expenditures have a great impact on the economy (economic growth, labor market, private spending productivity etc. D.A. Aschauer 1989). A similar approach is presented by A.Adam, M.D. Delis, P.Kammas (2011).

Table 1 Summary statistics for inputs and outputs

Outputs	Mean	Std. Dev.	Min	Max
Unemployment rate (annual %)	8.05	2.99	4.02	14.03

GDP growth rate (annual %)	2.17	1.18	0,68	4.48
GDP per capita (US$)	33,199	19,103	8,819	82,495
Inflation rate (consumer process annual%)	2.69	1.20	1.59	5.86
Inputs	**Mean**	**Std. Dev.**	**Min.**	**Max**
General government expenditure (%GDP)	46.16	4.86	39.45	53.43
Public spending on economic affairs (%GDP)	4.78	1.25	3.20	7.94

Source: Author's calculation

The data was standardized and used for the DEA VRS analysis, output oriented. The variables such as: inflation rate and unemployment were reverse outputs. The study allows to select countries which at the certain value of the public expenditures achieved the best outputs taking into account Maastricht criteria (deficit, debt, inflation) and the best dealt with unemployment problem.

RESULTS AND DISCUSSIONS

According to the results of the public expenditures efficiency analysis with DEA methods Luxemburg every year was the most efficient in spending public sources (with special attention to spending on economic affairs) in the sample of the DMU and was the leader (Table 2). The countries with the highest efficiency of the public spending were those whose public deficits generally encounter Maastricht criteria and those which imposed fiscal discipline.

Table 2. Efficiency scores by public spending for 12 OECD countries, (2000-2011)

DMU	Score	Rank
Austria	0,9225	4
Finland	0,8981	7
France	0,9062	5
Germany	0,9018	6
Hungary	0,7048	11
Ireland	0,9608	3
Italy	0,7414	9
Luxemburg	1,0000	1
Poland	0,8296	8
Portugal	0,6965	12
Spain	0,7240	10
United Kingdom	0,9708	2

Results calculated by the DEA VRS, output oriented model

For all high efficient states the inflation rate did not exceed 3% and the unemployment rate was under 8%. It might be the result of the fiscal consolidation and fiscal stimulus which was the obligation during and after the economic slowdown accompanied by public finance crisis which spilled over the European Union after 2007.

The less efficient OECD of the examined sample countries was Portugal which belongs to so called PIGS states - the group of countries with the biggest problem of stabilizing of public finance inclusive the budget what results with very high threats of insolvency. The second country belonging to PIGS is Spain with unsound public finance and huge value of deficit and debt which are still under control of the

European Commission after numerous bailouts. Poland and Hungary were transition countries which adjusted the economies to the liberal market mechanisms and nowadays represent the group of democratic, developed countries. Poland's case is special for the study because of the significant financial support from European Union budget in the period 2007-2013 and 2014-2020 (over 80 billion euro for public spending from structural funds and Cohesion Fund).

The study confirms the close relation between efficiency of the public spending, sound public finance and general macroeconomic condition of the state. The countries with low level of public spending efficiency are more prone to the insolvency risk which results from excessive deficit and debt.

CONCLUSIONS

The efficiency assessment of public spending in the selected OECD countries confirmed the linkage between the overall economic condition of the country and the efficiency of its spending. The most efficient OECD states were characterized by the adjustments made to the Maastricht criteria deficit and debt level. The efficient DMU which dealt well with labor market and fiscal policy was reflected by inflation rate and unemployment rate. The poorest DEA efficiency that reached the countries with unbalanced public budgets with excessive deficit and debt problem very often was the states which were bailout recently. The inputs and outputs parameters showed that in some countries the European Commission intervention (excessive deficit procedure and six pack reform) was successful for sound public finance.

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RANKING ALL UNITS BASED ON MODIFIED CONSTANT RETURNS TO SCALE DATA ENVELOPMENT ANALYSIS

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ABSTRACT

The motivation of this study is to propose an equitable method for ranking all decision making units based on modified constant returns to scale Data Envelopment Analysis model using facet analysis. For this purpose, first the minimum efficiency values of each unit are computed under the assumption that the sum of efficiency values of all decision making units is equal to unity using modified Data Envelopment Analysis model. Then the rank of each decision making units is determined in proportion to a combination of this minimum and maximum efficiency values.

***Keywords**: Data Envelopment Analysis, Ranking, Facet Analysis, Modified Model*

INTRODUCTION

Nowadays, change and competition are the main characteristics of this world and only organizations can achieve their objectives which are able to allocate their available resources effectively in these complex and dynamic conditions. Using modern technologies and determination of opportunities and restrictions depend on identification of present status. In this regard, performance evaluation plays the significant role and it can be used to identify strong and weak points of organizations. One of the most important techniques in evaluating performance is Data Envelopment Analysis (DEA). DEA is an objective method for evaluating efficiency of Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. In DEA, the organization under study is called a DMU and is regarded as the entity responsible for converting inputs into outputs and whose performances are to be evaluated. DEA is an extension of Charnes, Cooper and Rhodes work by introducing CCR model in 1978 [1]. This technique has been used extensively and successfully to improve performance in a wide variety of organizations.

Ranking DMUs is one of the main purposes of DEA in management and engineering. DEA divides DMUS into two efficient and inefficient groups since DEA requires no assumption of the functional relationships between inputs and outputs and allows individual DMUs to evaluate their efficiencies with the input and output weights that are only most favorable to themselves. This flexibility in the selection of input and output weights often causes more than one DMU being evaluated as DEA efficient leading to them being unable to be fully discriminated. Therefore, we need to produce a reliable method for fully ranking DMUs. Some methods have been proposed in this concept (see, for example, [2-18]) and recently Khodabakhshi and Aryavash [19] ranked DMUs relative to their combined maximum and minimum efficiency scores. This method is illustrated in the next section. Then we produce precise and equitable ranking for all DMUs using this method in section 3 and determination of epsilons is demonstrated in section 4. Our method is illustrated in section 5 and finally we end this paper with conclusions and suggestions.

AN INTRODUCTION TO A RANKING METHOD

Here we introduce a ranking method presented by Khodabakhshi and Aryavash in 2012. Suppose there are n DMUs and each DMU converts m inputs into s outputs. Let x_{ij} and y_{rj}, which are assumed to be positive for all DMUs, be input and output of DMU_j, respectively. Then relative efficiency is defined as the ratio of total weighted outputs to total weighted inputs. Let DMU_j to be evaluated on any trial be designated as DMU_o where o ranges over $1, 2\ldots n$. In this regard, minimum and maximum efficiency values of each DMU are computed once under the assumption that sum of efficiency values of all DMUs is equal to unity and they obtain values for input weights v_i and output weights u_r as variables by solving the following problem.

$$Min\ and\ Max\ \theta_o \qquad (2.1)$$

$$\text{s.t.} \quad \theta_j = \textstyle\sum_{r=1}^{s} y_{rj}\ u_r \,/\, \sum_{i=1}^{m} x_{ij}\ v_i \qquad j = 1 \ldots n$$

$$\textstyle\sum_{j=1}^{n} \theta_j = 1$$

$$v_i \geq 0 \quad i = 1 \ldots m$$

$$u_r \geq 0 \quad r = 1 \ldots s$$

$$\theta_j \geq 0 \quad j = 1 \ldots n$$

This fractional programing is replaced by the following linear program:

$$Minand\ Max\ \theta_o = \textstyle\sum_{r=1}^{s} y_{ro}\ u_r \qquad (2.2)$$

$$s.t. \quad \textstyle\sum_{i=1}^{m} x_{io}\ v_i = 1$$

$$\textstyle\sum_{i=1}^{m} x_{ij}\ v_i\theta_j - \sum_{r=1}^{s} y_{rj}\ u_r = 0 \qquad j = 1 \ldots n$$

$$\textstyle\sum_{j=1}^{n} \theta_j = 1$$

$$v_i \geq 0 \quad i = 1 \ldots m$$

$$u_r \geq 0 \quad r = 1 \ldots s$$

$$\theta_j \geq 0 \quad j = 1 \ldots n$$

Using transformation $h_{ij} = v_i\,\theta_j$, minimum and maximum scores of θ_j are obtained by solving this problem.

$$Min\ and\ Max\ \theta_o = \textstyle\sum_{r=1}^{s} y_{ro}\ u_r \qquad (2.3)$$

$$s.t \quad \textstyle\sum_{i=1}^{m} x_{io}\ v_i = 1$$

$\sum_{i=1}^{m} x_{ij} h_{ij} - \sum_{r=1}^{s} y_{rj} u_r = 0 \qquad j = 1 \dots n$

$\sum_{j=1}^{n} h_{ij} = v_i \qquad i = 1 \dots m$

$v_i \geq 0 \qquad i = 1 \dots m$

$u_r \geq 0 \qquad r = 1 \dots s$

$h_{ij} \geq 0 \qquad i = 1 \dots m \qquad j = 1 \dots n$

We have this interval for each θ_j: $\theta_j^{min} \leq \theta_j \leq \theta_j^{max}, \quad j = 1, \dots, n$ (2.4)

Then we rewrite the intervals as the following convex combination:

$\theta_j = \theta_j^{min} \lambda + \theta_j^{max} (1 - \lambda), \ \forall \lambda, 0 \leq \lambda \leq 1, \quad j = 1, \dots, n$ (2.5)

The value of λ can be easily obtained as follows:

$1 = \sum_{j=1}^{n} \theta_j = \sum_{j=1}^{n} (\theta_j^{min} \lambda + \theta_j^{max} (1-\lambda)) = \lambda \sum_{j=1}^{n} (\theta_j^{min} - \theta_j^{max}) + \sum_{j=1}^{n} \theta_j^{max}$ (2.6)

Then $\lambda = (1 - \sum_{j=1}^{n} \theta_j^{max}) / \sum_{j=1}^{n} (\theta_j^{min} - \theta_j^{max})$ (2.7)

Using value of λ and equations 2.5, the values of θ_j are determined. Now DMUs are ranked according to their efficiency scores.

RANKING ALL DMUS IN DEA

Evaluating efficiency measure which is able to rank all DMUs is one of the most important purposes of DEA. One difficulty that has been discussed recently is lack of discrimination in DEA applications. In evaluating DMUs, it happens that more than one DMU got efficiency score one as efficient DMUs and DEA may not provide enough information for ranking efficient DMUs. Another difficulty is evaluating weak efficient DMUs as efficient DMUs when some of their input and output weights are equal to zero because of eliminating effect of corresponding inputs and outputs on DEA evaluation. To remove this difficulty, we use epsilons as lower bounds on each weight in the introduced model as follows:

Min and max $\theta_o = \sum_{r=1}^{s} y_{ro} u_r$ (3.1)

s.t. $\sum_{i=1}^{m} x_{io} v_i = 1$

$\sum_{i=1}^{m} x_{ij} h_{ij} - \sum_{r=1}^{s} y_{rj} u_r = 0 \qquad j = 1 \dots n$

$\sum_{j=1}^{n} h_{ij} = v_i \qquad i = 1 \dots m$

$v_i \geq \varepsilon_i \qquad i = 1 \dots m$

$u_r \geq \varepsilon_r \qquad r = 1 \dots s$

$h_{ij} \geq 0 \qquad j = 1 \dots n$

We determine epsilons such that efficiency scores of weak efficient DMUs and DMUs which are compared with them have been evaluated correctly. Epsilon is non-Archimedean element regarded to a small positive value. Epsilons force weights to be non-zero and then corresponding weights can reflect in evaluation. Using facet analysis, we compute epsilons while satisfying properties of Production Possibility Set (PPS) to remain feasibility.

Facets are an important concept used to evaluate efficiency in DEA [20]. Only part of efficient frontier is relevant when evaluating efficiency of a specific DMU. The relevant portion of efficient frontier is called facet. The concept of facet can be considered for more general concept of supporting hyperplane in multiple inputs and outputs case. Consequently, for a CCR-efficient DMU say (X_o, Y_o), feasible solution of CCR model is normal vector $(-V, U)$ for the corresponding supporting hyperplanes of PPS which passes through the origin. Weights in multiplier side are relevant slacks in envelopment side of CCR model. Based on complementary slackness theorem, if any slack is positive for optimal solution $\theta^* = 1$ of CCR model then corresponding weight must be zero. In this case, DMU under evaluation is weak efficient. Hence hyperplane which passes through weak efficient DMU has at least one zero component in its normal vector *(-V,U)*, that is an *r* or *i* exists such that $u_r = 0$ or $v_i = 0$. Geometrically, this hyperplane is parallel with the corresponding axes by zero components in its normal vector.

In fact, epsilons impose positivity on weights and move normal vectors of weak hyperplanes causing their efficiency to be measured correctly. Simultaneously, epsilons change efficiency scores of DMUs which are compared with weak efficient DMUs. Usage of epsilons moves hyperplanes which pass weak efficient DMUs and do not allow them to be formed. Figure 3.1 portrays the situation geometrically. Furthermore, we provide a full and precise ranking for all DMUs.

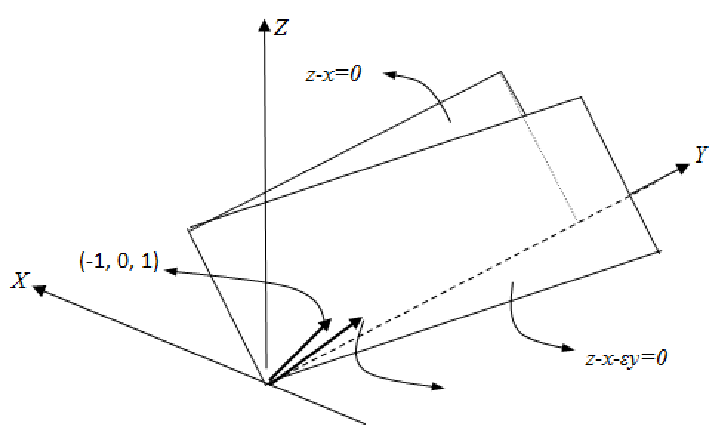

Figure 1: Plane with Zero Components in Its Normal Vector

DETERMINING EPSILONS

Here we describe how to determine epsilons. We first identify efficient DMUs using CCR model and then we consider DMUs which are located on the region formed by intersection of efficient and weak efficient frontiers. For this, we consider the following model for efficient DMUs based on complementary slackness theorem.

$$
\begin{aligned}
Max \quad & \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ && (4.1)\\
s.t \quad & -x_{io} + \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = 0 \quad i = 1,2,...,m \\
& -y_{ro} + \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^- = 0 \quad r = 1,2,...,s \\
& \lambda_j \geq 0 \quad j = 1,2,...,n \\
& s_i^- \geq 0 \quad i = 1,2,...,m \\
& s_r^+ \geq 0 \quad r = 1,2,...,r
\end{aligned}
$$

Let *Z* be set of these DMUs with positive optimal value of this model. Now for the DMUs belong to *Z*, we determine maximum values of input and output weights by solving the following problems.

Assume that v_{iw}^+ and u_{rw}^+ are the optimal values of model 4.2 and model 4.3, respectively.

$$
\begin{aligned}
Max \quad & v_i && (4.2)\\
S.t \quad & \sum_{i=1}^{m} v_i x_{iw} = 1 \\
& \sum_{r=1}^{s} u_r y_{rw} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 1 \quad j = 1,...,n \\
& u_r \geq 0 \quad r = 1,...,s \\
& v_i \geq 0 \quad i = 1,...,m
\end{aligned}
$$

$$
\begin{aligned}
Max \quad & u_r && (4.3)\\
S.t \quad & \sum_{i=1}^{m} v_i x_{iw} = 1 \\
& \sum_{r=1}^{s} u_r y_{rw} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 1 \quad j = 1,...,n \\
& u_r \geq 0 \quad r = 1,...,s \\
& v_i \geq 0 \quad i = 1,...,m
\end{aligned}
$$

Finally we obtain epsilons while satisfying properties of PPS using the following equations.

$$\varepsilon_r = Min\{u_{rw}^+ \neq 0 \mid DMU \in \mathrm{Z}\} \quad \forall r = 1,2,..,s \quad (4.4)$$

$$\varepsilon_i = Min\{v_{iw}^+ \neq 0 \mid DMU \in \mathrm{Z}\} \quad \forall i = 1,2,...,m \quad (4.5)$$

A NUMERICAL EXAMPLE

n this section, our method is illustrated via a numerical example. In this example, there are eight DMUs with one input and two outputs as shown Table 1.

Table 1: Data of Example

DMUs	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***

Input *x*	1	1	1	1	1	1	1	1
Output1 y_1	1	1	2	3	4	4	5	6
Output2 y_2	7	5	7	4	3	6	5	2

We first identify efficient DMUs using CCR model and then for DMU_3 and DMU_8 belong to set *Z*, we determine maximum values of input and output weights as shown in Table 2.

Table 2: Optimal Values of Model 4.2 and Model 4.3

DMUs	v_1^+	u_1^+	u_2^+
3	1	0.0625	0.1429
8	1	0.1667	0.0500

Finally we obtain epsilons using the following equations:

$\varepsilon_1^v = Min\{1,1\} = 1 \quad , \varepsilon_1^u = Min\{0.0625, 0.1667\} = 0.0625 \quad , \varepsilon_2^u = Min\{0.1429, 0.05\} = 0.05$ Then, minimum and maximum efficiency scores of DMUs are determined in Table 5.3 using new method and minimum and maximum scores are integrated into a single number. Finally, DMUs are ranked according to their scores.

Table 3: A Full Ranking of DMUs

DMU	CCR Results	Khodabakhshi&Aryavash Results	[θjmin , θjmax]	θj	Rank
1	1	0.1090 (6)	[0.0400, 0.2188]	0.0987	7
2	0.714	0.0834 (8)	[0.0400, 0.1562]	0.0781	8
3	1	0.1282 (4)	[0.0800, 0.2188]	0.1256	3
4	0.688	0.1090 (7)	[0.1200, 0.1250]	0.1216	4
5	0.750	0.1154 (5)	[0.0938, 0.1600]	0.1155	6
6	1	0.1538 (2)	[0.1600, 0.1875]	0.1690	2
7	1	0.1603 (1)	[0.1562, 0.2000]	0.1706	1
8	1	0.1411 (3)	[0.0625, 0.2400]	0.1208	5

Notice that all computations are done using software GAMS. In addition, results of the CCR model and the model presented by Khodabakhshi and Aryavash are summarized in Table 5.3. Obviously, these results differ from our ranking in some cases. For example, rank of DMU_3 is third position in our method whereas third position of Khodabakhshi and Aryavash ranking belongs to DMU_8. All DMUs have been completely ranked using this method. This implies the power of the proposed method in discriminating DMUs, especially efficient DMUs.

CONCLUSION

This study has provided a new method for ranking all DMUs in DEA. We expand usage of facet analysis to produce a ranking method. Using facet analysis, we determine epsilons as lower bound on each weight causing efficiency scores of weak efficient DMUs and DMUs which are compared with them, have been evaluated correctly and we observe a full ranking for both efficient and inefficient DMUs. Our method is based on both pessimistic and optimistic attitudes of DEA, so it can be more equitable than the methods that are based on only one of these attitudes. Infeasibility and instability that happen because of extreme sensitivity to small variations in data are removed in this approach. Our model can be easily used when there are insufficient DMUs. Moreover, we reduce the number of problems using complementary slackness theorem and computational burden is considerably decreased. The importance of ranking subject in DEA has shown that future study in this direction is necessary and our study opens up several research directions. A research on incorporating our study with other DEA models is recommended such as output-oriented models. Another direction for research can be developed to rank DMUs with imprecise data. Moreover, determination of λ can be expanded in this method.

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REGIONAL EFFICIENCY MEASUREMENT OF TURKISH MANUFACTURING INDUSTRY

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ABSTRACT

Regional development is an important issue in countries' agenda. At regional level, industrial planning and implementation of development policies play a critical role. Decision makers of economy consider about efficiency levels for planning and policy making of industry. The basic determinant of economic growth is manufacturing industry. There are many studies on structural analysis and dynamics of progress in literature. Nevertheless, there is a lack of studies at the regional level in Turkish manufacturing industry so; this is the motivation of this study. At this context, Turkey's regional efficiency measurement of manufacturing industry between 2004 and 2009 is conducted with Data Envelopment Analysis. Turkey has 26 regions due to NUTS (Nomenclature of Territorial Units for Statistics) Level-2, and this study covers these regions. Employment, electricity consumption and capital stock are used as the input and production value is used as the output. Also for environmental performance measurement, an alternative model using CO_2 emissions as undesirable output is conducted and comparisons between these two models' efficiency scores are given. U shape relationship is found between average efficiency scores and gross value added per capita of regions.

Keywords: Data Envelopment Analysis, regional efficiency, environmental performance, Turkish manufacturing industry

INTRODUCTION

The spatial distribution and organization of economic activities has been unequal since the beginning of industrial production. Process of development did not begin in an equal, balanced and uniform manner, so all economic activities are geographically concentrated in certain places. Differences of the development rate, wealth and prosperity at regional level continue specially in developing countries. Turkish economy made a considerable progress in terms of structural transformation, competitiveness, integration into the international markets and achieved recently a long-term economic growth performance. In 2002, by the European Union candidateship progress Turkey made its own NUTS system and then Turkey has constituted regional development agencies at NUTS-2 level for effective initiation of regional policies by the year 2009. As a developing country, Turkey has regional disparities and different regional dynamics. Measuring the efficiencies of the regions is important for making regional policies especially in manufacturing industry. Cause of being productive power of the whole economy, manufacturing industry plays a critical role in development, employment and environmental issues in Turkey.

Number of studies on efficiency at regional level is increasing in recent years. Data Envelopment Analysis (DEA) has been widely applied at the macro- economy level to measure the energy and environment efficiency in recent years. DEA gives a convenient framework to combine multiple inputs and multiple outputs in examining relative efficiency of decision making units (DMU). Hu and Wang (2006) analyzed China's regions in the scope of total factor energy efficiency. They used labour, capital stock and energy as inputs and GDP as output. Hu et al (2006) analyzed water efficiency by incorporating water as an input as well as using conventional inputs such as labor employment and capital stock. GDP was used as output. Watanabe and Tanaka (2007) estimated two efficiency measures of Chinese industry at the provincial level from 1994 to 2002, using a directional output distance function. One model contains desirable outputs; the other one contains both desirable and undesirable outputs. Yu and Wan (2010) evaluated China's urban environmental sustainability in 46 cities in 2007 with DEA. The roles of GDP per capita, city scale, and industrial structure as influence factors of environmental sustainability were explored and the regional disparity of urban environmental sustainability was also investigated. Wang et al (2012) improved DEA models to measure the energy and environmental efficiency of 29 administrative regions of China during the period of 2000–2008 within a joint production framework of considering both desirable and undesirable outputs, as well as energy and non-energy inputs. For an European Union region, the first study that developed for regional environmental performance indicators is given by Halkos and Tzeremes (2012). They have measured Germany's regional environmental efficiency by using Kuosmanen technology

There are a few studies about regional efficiency in Turkey. Some studies were performed (Önder et al (2003), Yavuz (2003)) but they used data before the year 2001 and territorial scope was provinces. In 2002 Turkey has experienced a structural change by being a candidate of EU so their scope and data structure is different from studies after 2002. Köse et al (2011) evaluated the economic performances of level-2 regions (NUTS-2) in Turkey through the impacts of developments in aggregate employment, employments by main sectors, human capital, public infrastructure investments, entrepreneurship, innovations, technology levels and exports on growths of per capita gross value added between 2004-2008. Örkcü and Bal (2012) proposed a new approach with cross-efficiency evaluation and ranked the Turkish cities with some socio-economic variables for the year 2003. Şengül et al (2013) calculated economic efficiencies of NUTS Level 2 region of Turkey in 2007-2008. Some financial data was used as input and outputs.

To the best of our knowledge, no studies have attempted to calculate regional efficiency of manufacturing industry in Turkey using a total-factor framework as labour, capital stock and energy are inputs; production value is output. In our study, two input oriented DEA models are considered. First one is in total factor framework and output is desirable. The other model is like the first model but there is CO_2 emissions as undesirable output.

METHODOLOGY

Data Envelopment Analysis (DEA) is the most popular and widely used method for efficiency measurement and it is a non- parametric method based on linear programming. Considering undesirable (bad) outputs in energy and environmental studies has become an important issue in recent years. Many methods comprising undesirable outputs have been proposed. Generally, these methods can be divided into two groups. First is based on data translation and the utilization of traditional DEA models. The other group uses the original data on the concept of weak disposability reference technology (Zhou et al, 2008).

The weak disposability assumption implies that reduction of undesirable outputs is costly, so this can be only by concurrent reduction of desirable outputs. In addition the assumption indicates that the desirable outputs are null-joint with undesirable outputs and this means undesirable outputs are byproducts of the production process when producing desirable outputs (Färe and Grosskopf, 2004).

In our first model only good output and other inputs are preferred, bad output is not in account. According to this input oriented model, DMU efficiency is defined as the ability to contract the amount of inputs without reducing the corresponding output volumes. The formulations of the models are as follows:

Model 1

$$
\begin{aligned}
&\min \theta \\
&s.t. \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rjo}, \quad r = 1,\ldots,q \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ijo}, \quad i = 1,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0, \qquad j = 1,\ldots,n
\end{aligned}
$$

Model 2

$$
\begin{aligned}
&\min \theta \\
&s.t. \sum_{j=1}^{n} \lambda_j y_{rj}^{g} \geq y_{rjo}^{g}, \quad r = 1,\ldots,q \\
&\sum_{j=1}^{n} \lambda_j y_{kj}^{b} = \theta y_{kjo}^{b}, \quad k = 1,\ldots,l \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ijo}, \quad i = 1,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0, \qquad j = 1,\ldots,n
\end{aligned}
$$

For our second model we put an undesirable output CO_2 under weak disposability assumption where y^g is good output, y^b is bad output. Here, efficiency measure can evaluate the ability to contract all inputs of the production process without increasing the amount of emission (Riccardi et al., 2012).

The comparison between first and second models can emphasize the importance of considering CO_2 emissions in efficiency measurement in existence of environmental regulations which limit CO_2 emissions. The analysis of weak and strong disposability assumptions gives information on how the use of alternative energy inputs or other input materials can decrease CO_2 levels, conserving the same efficiency levels and output quantities (Riccardi et al., 2012).

REGIONAL DATA AND DESCRIPTIVE STATISTICS

In this study, we examined 26 NUTS Level 2 regions of Turkey and data is from 2004 to 2009. Source of the electricity data is Turkish Electricity Transmission Company and the other is from Turkish Statistical Institute (TurkStat). Input and output variables are defined as follows.

Employment data used in this study is number of persons employed in the manufacturing industry provided from the data set "Some basic indicators by local units" of NUTS 2. At the regional level NUTS-2, sufficient energy data (petroleum, natural gas, renewables etc) cannot be found (lack of data) and only the electrical energy consumed in the manufacturing industry is used as input. One of the most important input data is capital accumulation. For being a factor of production, the capital stock data is needed to represent the capital. Before 2001, some data which represent the capital stock is available, but there is no data for this series 2003 and after. Using the *perpetual inventory method* the capital stock of the manufacturing industry at the regional level is estimated. In this approach, $K_t = (1-d)K_{t-1} + I_t$ where K_t is the capital stock of the year t and *d* is the depreciation rate we select the depreciation rate of (1/26) for manufacturing industry following OECD (1998) and I_t is the investments of the year t. Initial capital stock for 2002 is estimated following Nehru and Dhareshwar (1993) by the formula $K_{t-1}= I_t/(g_y+d)$. Here g_y trend growth rate assuming equal to capital growth. After estimating capital stock of 2002 (initial year), capital stock series of regions are generated by $K_t = (1-d)K_{t-1} + I_t$ to the year 2009. An important output of this study is estimating regional capital stock series of manufacturing industry first time in Turkey.

One of our outputs is production value and estimated from turnover values. There are "production value", "turnover" and "value added at factor cost" data at country level in manufacturing industry, but unfortunately there is no data at NUTS-2 level except "turnover". Regional production values are estimated by using country level turnover and production value and regional level turnover data. In Turkey, green house gases emissions are only estimated at country level. At regional level there is no data of emissions, so in the sake of simplicity, country's carbon dioxide emissions of manufacturing industry are allocated to regions by population. Correlations between inputs and outputs are given in Table 1 and descriptive statistics in Table 2.

Table 1: Correlations between inputs and outputs

	Capital Stock	Employment	Electricity used	Production Value	CO_2 Emission
Capital Stock	1, 000				
Employment	0,982	1,000			
Electricity used	0,665	0,636	1,000		
Production Value	0,983	0,975	0,736	1,000	
CO_2 Emission	0,913	0,937	0,502	0,898	1,000

Table 2: Descriptive statistics of inputs and outputs

		Inputs			**Outputs**	
		Capital Stock (Million TRY-2003 prices)	Employment (100 people)	Electricity Used (1000 MWh)	Production Value (Million TRY-2003 prices)	CO2 Emission (10000 tonnes)
2004	Mean	8030	920	2186	9636	344
	Std. Dev.	18049	1619	2329	18019	279
	Max	90957	8296	8098	88382	1596
	Min	53	47	61	232	95
2005	Mean	8365	994	2277	9856	349
	Std. Dev.	18247	1718	2343	17979	283
	Max	91897	8803	8322	87534	1617
	Min	106	44	85	177	95
2006	Mean	9576	1031	2464	10902	388
	Std. Dev.	19353	1753	2572	19427	315
	Max	97029	8972	8722	93647	1797
	Min	133	38	59	130	106
2007	Mean	10270	1068	2703	11343	406
	Std. Dev.	19923	1805	2793	19831	331
	Max	99459	9261	9303	95679	1879
	Min	140	43	52	197	109
2008	Mean	10765	1101	2747	11677	316

	Std. Dev.	20507	1832	2865	20309	257
	Max	102113	9390	10127	98244	1460
	Min	255	71	75	277	85
2009	Mean	11251	994	2584	10332	320
	Std. Dev.	20751	1633	2588	17825	261
	Max	103363	8386	9795	87013	1479
	Min	250	46	79	135	85

RESULTS AND DISCUSSIONS

In this study we aim to measure regional efficiencies of Turkish manufacturing industry in total factor framework. Two DEA models are used. First one is traditional DEA model in which capital stock, labour and energy are inputs; production value is output. In order to evaluate environmental performance of the regions we put CO_2 emissions as undesirable output under weak disposability assumption in the second model. The comparison between the efficiencies of these two models is done and effects of CO_2 emission on efficiency are examined.

Table 3. Efficiency Averages of two models

	Model 1	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
CRS	Mean	0,702	0,695	0,601	0,797	0,768	0,775
	Std. Dev.	0,199	0,180	0,212	0,187	0,180	0,198
	Min	0,412	0,379	0,277	0,401	0,349	0,302
	Number of Eff. Regions	5	4	3	7	6	7
VRS	Mean	0,791	0,831	0,776	0,870	0,857	0,863
	Std. Dev.	0,189	0,177	0,222	0,161	0,150	0,136
	Min	0,418	0,506	0,321	0,499	0,613	0,627
	Number of Eff. Regions	8	8	7	13	9	10
Scale	Mean	0,894	0,851	0,798	0,919	0,900	0,899
	Std. Dev.	0,141	0,170	0,202	0,139	0,148	0,183
	Min	0,436	0,379	0,277	0,462	0,381	0,366
	Number of Eff. Regions	6	4	3	7	7	8
	Model 2						
CRS	Mean	0,758	0,803	0,745	0,843	0,848	0,864
	Std. Dev.	0,186	0,167	0,203	0,177	0,160	0,159
	Min	0,460	0,540	0,373	0,465	0,563	0,379
	Number of Eff. Regions	7	7	7	11	11	12
VRS	Mean	0,856	0,883	0,840	0,914	0,890	0,905
	Std. Dev.	0,167	0,152	0,178	0,127	0,139	0,112
	Min	0,518	0,568	0,505	0,649	0,661	0,685
	Number of Eff. Regions	13	13	12	15	14	13
Scale	Mean	0,891	0,915	0,895	0,926	0,955	0,953
	Std. Dev.	0,144	0,127	0,164	0,154	0,103	0,120
	Min	0,477	0,575	0,373	0,471	0,588	0,413
	Number of Eff. Regions	7	7	7	13	11	12

It's seen that the first three years and the last three years are different from each other in the meanings of mean values, standard deviation and number of efficient regions. Looking at the investment data, it is obviously seen that investment in first three years are very high and this grows capital stock. The growth of the capital stock couldn't effect the production in short term, so after 2006 efficiency scores are higher because of these high investments and capital accumulation.

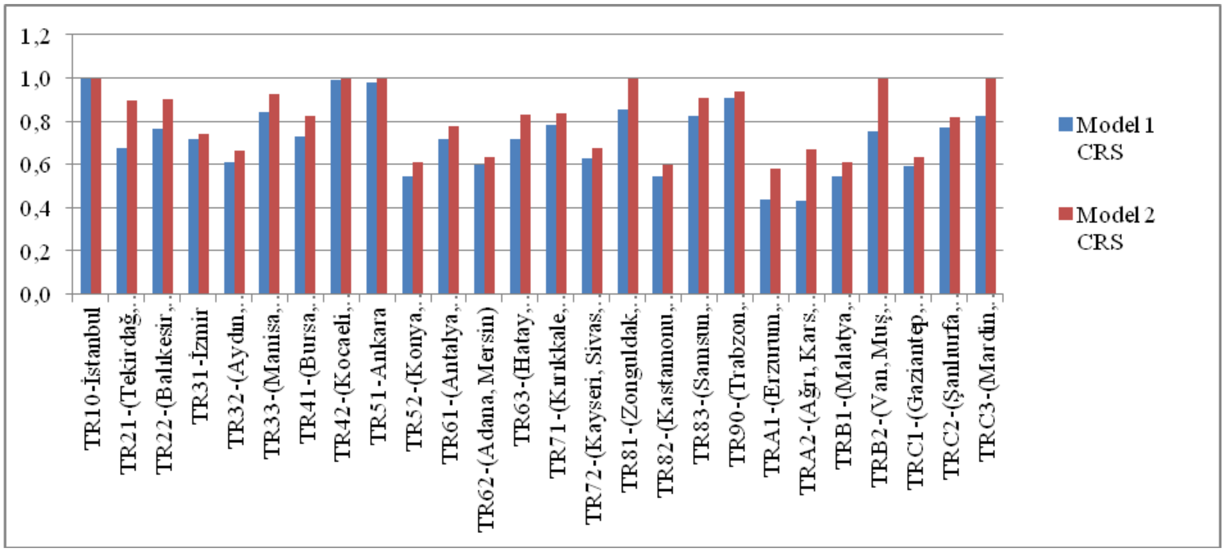

Figure 1. Average efficiency scores of regions between 2004-2009

In figure 2, the difference between first and last three years is easily seen for two models. Efficient and inefficient production values are also given and the effect of the global crisis on manufacturing industry can be seen in 2009.

Gross value added per capita is an important development indicator. Comparisons and evaluations with this indicator can give us some information about efficiency characteristics of regions. Figure 3 gives the relations of gross value added per capita and efficiency.

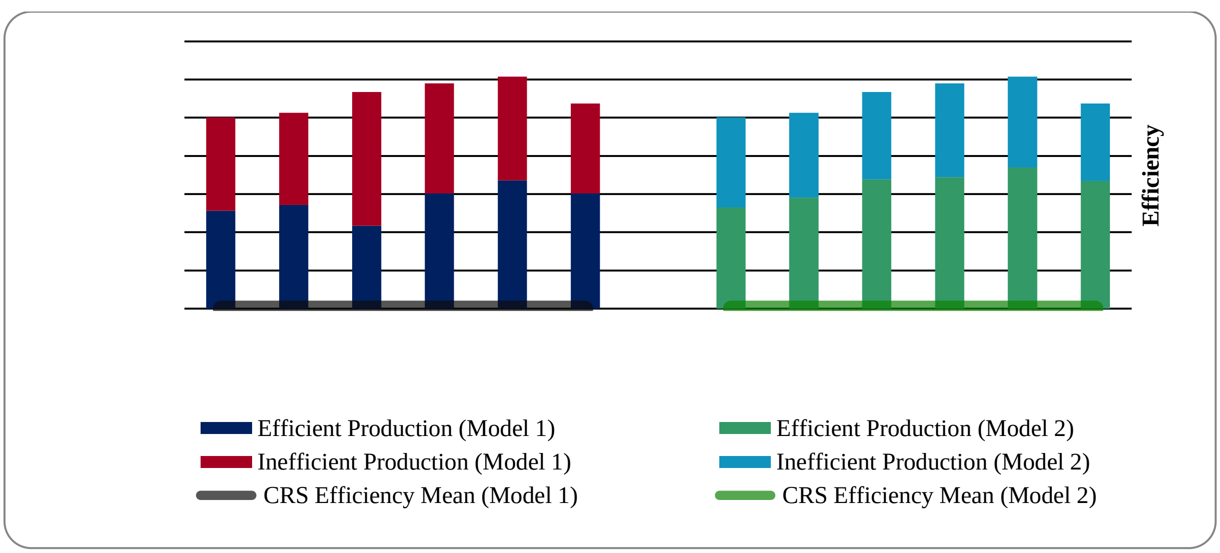

Figure 2. Production and mean efficiency scores of Model 1 and Model 2

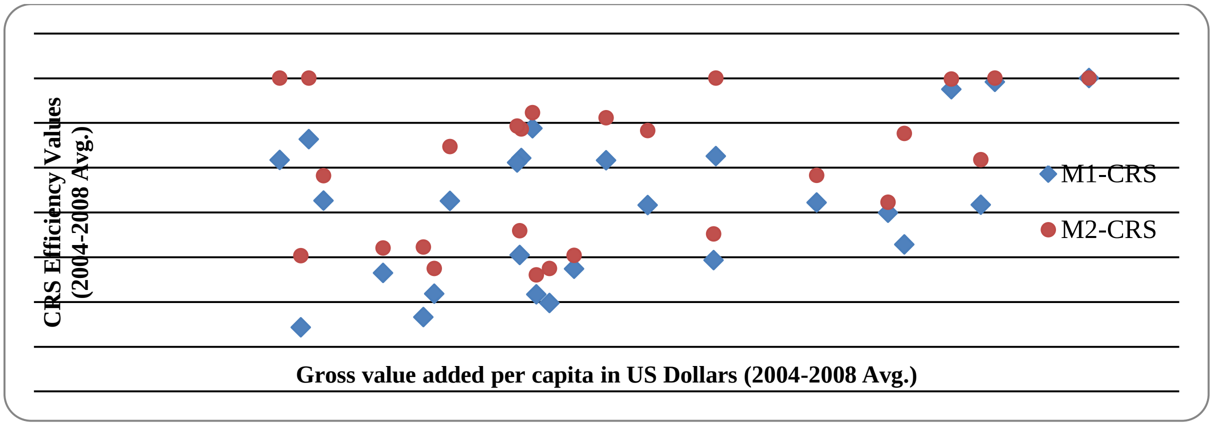

Figure 3. Relation between gross value added per capita and efficiency of 26 regions

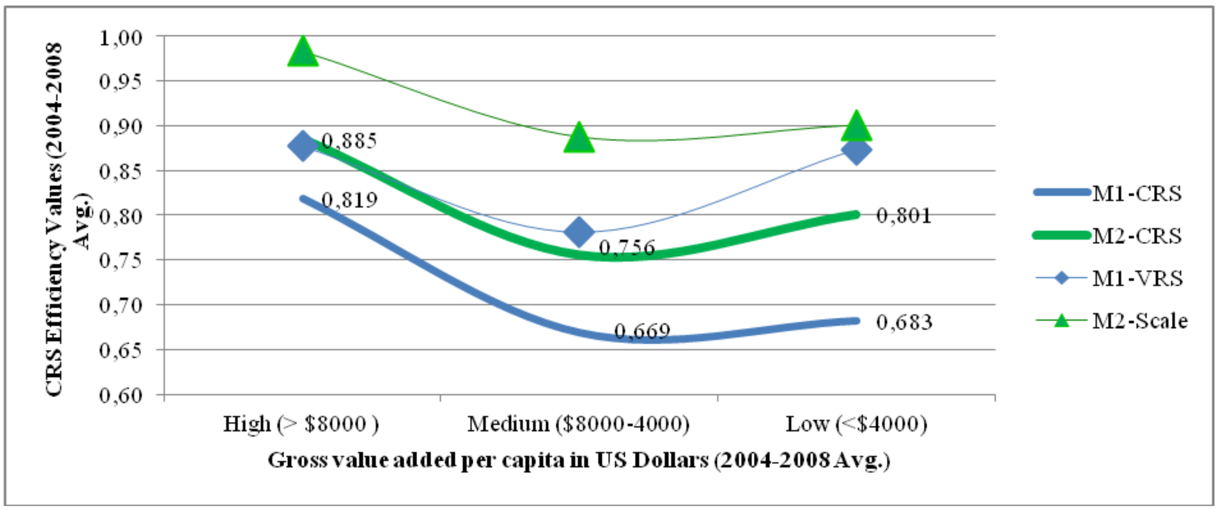

Figure 4 U-shape relation between gross value added per capita and efficiency

For a detailed analyse, regions are grouped into three groups as high, medium and low according to gross value added per capita. In figure 4, it is given that there is an U-shape relationship between efficiency and gross value added per capita. Regions with high gross value added per capita have the highest efficiency scores in both models as expected. In the medium gross value added group has the lowest scores. In order to find the reason of this U-shape relationship, scale and variable returns to scale (VRS) efficiencies are investigated. For model 1, scale efficiency scores increase by the value added per capita and the determinant of its shape is VRS efficiency. In development progress, regions show a bad performance with low VRS efficiencies and then they improve both scale and technical efficiencies. For model 2, determinant of this U-shape is scale efficiency. In development progress scale size of regions grow but scale efficiencies decrease.

CONCLUSIONS

Efficiency of Turkish manufacturing industry between 2004 and 2009 is calculated using DEA in this study. Two input oriented models are used in total factor framework. First model is conventional and the second one is environmental model. The second model is uses the same input-output of first model but additionally there is CO_2 emissions as undesirable output. Model results give information that regions with high gross value added per capita have the highest efficiency scores. Manufacturing industry of less developed regions is more environmental according to the medium developed regions. Determinant of CRS efficiency is VRS efficiency according to conventional model and the determinant of environmental CRS efficiency is scale efficiency. Also it is seen that 2006 is a critical year. Before and after 2006 efficiency trends in manufacturing have different characteristics While designing environmental productivity policies, these relations and characteristics should be taken into account and policies focusing on scale size should be planned and implemented with this point of view.

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RELEVANCE OF DATA ENVELOPMENT ANALYSIS TO THE ESTIMATION OF PRODUCTIVE EFFICIENCY IN THE INDIAN PORT INDUSTRY

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ABSTRACT

In this paper an attempt has been made to estimate the dimensional efficiency of major ports of India. In the original formulation, and in the vast literature that followed, the assumption was that all members of the input bundle affected the output bundle [1]. There have been efforts to employ split in input for DEA applications [1] and use of DEA/Factor Analysis [2] for improved results especially from policy making perspective. Several studies exists on application of conventional DEA approach to determine the efficiency of sea ports including major ports of India [3,4]. No studies suggest use of such deviations from conventional approach to Indian ports. In this paper the dimensions of performances of Indian ports have been captured using Varimax-Rotated Factor Analysis. The study identifies two major dimensions namely capacity dimension and the efficiency dimension that affect the port performance. The variables associated with each of these two dimensions were considered separately as inputs and Average Turn Round Time of ships (ATRT) as output, to measure the efficiency levels of the ports using DEA. The ranking of ports differed in these two cases and were also in different order when all members of the input bundle were used to determine the efficient ports. This implied that policies for performance improvement differ amongst ports. Some ports required capital-investments to improve its capacity dimension, while others required thrust on efficiency dimension, i.e., making policy changes related to process reengineering, structural and financial aspects of ports.

Keywords: *Data Envelopment Analysis, Port Performance Indicators, Average Turn Round Time, Varimax-Rotated Factor Analysis, Indian major ports*

INTRODUCTION:

INTERNATIONAL SEA BORNE TRADE

In tandem with the world economy and global merchandise trade, international seaborne shipments continued to grow in 2011, albeit at a slower rate than in 2010. Fuelled by strong growth in container and bulk trades, world sea borne trade grew by 4 per cent in 2011, taking total volume of goods loaded worldwide to 8.7 billon tons (UNCTAD, 2012).

THE PORT SYSTEM

Seaports act as an interface between land and sea or land and waterways. It is a part of transportation network through which cargoes are routed to different destinations.The ports originally under government control and serving as service ports were performing below the desired level of efficiency (Sinha, 2005). Many ports across the world re-oriented their business policies to become competitive. Ports in China and Malaysia are the glaring examples of such re-structuring. In China, 7 container handling ports are within the top 10 ports of the world (http_1, 2013). China and Malaysia ranks 1 and 5 respectively in UNCTAD

Liner Shipping Connectivity Index(UNCTAD, 2012). The Indian Ports, however, were not able to reach these levels. Ship's costs at ports constitute around 10 percentof the total freight, however, the delays in (inefficient) ports together can significantly influence the logistics costs and hence the final price of a product. The total costs incurred in port are found by adding together (1) actual port costs and (2) the cost of ship's time in port.

PORT SECTOR IN INDIA

India accounts for 7517 km of coastal line spread over 13 states and Union Territories. There are 13 major ports and about 200 non-major ports. The major ports are under control of Union Government of India. The share of the major ports decreased over a period of time. Figure 1 below shows the declining trend in major ports of India.

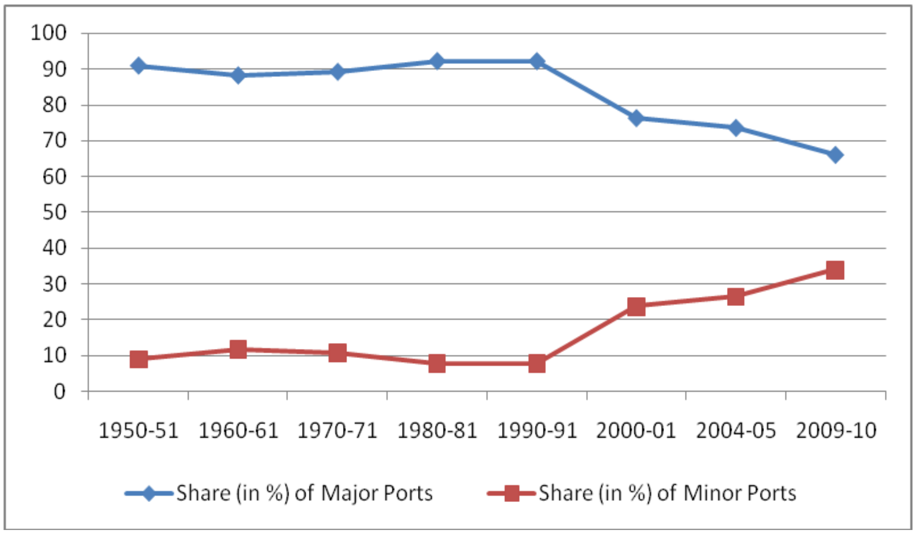

Figure 1: Share of major vs minor ports in India

Source: Various issues of Major Port of India : A Profile, IPA

The Compounded-Annual Growth Rate (CAGR) of the major ports is lower that of minor ports. The table 1 below shows the CAGR for different time periods for major and minor ports.

Table 1

Year	Major Ports	Non-Major Ports	All Ports
1950-51 to 1960-61	5.51	8.67	5.83
1960-61 to 1970-71	5.31	4.26	5.19
1970-71 to 1980-81	3.74	0.06	3.40
1980-81 to 1990-91	6.57	6.62	6.57
1990-91 to 2000-01	6.35	21.18	8.40
2000-01 to 2009-10	7.98	14.22	9.75
1950-51 to 2009-10	5.87	8.87	6.45

Source : Various issues of Major Port of India : A Profile, IPA

The decrease in share or lower CAGR is despite the fact that investments in major ports are more than in comparison to investments in minor ports.

THE RESEARCH QUESTIONS

- Which Indian major ports are efficient or in-efficient?
- Are Indian Ports investing in the right direction?
- Which dimension(s) of individual ports need attention?

OBJECTIVES

The underperformance of major ports in India has led to the need for a study that identifies the relative importance of the factors which determine the port performances. It is also essential from the policymakers' point of view to establish a causal relationship between these factors and articulate the overall efficiency level of the port. Keeping this in view, the objectives of this paper are set as to determine the efficiency level of the major ports of India and identify the dimension/s that need/s focus for improvement of port efficiency.

METHODS

DATA ENVELOPE ANALYSIS (DEA) AND FACTOR ANALYSIS – AN INTEGRATED APPROACH

An attempt has been made to integrate two salient methods namely Factor Analysis and Data Envelop Analysis (DEA) to determine port efficiency and identify the dimension that needs focus for improvement of port efficiency. The selected indicators relevant to container handling ports in India have been compiled and have been subjected to factor analysis for identifying the dimensions of port performance. The efficiency of the Indian ports was determined using Data Envelopment Analysis (DEA) and then compared with DEA results obtained separately for each of the dimensions of the individual ports to identify the cause of inefficiency, if any. The dimensions have been obtained through use of Rotated Factor Analysis. The analysis has been done using SPSS and DEAP software packages.

LITERATURE REVIEW

Roll and Hayuth (1993) made an attempt to compare port performance by applying Data Envelopment Analysis (DEA). Several attempts have been made to combine DEA and factor analysis to improve evaluation of decision making units (DMU). They suggested that an approach to imposing weight restrictions is to use factor analysis (FA), both for reduction of the inputs and outputs set via aggregation, and for specification of discrete data in a continuous domain. They used FA for extracting the underlying constructed outputs rather than selecting them, FA is also being used in this work for the purpose of transforming the original data set from a discrete domain into a continuous domain (Vargas S. & Bricker, 2000). The authors identified that DEA encounters when there is an excessive number of inputs or outputs, and suggested to employ principal component analysis (PCA) to aggregate certain, clustered data, whilst ensuring very similar results to those achieved under the original DEA model (Adler&Golany, 2001, 2002,2007; Ueda &Hoshiai, 1997; Adler, Yazhemsky, Tarverdyan , 2010). This paper by Premchandra (2001) considers a previous article published by Zhu in the European Journal of Operational Research which describes a joint use of Data Envelopment Analysis (DEA) and principal component analysis (PCA) in ranking of decision making units (DMUs). In Zhu's empirical study, DEA and PCA yield a consistent ranking. However, his paper finds that in certain instances, DEA and PCA may yield inconsistent rankings. The PCA procedure adopted by Zhu is slightly modified in this article by incorporating other important features of ranking that Zhu has not considered. Numerical results reveal that both approaches show a consistency in ranking with DEA when the data set has a small number of efficient units. But, when a majority of the DMUs in the sample are efficient, only the modified approach produces consistent ranking with DEA.

Literature review suggests that, so far, there has been no attempt to analyse the efficiency of DMUs on the basis of different dimensions. In this paper an attempt has been made to identify the different dimensions of Indian major ports using rotated FA and determine the efficiency of individual ports on each of this dimension separately.

RESULTS AND DISCUSSIONS

COLLECTION OF DATA

The following DMUs (major Indian ports/terminals) were put under the purview of this paper.

1. KOLKATA DOCK SYSTEM (KDS), 2. HALDIA DOCK COMPLEX (HDC), 3. PARADIP PORT TRUST (PPT), 4. VISAKHAPATNAM PORT TRUST (VPT), 5. CHENNAI PORT TRUST (ChPT), 6. TUTICORIN PORT TRUST (TPT), 7. COCHIN PORT TRUST (CoPT), 8. NEW MANGALORE PORT TRUST (NMPT), 9. MORMAGAO PORT TRUST (MgPT), 10. MUMBAI PORT TRUST (MbPT), 11. JAWAHARLAL NEHRU PORT TRUST (JNPT) 12 NSICT 13. GTIPL and 14. Kandla PORT TRUST (KPT).

The input variables chosen were (1) TRAFFIC, (2) VESSEL TRAFFIC(VTRAFFIC), (3) AVERAGE PRE BERTHING TIME (APBT), (4) AVERAGE PARCEL SIZE (APS), (5) AVERAGE OUTPUT PER SHIP BERTH DAY (AOPSBD), (6) PERCENTAGE OF NON WORKING TIME TO SHIP'S TIME AT PORT (PNWTSP), (7) DRAFT, (8) PVTO, (9) CRANES, (10) BERTHS, and (11) CAPACITY

The inverse of ATRT (Average Turn Round Time) that is influenced by the above variables and the increase in whose value (i.e., decrease in the value of ATRT) reduces the total transport cost has been taken as OUTPUT.

The sources for data are

- Major Ports of India : A Profile 2008-09
- Annual Administration Reports of all Major ports, 2008-09.

ANALYSIS OF DATA

The rotated factor analysis of the data set for the 14 DMUs identifies to two factors as shown below in the table 2 below:

Table 2: Rotated Component Matrix

Variables	Component 1	Component 2
VTRAFFIC	.931	.133
CAPACITY	.910	.288
TRAFFIC	.889	.416
CRANE	.870	.453
AOPSBD	.761	.532
BERTH	.733	-.140
DRAFT	-.029	.926
PNWTSP	-.360	-.674

Extraction Method – Principal Component Analysis; Rotation Method – Varimax with Kaiser Normalization and Rotation converged in 3 iterations

The variables for two different factors considered on the basis of factor loadings are shown below.

FACTOR 1: VTRAFFIC, CAPACITY, TRAFFIC, CRANE, AOPSBD, BERTH

FACTOR 2: DRAFT, PNWTSP

Traditionally DEA in port sector has been done with taking all the performance indicators. This paper does this also separately for the factors identified by factor analysis. As we are more concerned with the value of the ATRT (and hence the inverse of it), an output oriented DEA model has been chosen.

Table 3: Model : Output Oriented 1-stage DEA (CRS & VRS)

PORT	TE-OOCRS ORIGINAL	TE-OOCRS FACTOR1	TE-OOCRS FACTOR2	TE-OOVRS ORIGINAL	TE-OOVRS FACTOR1	TE-OOVRS FACTOR2	SE ORIGINAL	SE FACTOR1	SE FACTOR2
KDS	0.609	0.251	0.316	1.00	0.328	1.00	0.609	0.766 DRS	0.316 IRS
HDC	1.00	0.506	0.632	1.00	0.584	1.00	1.00	0.866 DRS	0.632 IRS
PPT	1.00	1.00	0.520	1.00	1.00	0.555	1.00	1.00	0.938 IRS
VPT	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ChPT	1.00	0.114	1.00	1.00	0.365	1.00	1.00	0.312 DRS	1.00
TPT	1.00	0.606	1.00	1.00	0.606	1.00	1.00	1.00	1.00
CoPT	1.00	0.424	0.756	1.00	0.671	0.846	1.00	0.633 DRS	0.894 DRS
NMPT	1.00	1.00	0.487	1.00	1.00	0.507	1.00	1.00	0.960 DRS
MgPT	1.00	1.00	0.582	1.00	1.00	0.674	1.00	1.00	0.864 DRS
MbPT	0.873	0.593	0.452	1.00	0.630	0.572	0.873 IRS	0.942 DRS	0.790 IRS
JNPT	1.00	0.151	0.461	1.00	0.328	0.538	1.00	0.461 DRS	0.856 DRS
NSICT	1.00	0.230	0.645	1.00	0.460	0.754	1.00	0.500 DRS	0.856 DRS
GTIPL	0.812	0.255	0.717	0.837	0.511	0.837	0.969 drs	0.500 DRS	0.856 DRS
KPT	0.934	0.934	0.483	0.934	0.934	0.508	1.00	1.00	0.949 IRS
MEAN	0.945	0.576	0.646	0.984	0.673	0.771	0.961	0.784	0.851

TE – Technical Efficiency, OOCRS – Output Oriented CRS, OOVRS – Output Oriented VRS, SE – Scale Efficiency

The above results clearly show that the Technical Efficiency on constant and variable returns to scales for all variables, for Factor 1 and Factor 2 may vary. For example Paradip Port (PPT) though has TE over CRS and VRS as 1.00 when all variables are taken simultaneously; the scores are less than 1.00 in case of factor 2 when DEA is performed over variables associated with factors 1 and 2 respectively. This implies that this port though appears to be over all efficient, may require attention to its infrastructure dimension comprising variables berth and draft (navigable depth) i.e. the Factor 2. Thus by combining the two approaches, namely FA and DEA, not only we could find the efficiency of the DMUs but also the dimensions that require attention.

Moreover for large variable set compared to number of DMUs, DEA over all variables may produce spurious results or in other words DEA loses its discriminatory power (Fried et al. (2008)). As in this case the number of variables is almost equal to number of DMUs and as such if the DMUs are ranked one, i.e., highest value in only one of the variables, the TE score for the DMUs may be equal to 1.00. Hence, it may be concluded that DEA performed over factors not only enhances the discriminatory power of the tool but also has directional property enabling the decision maker to take decision on the right cause.

CONCLUSION

The efficiency of major Indian ports needs to be improved to the global standards. The investments and decisions are required to be made in the right direction to achieve the above objective. The use of DEA alone is not sufficient to measure the right efficiency of the major ports. The combined use of factor analysis and DEA will enable to determine the dimensions that affect the output of the ports and also the technical efficiency scores over these dimensions. The dimensions with low scores require attention and the variables that constitute the dimensions will guide to the right decision.

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SELECTION BEST LOCATION OF WIND PLANTS IN TURKEY USING DEA

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ABSTRACT

Newly emerging renewable alternative energy resources are expected to take an increasing role in future energy scenarios. Environmental and technical benefits of wind energy have made it a promising alternative to conventional energy resources. Wind energy is a most ancient energy source and is the root material for almost all fossil and renewable types. Determining the priority of different locations has special importance for placing wind systems. Different factors may affect the selection of a suitable location for wind plants. These factors must be considered concurrently for optimum location identification of wind plants. This article presents an approach for location of wind plants by use of Data Envelopment Analysis (DEA). Efficiency scores of 12 months are evaluated by using the modified technique for order preference by similarity to ideal solution (TOPSIS) method. The administrated approach was tested for 34 different cities in Turkey in different regions

***Keywords**: **Wind** Plants, Data Envelopment Analysis (DEA), TOPSIS, Location*

INTRODUCTION

The negative effects of fossil fuels on the environment have forced many countries to use renewable energy sources. The technical benefits of wind energy have made it a promising alternative to conventional energy resources. Use of wind energy is rapidly developing in the world. These facilities have a great potential for supplying energy in remote regions. Determining the priority of different locations has special importance for the placement of wind systems.

Since the cost of investment in wind tribunes is high, feasibility studies prior to implementation of the projects is important. Problems encountered in the process of choosing the proper place for wind turbines, next to the examination of technical factors in overcoming the physical, economic, social, environmental and political factors, in order to support the decision making process of such complex applications, scientific studies are needed.

There are two basic criteria in the selection of the wind turbines. The first is efficiency of the area in terms of wind. The second fundamental fact is reduction of energy production cost to the minimum. The costs of land which the wind turbines are established in are one of the fundamental features in the second criterion. Credibility in availability and transportation and distance to the transformer centers, the topography, the land cover, the slope, the maintenance of turbines, the conservation areas, landslide areas and residential areas are significant factors about the area.

Deriving a model from the relationship between these factors create multiple relationships to determine the locations for wind power plants, will give investors the opportunity to pre-feasibility. Therefore, in this study, we will express a numerical example by use of Data Envelopment Analysis and the TOPSIS model and utilization of average wind speed, cost and distance to the power distribution networks which are the main factors of choosing suitable location for wind power plants in Turkey and by using the results of this example will help us in determination the most appropriate for the wind turbines in Turkey.

When analyzing the results obtained which are not directly reflected in the numerical size, the cost of energy which is the basic variable of second criterion must be considered in the assessment.

Papers on multi-criteria location problems were scarce until the past decade, when presenting and solving multi-criteria location problems have seen substantial growth and have opened new windows to location science indifferent areas of application (Zhong, et al., 2011).

To approach this issue, we have considered location selection of wind plants in this article. Determination of where to build wind observation stations is very important, and ideal location for such a region should in particular be able to represent the area well. Location problems are likely to have multiple objectives. The use of multi-criteria methods such as MCDM (Multiple Criteria Decision Making) and MADM (Multiple Attribute Decision Making) have become more common for considering different indicators for location optimization of such plants. In this article, DEA is used as a multi-criteria method for location of wind plants. This paper utilized 2010 wind speed data from 34 cities to assess the best location for wind plants. The obtained results of DEA efficiency scores in 12 months have been ordered by TOPSIS for selection of best place.

METHODS

In this study we have applied DEA model for optimizing locations of wind plants in 34 cities in Turkey. Selected cities are those which have windy weather in Turkey, which has led to the wide coverage of the model.

For determining the best city/cities, 3 different parameters were used. These parameters were as follows:

Distance to power distribution networks (km): As noted for establishing power plants, selection of regions with low distance to power distribution networks is a plus. The cost of electrification from the central power network is very high and hence supplying energy from local power generators that have low maintenance and operational costs is preferred. For this purpose, wind plants for windy locations are an excellent solution. Under this assumption, this parameter has an input structure.

Land cost (Turkish Lira (1TL ≈ 1.8$)): For wind plants, another aspect must be considered. Land is the underlying infrastructure for construction of each plant. This is more important for wind than for other plants because they considerably need more land than other methods of energy generation.

Average wind speed (km/h): Considering the output indicators of the DEA model, the most important factor for region selection of a wind plant is the regional wind rate. As slight changes in the location of a wind power plant through a particular region would not cause significant alterations in geographical factors, wind speed is considered as a level 1 indicator. In location feasibility studies of wind plants, higher wind speed will increase the possibility of selection of a particular location for wind plant establishment. This is why this indicator is considered an output indicator (Zhong et al.,2011).

Cities used in the proposed model (which are the DMUs of level 2) and the quantity of related indicators are presented in Table1 and Fig.1. Land cost and distance to power distribution networks are presented in

Table 1. Average wind speeds are presented in Table 2. The values of level 1 indicator distance to power distribution networks are based on the scores determined by the experts for each city. Therefore, this indicator has an increasing structure. The required data indicators which were used in the proposed model were gathered from the Turkish Meteorology web page (http:/www.mgm.gov.tr).

Table 1. Statistical values of the land cost, distance and wind speeds

Figure1. Selected cities in Turkey

DATA ENVELOPMENT ANALYSIS

Data Envelopment Analysis (DEA) is a nonparametric method for measuring the efficiency of a decision-making unit (DMU). Any group of entities that receives the same set of inputs and produces the same set of outputs could be designated as a DMU; it could be a group of people, a company, hospital, school, industry, or country. To determine the relative efficiency of each DMU in the group, DEA collapses inputs and outputs defined by the model into a ratio of a single meta-input and meta-output and uses linear programming methods to calculate the efficiency score for each DMU, where they obtained score is reflective of the performance (Shimshak et al., 2009;Bougnol et al., 2009;Morais and Camanho, 2011;Zhong et al., 2011, Sozen and Alp, 2013).

In order to reach the efficient solution, DEA can use an input oriented (holding outputs constant and minimizing amount of inputs) or an output oriented approach (holding inputs constant and maximizing amount of outputs). Our DEA model provide information about how well location perform their tasks when compared to their references. Determination can be done assuming Constant Returns to Scale (CRS) which implies that increase in inputs leads to a proportional increase of outputs, or Variable Returns to Scale (VRS) which implies that increase in inputs leads to changes in outputs in a variable rate.

In this study we have used CCR and input-oriented models. By use of the input oriented of the CCR model of DEA, by minimizing inputs, the cities which can have the maximum output will be efficient and by respecting it the optimal location of turbines in the most efficient cities will be determined in this article.

CCR method is based on the assumption "constant returns to scale". If the activity of j. decision making unit is hj, the goal should be the maximization of this value. So, the goal function can be stated as in the (Eq.2) formulation under the input oriented assumption (Tarım, 2001).

$$\max h_j = \frac{\sum_{r=1}^{n} u_r y_r}{\sum_{i=1}^{m} v_i x_i} \tag{1}$$

Constraints can be stated as in the (Eq.3) formulation.

$$\frac{\sum_{r=1}^{n} u_r y_r}{\sum_{i=1}^{m} v_i x_i} \leq 1$$
$$u_r \geq 0$$
$$v_i \geq 0 \tag{2}$$

As mentioned above, the solution of the fractional programming set is more difficult compared to the linear programming set. When the (Eq.1) and (Eq.2) formulations are stated with linear programming logic, (Eq.3) and (Eq.4) formulations can be achieved.

$$\max h_j = \sum_{r=1}^{n} u_r y_r \tag{3}$$

$$\sum_{i=1}^{m} v_i x_i = 1 \tag{4}$$

$$\sum_{r=1}^{n} u_r y_r - \sum_{i=1}^{m} v_i x_i \geq 0$$
$$u_r, v_i \geq 0$$

(Eq.3) and (Eq.4) formulations are organized for the input-oriented situation. If the output-oriented situation will be used for CCR method, the linear programming model will be as in the (Eq.5) and (Eq.6) formulations.

$$\min g_j = \sum_{i=1}^{m} v_i x_i \tag{5}$$

$$\sum_{r=1}^{n} u_r y_r = 1$$

$$-\sum_{r=1}^{n} u_r y_r + \sum_{i=1}^{m} v_i x_i \geq 0$$
$$u_r, v_i \geq 0 \tag{6}$$

Considering whether the model is input-oriented or output-oriented, if a decision maker wants to make a decision regarding the activities of the decision points with CCR method, the above mentioned model must be applied for all decision points. When the model is solved for each decision point, total activity standards will be obtained for each decision point. If these standards are equal to 1', this indicates activity for decision points, if they are smaller than 1', this indicates inactivity for decision points.

MODIFIED TOPSIS METHOD

Here we use the TOPSIS method, The TOPSIS method proposed by Hwang and Yoon in 1981 and is applied many of decision making problems (Boran, 2013). In this paper, we represent a modified TOPSIS method which was proposed by Deng et al in 2000. The modified TOPSIS has been reported as a rational and comprehensible method. The concept of TOPSIS lets us compare objective weights.

The concept of TOPSIS is that the most preferred alternative should not only have the shortest distance from the positive ideal solution, but also have the longest distance from the negative ideal solution.

Let A = {A1; A2; … ; Am} be a set of alternatives, W = {w1; w2; w3; … ;wn} be a set of weights and C ={C1; C2;…; Cn} be a set of criteria.

All the ratings are assigned to alternatives with respect to a decision matrix denoted by X(xij)mxn. Normally, a modified TOPSIS has a process like the following:

Step 1. Normalize the decision matrix.

The normalized value {rij} can be computed by:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}} \quad i=1,2,\dots,m; \quad j=1,2,\dots,n \tag{7}$$

We will not need the above step if Efficiency scores are between 0 and 1 in DEA result.

Step 2. Determine positive and negative ideal solutions.

The positive ideal solution and negative ideal solution are determined, respectively as follows:

$$A^* = \{v_1^*, v_2^*, ..., v_n^*\} = \{(\max_j v_{ij} \mid j \in I_1), (\min_j v_{ij} \mid j \in I_2)\} \tag{8}$$

$$A^- = \{v_1^-, v_2^-, ..., v_n^-\} = \{(\min_j v_{ij} \mid j \in I_1), (\max_j v_{ij} \mid j \in I_2)\} \tag{9}$$

I1 represents benefit criteria, and I2 represents cost criteria.

Step3. Obtain the weighted separation measures for positive and negative ideal solutions.

Separation measures based on weighted Euclidean distance are calculated for positive and negative solutions, respectively.

$$D_i^* = \sqrt{\sum_{j=1}^{n} w_j (v_{ij} - v_i^*)^2} \qquad \text{i=1,2,…,n} \qquad (10)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} w_j (v_{ij} - v_i^-)^2} \qquad \text{i=1,2,…,n} \qquad (11)$$

wj is the weight of the jth criterion and $\sum_{j=1}^{n} w_j = 1$

Step 4. Calculate the relative closeness to the ideal solution and rank the alternatives.

The relative closeness for alternative Ai according to A* is defined as follows:

$$C_i^* = \frac{D_i^-}{D_i^* + D_i^-} \qquad (12)$$

According to the relative closeness to the ideal alternatives, the bigger is the C*i, the better is the alternative Ai.

RESULTS AND DISCUSSIONS

By analyzing the results, critical indicators for each DMUs were identified. Land cost was the most critical indicator for about 85% of the cases and distance to power distribution networks was the most critical in15% of the cases. This shows the importance of land cost factors for selecting the location of solar plants within a city in Turkey. The results have been presented in Table 6. According to result obtained for year 2010, Bodrum, Marmaris, Sinop and Kusadasi are the most effective cities in the order shown, meaning that they are the most suitable cities for location of wind plants in Turkey for February.

As it can be seen in the following table, each city can find out that how much they must they change their inputs to be efficient.

Considering the Table 2 of average wind speeds and the comparison of that with efficiency values it becomes clear that although Istanbul, Gokceada, Balikesir and Izmir cities have greater values in wind speed, they're not accepted as efficient cities; considering it is evident that land price and also the distance from electricity distribution center has caused these cities to not be in the list of efficient cities.

The required resemblance percentage for locations (cities) to resemble a referenced location is given for each location in the references column in Table 3. Moreover, the redundancies in inputs and outputs are given in this table.

For instance, the city of Kusadasi is efficient in the second month but in order to be efficient in the first month it must change its input parameters, land prices and the distance with electricity distribution center. For Kusadasi, in the first month, if the land price decreases from 20 to 19.95 Turkish Lira (1TL ≈ 1.8$) and the distance from electricity distribution center decreases from 15 Km to 13.3 Km, this city will be efficient for February. In another example, in fifth month for Bodrum city, efficiency score is 0.81 and its benchmarks is Sinop with 0.83. This means that Bodrum could be efficient if reaches 0.83 entrances of the Sinop inputs for February.

As illustrated on the Table 2, monthly average wind speed at coast al towns in Aegean Sea and Black Sea are very high, as seen in Table 4, few of these cities (Sinop, Bodrum, Kuşadası, Gökçeada and Marmaris) are efficient. Because of the reason the prices of land cost in the Aegean Sea and Black Sea cities are very high in contrast to the efficient cities, and also another reason is being far from the electricity transmission networks.

The statistics and results of efficiency scores are given in Table 4.The cities which the efficiency score of them is 1 or nearly 1 are known as efficient cities.

Between these cities, the cities have been selected for establishment of wind turbines that in term of proximity to transformers and land cost can have the maximum outputs (average wind speed) with minimum inputs. For this reason, these are the best cities for establishment of the wind turbines.

Because the efficiency scores are changing 12 months we need to classify by TOPSIS method. The TOPSIS method assesses gives one answer for the efficiency scores which have been calculated for 12 months separately and by classifying according to the obtained results the highest numbers will show the most appropriate cities for establishment of wind turbines.

Table 3.Efficiency scores for February, June and September

DMU	Numbers on the right indicate the references for efficient DMUs (in cases with dark background colors); and The peer names and weight values for inefficient DMUs which are indicated by a white background		
	February	June	September
ZONGULDAK	BODRUM (0,95)	BODRUM (0.53)	BODRUM (0,59)
SINOP	8	BODRUM (0.10) ICEL (0.89)	BODRUM (0.23) MARMARIS (0.41)
SAMSUN	SINOP(0,32) BODRUM (0,16)	BODRUM (0.19) ICEL (0.29)	BODRUM (0,23) MARMARIS (0.14)
ORDU	KUSADASI (0,20)	MARMARIS (0,34)	KUSADASI (0,24)
GIRESUN	KUSADASI (0,28)	MARMARIS (0,38)	KUSADASI (0,22)
TRABZON	KUSADASI (0,31)	MARMARIS (0,35)	KUSADASI (0,35)
ARTVIN	KUSADASI (0,24)	MARMARIS (0,48)	KUSADASI (0,37)
ISTANBUL	SINOP(0,38) BODRUM (1,92)	BODRUM (1,61) ICEL (0,28)	BODRUM (2.41) MARMARIS (0.21)
EDIRNE	KUSADASI (0,31)	MARMARIS (0,40)	KUSADASI (0,30)
GOKCEADA	KUSADASI (0,74)	MARMARIS (0,70)	KUSADASI (0,66)
BALIKESIR	SINOP(0,52)MARMARIS (0,39)	ICEL (0,75) MARMARIS (0.22)	BODRUM (0,20) MARMARIS (0,92)
IZMIR	SINOP(0,84)BODRUM(0,07)	BODRUM (0,16) ICEL (0,79)	BODRUM (0.28) MARMARIS (0,38)

MANISA	KUSADASI (0,22)	MARMARIS (0,31)	KUSADASI (0,25)
AFYON	KUSADASI (0,43)	MARMARIS (0,61)	KUSADASI (0,37)
USAK	KUSADASI (0,27)	MARMARIS (0,41)	KUSADASI (0,25)
AKSARAY	KUSADASI (0.48)	MARMARIS (0.50)	KUSADASI (0,36)
DENIZLI	SINOP(0,53) MARMARIS (0,25)	ICEL (0,53) MARMARIS (0.06)	BODRUM (0.10) MARMARIS (0,36)
BURDUR	KUSADASI (0,45)	MARMARIS (0,44)	KUSADASI (0,30)
ISPARTA	KUSADASI (0,24)	MARMARIS (0,31)	KUSADASI (0,20)
DIYARBAKIR	SINOP(0,43) MARMARIS (0,01)	BODRUM (0.08) ICEL (0,75)	BODRUM (0.13) MARMARIS (0,25)
HAKKARI	KUSADASI (0,21)	MARMARIS (0,44)	KUSADASI (0.28)
CANKIRI	KUSADASI (0,21)	MARMARIS (0,32)	KUSADASI (0,19)
SAKARYA	KUSADASI (0,34)	MARMARIS (0,51)	KUSADASI (0,46)
BOZCAADA	KUSADASI (0,29)	MARMARIS (0,57)	KUSADASI (0,37)
ADANA	SINOP(0.24)BODRUM (0,87)	BODRUM (0,55) ICEL (0.14)	BODRUM (0,60) MARMARIS (0.07)
SAMANDAG	MARMARIS (0,25) KUSADASI (0,07)	MARMARIS (0.48)	MARMARIS (0,32) KUSADASI (0.09)
ISKENDERUN	KUSADASI (0,24)	MARMARIS (0,54)	KUSADASI (0,31)
FETHIYE	KUSADASI (0,44)	MARMARIS (0,55)	KUSADASI (0.32)
MUGLA	MARMARIS (0,33) KUSADASI (0,03)	MARMARIS (0,42)	MARMARIS (0,34) KUSADASI (0. 03)
AYDIN	MARMARIS (0,28) KUSADASI (0,06)	MARMARIS (0,40)	MARMARIS (0,30) KUSADASI (0.06)
BODRUM	5	7	10
ICEL	SINOP(0,43) MARMARIS (0,13)	8	BODRUM (0.14) MARMARIS (0.41)
MARMARIS	7	24	12
KUSADASI	21	MARMARIS (0,96)	21

In Table 5, the values which these cities must reach in order to be efficient is shown.

Table 5. Analysis of Efficiencies

	1	2	3	4	5	6	7	8	9	10	11	12
GOKCEADA	15 10	15 11.25	* **	15 11.25	15 10	15 10	15 10	15 11.25	15 11.25	* **	* **	* **
IZMIR	11.4 1.9	16.5 6.6	17.55 7.02	17.55 7.02	6,03 7,37	13 6	7.65 5.1	6.6 4.94	7.65 5.1	16.2 6.48	5.55 4.44	7.2 4.8
MARMARIS	* **	* **	* **	11.4 8.55	8,82 0,78	* **	* **	12.8 9.6	* **	10.05 8.04	11.7 9.36	* **

KUSADASI	19.95 13.3	* **	12.45 9.96	* **	11.7 14,03	11.7 14,03	11.7 14,03	* **	* **	17.55 14.04	19.35 15.48	12.45 9.96

*Land Cost

**Distance from Distribution

With constant input values, the efficiency value changes by increase of the monthly average wind and will be follow its changes (Figures 2-3). The Figure 2.5 shows that the efficiency scores and wind speed are parallel. These graphics of the cities which are efficient or are nearly efficient, indicate that they are efficient continuously in some months and have missed their efficiency in some other months numerically.

As the efficiencies which are 1 or nearly 1 are parallel to wind speed have high potential in selection of the optimal locations. It must be reminded that for the cities like Izmir (Fig.3) which their efficiency are nearly 1 for all months we can earn efficiency by reduction of land cost or distance to transformers.

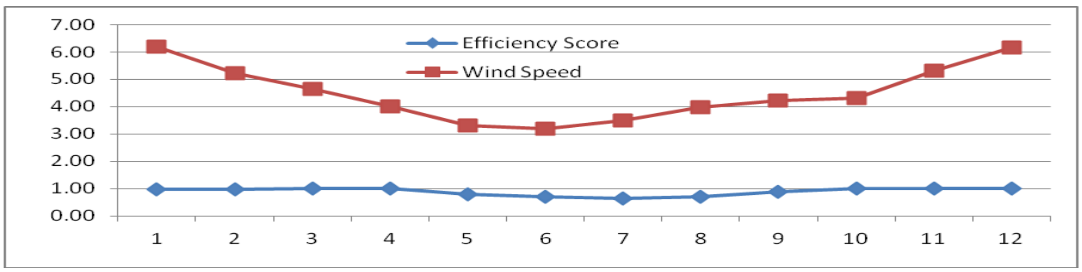

Figure 2.Comparison of Efficiency Scores by Average Wind over a 12 Month Period for Gokceada City

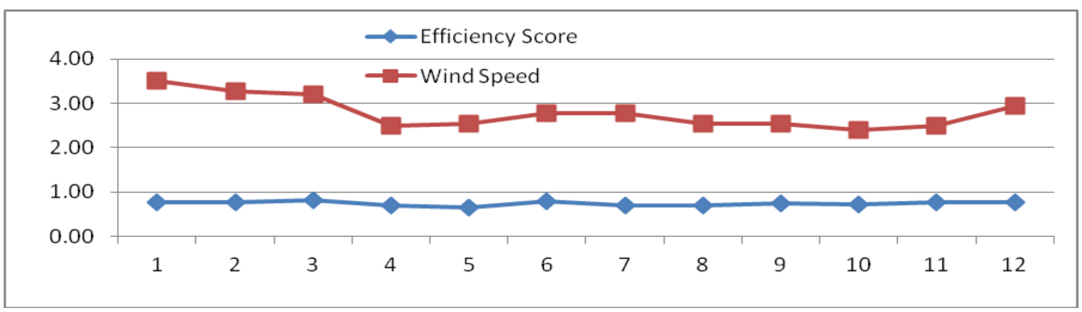

Figure 3.Comparison of Efficiency Scores by Average Wind over a 12 Month Period for Izmir City

The TOPSIS in this analysis; the efficiency analysis, has been calculated separately for each month and by use of these efficiency results and using the prioritizing method has been recognized and the distances have been specified from ideal answer and the priority of TOPSIS has been measured for 12 months and has been specified with location(Table 6). The results obtained with currently established turbines in places where wind turbines are much fit 2,000 MW.

In terms of efficiency scores for the power production continuous in centrals, the assessment of centrals for 12 months would be a correct approach. For this reason even if the results of TOPSIS method be the same with average values of 12 months, it can make the analysis more valuable and give new dimension to the analysis.

CONCLUSIONS

Wind plants are very desirable as an alternative source of energy. Hence, determination of the optimum locations for use of this resource is a vital issue. Generally, average wind speed as a primary criterion is used for determining the optimum locations for wind plants. Therefore, in this approach some local and social considerations are ignored.

Some criteria such as distance to power distribution networks, land cost and monthly average wind speed are considered in this work. In this article, a DEA approach that uses a number of predefined indicators has been used to identity optimum locations of wind plants in Turkey, DEA was used to rank various locations' capabilities with respect to some output and input indicators for 34 cities in Turkey.

The obtained results for locating the most suitable lands for establishment of wind centrals in Turkey in the cases which are not computable as like as the vegetation, protected areas, the resident areas have not any conflict. Even though, the land cost which is determined in scientific researches has been used in analysis the costs are not considered by the selection of provinces and the capital of them but the optimum pricing for suitable land for the establishment of centrals and the distance to distribution networks has been recognized.

Before installation and implementation the wind powerhouses which are naturally compatible, according to the official accounting approaches, the report of the environment is getting ready.

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THE DEA AND FUZZY AHP APPROACH TO HEALTH-CARE ORGANIZATIONS' PERFORMANCES

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ABSTRACT

This paper processes of Fuzzy Analytic Hierarchy Process (FAHP) and Data Envelopment Analysis (DEA) to select the units with most efficiency. The research deals with an actual application of health-care organizations. This research is a two-stage model designed to fully rank the organizational alternatives, where each alternative has multiple inputs and outputs. DEA and FAHP ranking do not replace the DEA classification model; rather, it furthers the analysis by providing full ranking in the DEA context for all units. To achieve this goal, relative efficiencies of the selected health-care organizations are obtained by means of a detailed pair- comparison.

***Keywords**: Data Envelopment Analysis (DEA), Analytic Hierarchy Process (AHP), Data Envelopment Analysis and Fuzzy Analytic Hierarchy Method (DEA-FAHP)*

INTRODUCTION

The health care industry faces new challenges every day. Management in all industries is moving toward more objective performance evaluation and decision making. Performance evaluation based on optimization techniques and their normative structure not only creates benchmarks, but also provides information for lacking organizations and illustrates how to improve performance. During the past few decades, parametric and non-parametric methods have been employed increasingly to measure and analyze the performance of health care services. Performance, as in other service industries, can be defined as an appropriate combination of efficiency and effectiveness.

Comparative performance analysis can be undertaken by various methods. Different from the others, Data Envelopment Analysis (DEA) is a non-parametric technique and allows multiple inputs and outputs to be used in a linear programming model that develops a single score of efficiency for each observation used to measure technical efficiency, scale efficiency, allocative efficiency, congestion efficiency and technical change. The value of DEA lies in its capability to relatively evaluate the individual efficiency or performance of a decision making unit within a target group of interest that operates in a certain application domain such as the banking industry, health care industry, agriculture industry, transportation industry, etc. [10].

Analytic Hierarchy Process (AHP) proposed by Saaty [12] is very popular among the various Multi-Criteria Decision-Making (MCDM) techniques proposed, and has been applied in wide variety of areas including planning, selecting a best alternative, resource allocation and resolving conflicts. The primary advantage of the AHP is its use of pairwise comparisons to obtain a ratio scale of measurement. Ratio scales are a natural means of comparison among alternatives and enable the measurement of both tangible and intangible factors.

Fuzzy set theory is a mathematical theory pioneered by Zadeh [17]. It is designed to model the vagueness or imprecision of human cognitive processes. It aids in measuring the ambiguity of concepts that are associated with human beings' subjective judgment. Since the performance evaluations are done with decision makers' preferences, its evaluation must be conducted in an uncertain, fuzzy environment.

Therefore, in this paper, a hybrid model combining Fuzzy AHP and DEA is proposed to avoid the pitfalls of each method, and applied to evaluate the performance of seven hospitals investigated in Turkey.

LITERATURE REVIEW

The importance of healthcare efficiency is extremely high, given the rapid growth in healthcare costs and the increasing numbers of people covered by publicly-financed programs. To identify useful healthcare productivity improvements, efficiency must be validly measured. Hussey et al. [8] made a literature review of health care efficiency measures and classified the efficiency measures by perspective, outputs, inputs, methods used and reporting of scientific soundness. According to this study, DEA is one of the two most common approaches.

DEA is a non-parametric approach that does not require any assumptions about the functional form of the production. About 1000 articles have been written on the subject, providing numerous examples and further development of the model. In the simplest case of a unit having a single input and output, efficiency is defined as the ratio of output/input. DEA, however deals with units having multiple inputs and outputs that can be incorporated into an efficiency measure where the weighted sum of outputs is divided by the weighted sum of inputs [5].

As far as the authors know, the latest literature review over the applications of DEA is offered by Liu et al. [10]. They covered DEA papers published in journals indexed by the Web of Science database from 1978 through August 2010. Results show that among the multifaceted applications, health care is one of the top-five industries addressed in the literature and most of the papers on this area studied hospital performance. Hollingsworth [7] summarized the latest development of DEA application in the health care category. They pointed out that the techniques used in efficiency studies in the health care area are mainly based on DEA. Emrouznejad et al. [4] presented a listing of DEA research covering theoretical developments as well as ''real-world'' applications from inception to the year 2007.

AHP is a measurement theory that prioritizes the hierarchy and consistency of judgmental data provided by a group of decision-makers. AHP incorporates the evaluations of all decision-makers into a final decision without having to elicit their utility functions on subjective and objective criteria, by pair-wise comparisons of the alternatives. However, the conventional AHP method is incapable of handling the uncertainty and vagueness involved in the mapping of one's preference to an exact number or ratio. The major difficulty with classical AHP is its inability in mapping human judgements [3, 9]. In recent years it has been observed that due to confusion in the decision makers mind, probable deviations should be integrated to the decision making process. The fuzzy model can deal with this incapability by allowing metrics that can assess intangible factors. Fuzzy analytic hierarchy process (FAHP) can be used to evolve such a model [13]. Sun [15], Buyukozkan et al. [1], Sinimole [13] and Vahidnia et al. [16] developed evaluation models based on FAHP.

METHOD: DEA-FAHP

Based on two sets of multiple outputs contributing positively to the overall evaluation, DEA deals with classifying the units into two categories, efficient and inefficient [6]. The original DEA does not perform fully ranking, it merely provides classification into two dichotomic groups: efficient and inefficient. It does not rank them-all efficient units which are equally good in the pareto sense [11, 14].

Here in FAHP evaluation is expressed by linguistic term and then set into fuzzy numbers. DEA-FAHP model integrates into two well known methods. The steps of the methodology are as follows:

Step 1: Determine the decision matrix ($e_{k,k'}$) using DEA method. With *m* alternatives and *n* criteria, $e_{k,k'}$ can be expressed by the Mathematical (Weighted Linear) Representation of the problem, which is given by Equations (1)-(6).

$$e_{k,k'} = MAX \sum_{r=1}^{s} u_r y_{rk} \quad (1)$$

Subject to

$$\sum_{i=1}^{m} v_i x_{ik} = 1 \quad \forall\, k \quad (2)$$

$$\sum_{r=1}^{s} u_r y_{rk} - \sum_{i=1}^{m} v_i x_{ik} \le 0 \quad \forall\, k \quad (3)$$

$$\sum_{r=1}^{s} u_r y_{rk'} - \sum_{i=1}^{m} v_i x_{ik'} \le 0 \quad \forall\, k' \quad (4)$$

$$where\ k = 1, \dots, n,\ \ k' = 1, \dots, n\ \ and\ \ k \neq k'.$$

$$u_r \ge 0 \quad r = 1,2, \dots, s \quad (5)$$

$$v_i \ge 0 \quad i = 1,2, \dots, m \quad (6)$$

By solving this mathematical model, $e_{k,k'}$ elements are solved and the binary compared matrix is obtained.

Step 2: Set up the Triangular Fuzzy Numbers. Each expert makes a pair-wise comparison of the decision criteria and gives them relative scores. The fuzzy conversion scale is as in Table 1.

Table 1: The 1-9 Fuzzy conversion scale [16]

Importance intensity	Triangular fuzzy scale $\widehat{G_1} = (l_i, m_i, u_i)$
1	(1, 1, 1)
2	(1.6, 2.0, 2.4)
3	(2.4, 3.0, 3.6)
5	(4.0, 5.0, 6.0)
7	(5.6, 7.0, 8.4)
9	(7.2, 9.0, 10.8)

Step 3: Compute the value of fuzzy extent. With respect to the i^{th} object, S_i is calculated as:

$$S_i = \sum_{j=1}^{m} H_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} H_{gi}^{j}\right]^{-1} \qquad (7)$$

Where g_i states the goals of the decision hierarchy and H_{gi}^{j} is the decision matrix with *n* objects and *m* goals, where $i = 1, \ldots, n$ and $j = 1, \ldots, m$, inverse of the vector is computed as follows [2]:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} H_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \qquad (8)$$

Step 4: The degree of possibility of $\mathrm{H_1 = (l_1, m_1, u_1) \geq H_2 = (l_2, m_2, u_2)}$ is defined according to Equation (9).

$$\mathrm{V(H_1 \geq H_2) = sup_{x \geq y}[min(\mu_{H1}(x), \mu_{H2}(y))]} \qquad (9)$$

This equation is defined as follows:

When a pair $\mathrm{(x, y)}$ exists such that $\mathrm{x \geq y}$ and $\mathrm{\mu_{H1}(x) = \mu_{H2}(y) = 1}$, then we have that $\mathrm{V(H_1 \geq H_2) = 1}$, since H_1 and H_2 are convex fuzzy numbers.

The corresponding membership functions are defined as follows [2]:

$$V(H_1 \geq H_2) = \mu_{H1}(d) = \begin{cases} 1, & if\ m_1 \geq m_2 \\ 0, & if\ l_2 \geq u_1 \\ \frac{l_1 - u_2}{(m_1 - u_1) - (m_2 - u_2)}, & otherwise \end{cases} \qquad (10)$$

The intersection of H_1 and H_2 is shown in Figure 1. To compare H_1 and H_2, we need the values of $V(H_1 \geq H_2)$ and $V(H_2 \geq H_1)$.

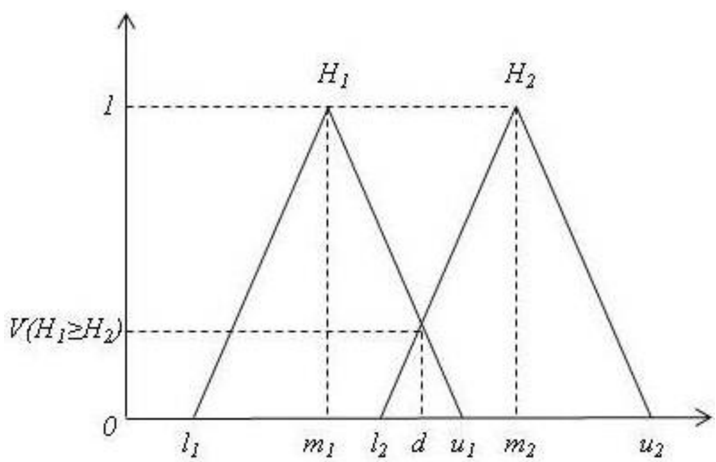

Figure 1. The intersection between H_1 and H_2

Step 5: The degree possibility for a convex fuzzy number to be greater than *k* convex fuzzy numbers, can be defined as:

$$V(H \geq H_1, H_2, \ldots, H_k) = V[(H \geq H_1)\ and\ (H \geq H_2)\ and \ldots$$

$$and\ (H \geq H_k) = \min V(H \geq H_i),\ i = 1,2,3 \ldots k \qquad (11)$$

Assume that $d'(A_i) = \min V(S_i \geq S_k)$. For $k = 1,2,\ldots,n$; the weight vector is given as follows:

$$W' = \left(d'(A_1), d'(A_2), \ldots, d'(A_n)\right)^T \qquad (12)$$

Step 6: The normalized weight vectors can be defined from

$$W = \left(d(A_1), d(A_2), \ldots, d(A_n)\right)^T \qquad (13)$$

where W is a non fuzzy number.

RESULT AND DISCUSSION

The aim of this research is prioritizing effective health-care organizations to improve performance. This research has been done two stages. Researchers used DEA-FAHP for prioritizing alternatives.

In this section we will describe how a DEA-FAHP method was applied via an example of a selected the most appropriate hospitals. Our data were provided from the seven hospitals for 2010 in Turkey in three cities. The suggested model demonstrated an example of selected Hospitals in Turkey, which is a comprehensive public Hospital. Seven Hospitals have been considered in our evaluation. In our study, we employ two input evaluation criteria and three output evaluation criteria. The attributes which are considered here in assessment of *Hi(i*= 1, 2, . . . , 6) are(1) *C1* , *C2* are inputs and (2) *C*3, . . . , *C5* are outputs.

i. Number of Doctors(*C1*)

ii. Number of beds(*C2*)

iii. Bed Ratio(*C3*)

iv. Total Surgery Operations(*C4*)

v. Number of Patient(*C5*)

From these data, we derived the variables used in the model depicted in Figure 2.

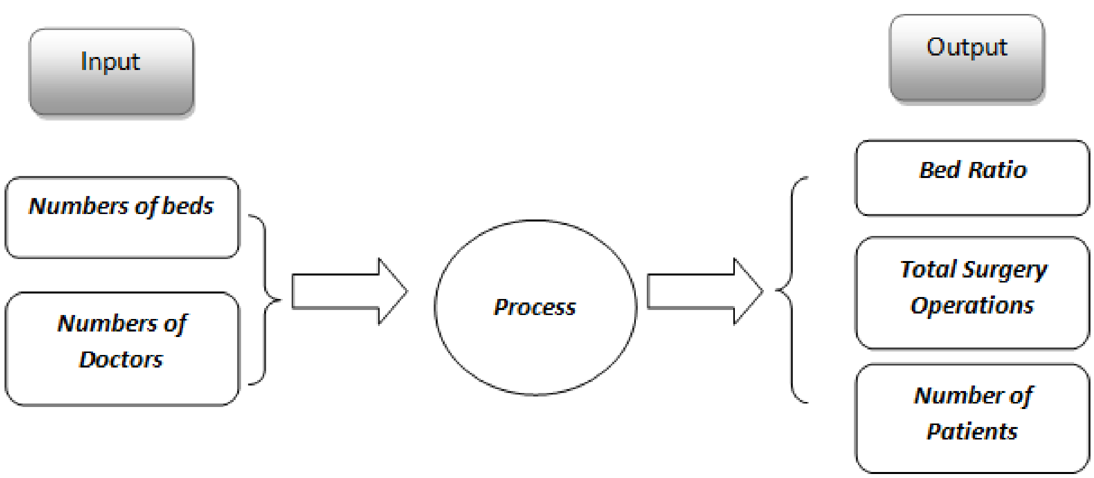

Figure 2. Variables of the model

Solution obtained by DEA-FAHP is presented in Table 2.

Table 2. Comparison table for DEA-FAHP method

Hospitals	DEA-FAHP	rank
H1	0.40	1
H2	0.028	4
H3	0.028	4
H4	0.229	3
H5	0.028	4
H6	0.26	2
H7	0.028	4

For each hospital, DEA-FAHP captures the proportion of the corresponding efficient frontier of the effectiveness that is achieved by the hospital. The result score is always the-bigger-the-better. The result show that, as regards the selected inputs and outputs, the efficiency score of the Hospital 1 (DEA-FAHP: 0.40) has the highest score due to its highest efficiency and performance. Hospitals 2, 3, 5 and 7 (DEA-FAHP: 0.028) has the lowest score of the seven hospitals, and is ranked in the last place.

CONCLUSIONS

The presented paper employs DEA-FAHP methods to evaluate in healthcare organization, mainly seven hospitals in Turkey. Performance evaluation and measurement in healthcare sector are important for all hospitals in order to determine gaps with respect to other competitors based on determined inputs and outputs. The hybrid model DEA-FAHP combines the best of both models by avoiding the pitfalls of each. Therefore, we have presented an effective model for rank scaling of the units with multiple inputs and multiple outputs using both DEA and FAHP to evaluate the performance of public hospitals located in Turkey.

The advantage of the hybrid DEA-FAHP ranking model is that the FAHP pair-wise comparisons have been derived mathematically from the multiple input/output data by running pair-wise DEA runs. Thus, there is no subjective evaluation. On the other hand, a human decision-making process usually contains fuzziness and vagueness, the FAHP is adapted to solve the problem. Finally, the DEA-FAHP method has capability to deal with similar types of situations with the presence of uncertainty in MCDM problems such as project selection, ERP selection, and many other areas.

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THE EFFICIENCY ANALYSIS OF ACADEMIC DEPARTMENTS USING DEA WINDOW ANALYSIS

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ABSTRACT

In today's global world, universities play a significant role in the development of a country. They now become centres of creating new ideas, generating and transferring knowledge that contributes to the quality of life of the country and its people. In Malaysia, higher education has undergone major and rapid changes. A large sum of funds has been allocated by the Malaysian Government for the higher education sector. To monitor the performance of these universities, relative efficiency of these universities need to be evaluated from time to time. In this paper, we propose an integrated model Assurance Region DEA Window Analysis (AR-WA) to measure efficiency trend of twenty four academic departments of a public university in Malaysia over a five year period (2006-2011. Analytic Hierarchy Process (AHP) is used to obtain the decision makers' preferences and the results are then used to determine the bounds of the output weights. The results reveal that the efficiency of most departments changes over time to different extents and quite substantially for some of them.

Keywords: *DEA window analysis; Assurance region model; Analytic Hierarchy; Academic departments*

INTRODUCTION

In Malaysia, higher education has undergone substantial and rapid changes compared to twenty years ago. The Ministry of Higher Education (MOHE) was formed in 2004 to take charge of higher institutions in Malaysia that covers 20 public universities and 33 private universities. The Malaysian Government has increased the allocation for MOHE from RM13.2 billion under the Eight Malaysian Plan to RM18.4 billion under the Ninth Malaysian. In an effort to be the hub of tertiary education in this region, some public universities have been given an autonomous status and they need to remain competitive. This has motivated university top management to seek effective strategies to measure relative efficiency of academic departments. DEA has been widely used to meet this purpose.

In many studies on higher learning sector, DEA is applied on a cross sectional data where each decision making unit such as academic unit or university is observed and measured only once (Abbott, 2003; Johnes, 2006; Kuah & Wong, 2011). These results can be misleading and biased because an academic department may be relatively efficient for a one time period but might not be consistently efficient in the long run (Cullinane & Wang, 2006; Kumbhakar & Lovell, 2003). Furthermore, according to Kumbhakar and Lovell (2003), cross-sectional data gives a snapshot of efficiency of DMUs but efficiency results provided by a panel data on the other hand, gives more reliable and valid evidence not only on their efficiency in a single period but also their efficiency trends over time. This fact is also supported by Asmild, Paradi, Aggarwall, & Schaffnit (2004). Therefore, DEA window analysis will be applied in this study.

One issue in the traditional DEA window analysis is the weight flexibility. The original DEA window analysis model allows each decision making unit (DMU) to choose its own input and output weights in order to maximize its efficiency score. However, this weight flexibility often leads to unrealistic and unacceptable efficiency results (Allen & Thanassoulis, 2004). The problem occurs when giving a big weight to input-output factors with less importance or giving small (or zero) weight to important variables. In the situation where inputs and outputs are assigned zero weight, these factors are neglected in the efficiency evaluation that may produce unrealistic efficiency results. The experts might have their own subjective opinions on the importance of inputs and weights. A good methodology should incorporate their expert judgment because their knowledge and experience will provide valuable information on the importance of the indicators.

This paper suggests assigning more realistic weights by incorporating value judgment from the experts into DEA window analysis. The model that is proposed is Assurance Region DEA Window Analysis (AR-WA). Analytic Hierarchy Process (AHP) proposed by Saaty (1990) is used to determine the bounds of output weights. The integrated method will be applied to measure efficiency trend of twenty four academic departments of a public university in Malaysia over a five year period (2007-2011).

Methods

The most basic DEA model is the CCR model that was proposed by Charnes, Cooper and Rhodes in 1978 (Cooper, Seiford, & Tone, 2007). It was developed to evaluate relative efficiency of homogeneous DMUs with multiple inputs and multiple outputs. In DEA, there are two choices of orientation: (i) input orientation that aims to minimize the inputs at given output, and (ii) output orientation that aims to maximize the output given the input level. In line with the Ministry of Higher Education agenda that emphasizes outcome based education in this country, the focus of an academic department is to maximize outputs (for example student enrolment, total of publications and amount of research grants) without changing the quantities of its inputs (for example academic staff, non-academic staff and operating expenses). In this paper, we propose output orientation-CCR model. The mathematical formulation is in the following form:

Supposedly there are n DMUs where each DMU_o $(o = 1, 2, .., n)$ utilizes m inputs and produces s outputs. The CCR output oriented is formulated in the following multiplier form:

$$\text{Min } \theta_o = \sum_{i=1}^{m} v_i x_{io} \qquad (1)$$

$$\begin{aligned} s.t \quad & \sum_{j=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0 \qquad (j = 1, 2., \dots, n) \\ & \sum_{r=1}^{s} u_r y_{ro} = 1 \\ & u_1, u_2, \dots, u_s \geq 0 \\ & v_1, v_2, \dots, v_m \geq 0 \end{aligned}$$

If θ_o= 1, it means that DMU_O is efficient relative to other units, otherwise it is inefficient.

On the other hand, DEA Window analysis is a time dependent version of DEA. Proposed by Charnes et al. (1985), this method captures the variations in relative efficiency of DMUs over time. This method is based on the moving average principle (Asmild, Paradi, Aggarwall, & Schaffnit, 2004; Cooper et al., 2007) where each DMU in different a period is treated as if it was a different entity. This makes it as a useful technique to detect and analyse the efficiency trends of a DMU over time (Asmild et al., 2004). In determining the size of window, Asmild et al. (2004) pointed out that the selection of window width should be as small as possible to minimize the unfairness comparison over time, but still large enough to have a sufficient sample size.

This traditional DEA window analysis model ignores the importance of inputs and outputs. To address this shortcoming, restrictions need to be imposed on weights in DEA to reflect the importance of the input-output factors in a real life situation. One method that has been proposed is the Assurance Region method (AR) that focuses on imposing bounds on ratio of multipliers. Additional constraints that include the lower and upper limits of weights of inputs and outputs are added in the standard model CCR model (Thompson, Singleton, Thrall, & Smith, 1986). This study proposes the Assurance Region DEA Window Analysis (AR-WA) model where it integrates the Assurance Region method and DEA window analysis. In this study, the weight restrictions will be imposed on outputs.

Given the weights of outputs are $(u_1, u_2, \ldots u_s)$. Then, the relative importance of the outputs is shown as follows:

$$L_{p,q} \leq \frac{u_p}{u_q} \leq U_{p,q} \qquad (2)$$

where u_p and u_q are the weights for output p and r respectively and $L_{p,q}$ and $U_{p,q}$ represent the upper and lower bounds on the allowable values of weights $\frac{u_p}{u_q}$. To set the lower and upper bounds discussed above, this study adopted the Analytic Hierarchy Process (AHP) method. Pairwise comparison of AHP is applied to obtain the experts opinions on the importance of each input and output. The experts selected are senior lecturers who have worked over twenty years and have experienced being part of the university management team. The results derived from the AHP analysis are further used to set the lower and upper bounds of weight restriction. The additional constraints will be added to the standard DEA window analysis.

In this study, four outputs and three inputs are chosen and these factors reflect the main functions of a university that are teaching and research. The output factors are i) enrolment of undergraduates, ii) enrolment of graduates, iii) total of research grant and iv) number of publications. On the other hands, the input factors chosen are: i) total number of academic staff ii) non-academic staff and iii) operating expenses.

The data used in this study covers a five-year span from 2007 through 2011 for twenty four academic departments of a public university in Malaysia. The data is obtained mainly from the Strategic Planning Unit, a unit of the university that manages the university's data officially. The subjective weights from the experts are derived using AHP results and are calculated by Microsoft Office Excel 2007. The Efficiency Measurement System version 1.3 software from Holger Scheel is used to solve the DEA window analysis with weight restrictions.

RESULTS AND DISCUSSIONS

Descriptive statistics of the data is shown in Table 1.

Table 1: Descriptive Statistics for Data

	Total Academic staff	Non-Academic staff	Operating Cost	Enrolment of Undergraduates	Enrolment of Postgraduates	Publications	Research Grants
Min	17	14	46074.00	0	0	0	0
Max	399	431	9564055.41	9388	2184	752	11547819.00
Average	134.54	51.13	2725536.52	2246.83	255.54	106.02	1362437.30
SD	96.88	46.83	1690678.34	1675.80	354.19	134.19	1896871.44

A two-year period is chosen as the window width that allows four windows. The window breakdown is given below:

Table 1. Window Breakdown

window 1	2007	2008			
window 2		2008	2009		
window 3			2009	2010	
window 4				2010	2011

Priorities of the outputs are obtained from the experts using AHP and the results are shown in Table 2.

Table 2. Priorities of the output vectors by the experts

	Expert 1	Expert 2	Expert 3	Minimum Priority	Maximum Priority
Enrolment of undergraduates	0.558	0.636	0.550	0.550	0.636
Enrolment of graduates	0.186	0.150	0.077	0.077	0.186
Total number of publications	0.120	0.158	0.196	0.120	0.196
Total amount of research grants	0.136	0.056	0.177	0.056	0.177

The lower and upper bounds for the weights are given in the following Table 3.

Table 3. Assurance region (AR) for outputs

Weight ratio	Lower bound	Upper bound

u_2/u_1	$0.077/0.636 = 0.121$	$0.186/0.550 = 0.338$
u_3/u_1	$0.120/0.636 = 0.189$	$0.196/0.550 = 0.356$
u_4/u_1	$0.056/0.636 = 0.088$	$0.177/0.550 = 0.322$
u_3/u_2	$0.120/0.186 = 0.645$	$0.196/.0.077 = 2.55$
u_4/u_2	$0.056/0.186 = 0.301$	$0.177/.0.077 = 2.30$
u_4/u_3	$0.056/0.196 = 0.286$	$0.177/.0.120 = 1.48$

The main finding for this study is that there is a significant difference in efficiency scores obtained by the two methods; traditional DEA window and the proposed method. The mean efficiency scores of all academic departments are lower in the proposed method compared to the traditional one. For example, when using the traditional DEA window method, Dept11 is found efficient and scored one for every window but the scores dropped when using the proposed method. The mean efficiency score dropped from 1 to 0.4241. For Dept9, the mean efficiency scores dropped from 0.9674 to 0.4616. This is also true for all departments. The illustration on the difference in the efficiency trends for 3 selected departments is given in Figure 1.

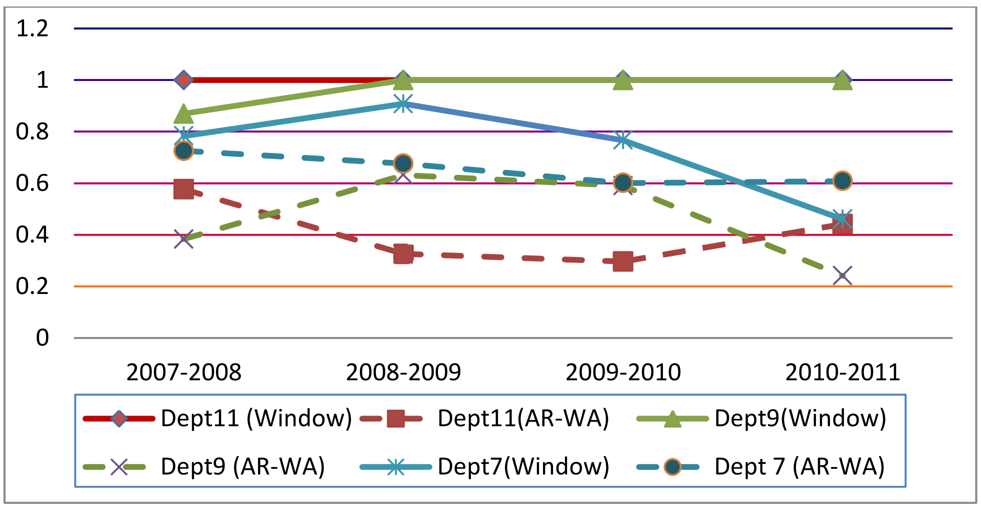

Figure 1. Efficiency trends for selected DMUs using both models

Based on the proposed model, the fluctuation in efficiency scores for all academic departments within the same window but different year indicates that the efficiency off all department changes from year to year. Different department showed different trend. Examining the average efficiency scores, Dept10 is the best academic department compared to its peers with the highest mean of 0.6529 followed by Dept7 and Dept12 with mean efficiency scores are 0.6393 and 0.5881 respectively. The most inefficient department over a period of time is Dept24 where the mean is 0.0531. The difference in the average efficiency scores between the most efficient department (Dept13) and the most inefficient one (Dept24) is 0.5998. The most efficient department that is Dept13 can be the best model for other departments to benchmark over a period of time. Efficiency trends for some mentioned departments are shown in Figure 2.

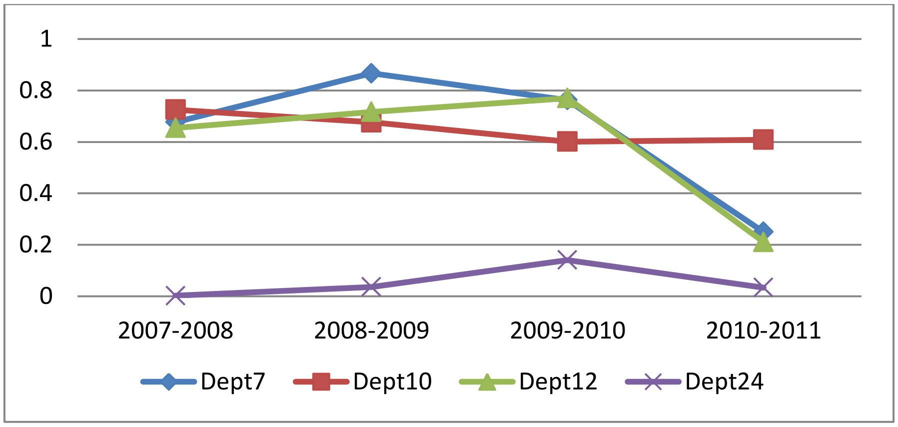

Figure 2. Efficiency trends for AR-WA model

The efficiency trends for academic departments can be examined by observing the values of average efficiency scores over time. The study reveals that the performance for most departments fluctuated between decrease and increase.

CONCLUSIONS

This paper adopted DEA window analysis to evaluate efficiencies of 24 academic departments of a public university in Malaysia during 2007-2011. This method is different from the standard DEA window analysis model because it incorporates expert value judgments. The AHP method is adopted to reflect expert preferences. This study reveals that there is a significant difference in the efficiency scores where the scores are lower when using the proposed method. This study also reveals that the efficiency of different departments fluctuates over time to different degree and quite substantially at some point of time. The findings also reveal that the efficiency of academic departments that are continuously measured over time will reflect the actual efficiency of an academic department. These findings can help the university's management in short-and long-term planning to improve efficiencies of the academic departments.

For further research, we can apply weight restrictions on Malmquist Index. More experts should be involved in order to obtain more valid and subjective judgments.

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THE EUROPEAN UNION MEASUREMENT OF ENVIRONMENTAL PERFORMANCE

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ABSTARCT

Among modelling energy and environment techniques, DEA is one of the nonparametric approach used often evaluation effectiveness of an activity. In this study, literature of applications of environmental performance evaluation in Data Envelopment Analysis is mainly presented. Furthermore, by utilizing 28 European Union countries data in 2010, environmental performance evaluation will be interpreted in DEA.

***Keywords**: Performance Evaluation, Data Envelpoment Analysis, Energy Efficiency*

INTRODUCTION

Performance assessment and planning techniques has found itself in a wide area of study related to energy and environmental studies. In investigating appropriate ways to produce and use energy more efficiently, managing environmental policies and producing for the future, measuring and evaluating performance of the existing production is evaluation undoubtedly a guiding. In this regard, a part of the energy and environmental studies techniques are used for monitoring the performance of micro or macro level studies. In today's world, we are facing with the negative impacts of excessive use of energy on human health and ecological balance. With the understanding the limitation of the energy sources and excessive use of energy causing serious problems gradually, effcient use of the energy produced, managing damages of the environment, and legislation of rational policies in environment and energy become more and more important Energy and environmental policies in order to manage more effectively by compliancing with the energy and environmental issues begin to be useding wide field of application. The basic principles of DEA are derived from the study of Farrell(1957) and Charnes, Cooper and Rhodes (1978) moved theseprinciples forward for DEA. In the first part of the study, the literature on Environmental Performance Measurement is represented and the second section provides information on Data Envelopment Analysis. Finally, 28 European countries Environmental Performance Measurements of will be evaluated by using DEA methods.

MATERIAL AND METHOD

In this study, the data form 28 European Union countries in 2010 is performed in three different models. For the first model the solid fuel consumption; whereas is used as input ratio of the total waste treatment, energy recovery amount, the amount of waste disposed of greenhouse gas emissions, is used as the output. For the second model, the chemical, pharmaceutical, plastic products production, mines and quarries, the processing of waste are used as input. The amount of energy recovery, the amount of greenhouse gas emissions and waste disposal are used as output. Aim of study, is to compare the environmental performance of countries and for the environmental performance of countries not efficient make better objectives achieved is to determine. Under the assumption of constant returns to scale the CCR model was used, measuring efficiency in the measurement of effectiveness. Inputs and outputs that are used in the evaluation of efficients of the countries are described below.

For model 1 ;

Inputs	Outputs
X_1: Solid fuel consumption	Y_1: The total amount of waste treatment
X_2: Mines and quarries waste processing	Y_2: The amount of energy recovery process
	Y_3: The amount of waste disposed
	Y_4: Greenhouse gas emissions

For model 2;

Inputs	Outputs
X1: Chemicals, pharmaceuticals, plastics products manufacturing	Y1: The amount of energy recovery,
X2: Mining and quarrying, waste processing	Y2:Ggreenhouse gas emissions
	Y3: The amount of waste disposed

RESULTS AND DISCUSSIONS

In this part of the study, 28 European Union countries included in the according to data in 2010, efficiency values are calculated according to the CCR output-oriented model. Thus, the effectiveness of different structures of countries are compared under the specified variables.

Table 1: According to data from the year 2010 to the First Model Output Oriented CCR Model Effcient Values

Countries	Efficient Values	Countries	Efficient Values
Belgium	0.53	Luxembourg	0.46
Bulgaria	0.88	Hungary	0.58
Czech Republic	0.40	Netherlands	0.65
Denmark	0.55	Austria	0.44
Germany	0.71	Poland	0.31
Estonia	0.73	Portugal	0.45
Ireland	0.37	Romania	1.00
Greece	0.32	Slovenia	0.39
Spain	0.51	Slovakia	0.65
France	1.00	Finland	0.72
Italy	0.64	Sweden	0.78
Cyprus	0.25	United Kingdom	0.86
Latvia	0.93	Norway	0.43
Lithuania	1.00	Turkey	1.00

Table 2: According to data from the year 2010 to the Second Model Output Oriented CCR Model Effcient Values

Countries	Efficient Values	Countries	Efficient Values
Belgium	0.03	Luxembourg	1.00
Bulgaria	0.55	Hungary	0.35
Czech Republic	0.18	Netherlands	0.98

Denmark	1.00	Austria	0.24
Germany	0.06	Poland	0.04
Estonia	1.00	Portugal	0.17
Ireland	0.09	Romania	0.80
Greece	0.43	Slovenia	0.39
Spain	0.13	Slovakia	0.20
France	0.46	Finland	0.66
Italy	0.07	Sweden	1.00
Cyprus	1.00	United Kingdom	0.11
Latvia	1.00	Norway	0.16
Lithuania	0.62	Turkey	1.00

CONCLUSIONS

In recent years, the energy demand is increasing a lot more than econimic growth. With the awayness of limitation of energy sources and careless us of energy sources causing increasimg damage on the environment, efficient way of energy production, efficient way of use of produced energy, and managing damages on the environment has bacome more important issues. Increasing awareness of energy and environmental issues, has led to the development of many techniques. In this study, 28 European Union countries evaluated the environmental performance according to statistics in 2010. In practice, the environmental performance of the countries in the border-effective, as well as countries that are not located on the border effectively to come target values that are required for the effective limit is determined. Standard Data Envelopment Analysis approach, a decision unit, but all outputs are not efficient on the border turned to the target values, it can reach efficient frontier. Data Envelopment Analysis is made first by model, processing of solid wastes fuel consumption and the amount of mineral-stone quarries kept constant; the total amount of waste treatment, energy recovery amount, the amount of waste disposed of coefficients of the expansion is increased up to and the shrinkage coefficient is reduced up to the amount of greenhouse gas emissions, effectively increase the number of countries and seen a significant reduction in environmental pollution.

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THE PERFORMANCE INVESTIGATION OF A PUBLIC BANK BRANCHES IN TURKEY BY DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Data Envelopment Analysis (DEA) is a linear-programming-based method for assessing the performance of homogeneous organizational units and is increasingly being used in banking. The unit of assessment is normally the bank branch in our country, the banking sector is developing quickly, and this development brings about an increasing competition in the sector. The banking system works in a way that it sells money to the customers and buys money from then in return, which makes the banks to become like a business establishment. This is why, to not to stay behind in the competition in the sector and provide better service to the customers in the fastest and most efficient way, banks are tended to enlarge their web in the country by opening new branches every year. For the sake of the maximum profit in these new branches, banks have to conduct periodical capacity usage analyses to inspect the efficiency and formulate their future management strategies accordingly. Data Envelopment Analysis is an important tool developed to measure the activities of the organizational entities like banking branches with multiply varied inputs and outputs. This analysis method works to find out the best input- output components. Because of this feature, it has the potential of being a strong systemic decision support tool for the bank directors.

Keywords*: Data Envelopment Analysis, banking efficiency.*

BANKING EFFICIENCY

Bank is an establishment authorized by a government to accept deposits, pay interest, clear checks, make loans, act as an intermediary in financial transactions, and provide other financial services to its customers. Banks act as payment agents by conducting checking or current accounts for customers, paying cheques drawn by customers on the bank, and collecting cheques deposited to customers' current accounts. The effectiveness in the banking sector is upon to the least resources usage of financial intermediation function of banks. Thus, the main function of the banking sector was fulfilled on the concept of failure to function more efficiency, how the subject is relevant for greater efficiency have taken place in the way. But you need to understand that the efficiency is not lower the cost only, it is just one of the aims of that.

See the banking sector in terms of efficiency, quality of service, rather than production, efficient use of resources collected, and measures to be taken against the possible risks and work towards customer satisfaction, but there are closely following innovations are measured.

LITERATURE REVIEW

Efficiency is defined as the extent to which a DMU can increase its outputs without increasing its inputs, or reduce its inputs without reducing its outputs. The efficiency of the banking sector is one of the most interesting economic issues for economists all over the world. Although there are many ways adopted to examine the efficiency of banks, DEA seems to be more popular among economists. DEA is a non-parametric technique, i.e. it can compare input/output data making no prior assumptions about the probability distribution under study. The origin of non-parametric programming methodology in respect to relative efficiency measurement lies in the work of Charnes, Cooper, Rhodes [1]. DEA was originally intended for use in the public sector and nonprofit DMUs such as educational institutions and health services. DEA was performed by Banker and Morey [2] for the evaluation of hospitals and restaurants and by Athanassopoulos and Shale [3] for the efficiency of universities. Since the mid-1980s, DEA has been receiving more importance as a technique for measuring the efficiency of banks in several countries. Casu and Molyneux [4] employed the DEA approach to investigate the efficiency of International Journal of Basic & Applied Sciences I European banking systems. They attempted to examine whether the productive efficiency of European banking systems improved and converged towards a common European frontier between 1993–1997. Jemric and Vujcic [5] applied DEA in order to analyze bank efficiency in Croatia. They attempted to measure the relative efficiency of banks in the Croatian market according to size and ownership structure in the period from 1995 until 2000. Halkos and Salamouris [6] illustrated the efficiency features of Greek commercial banking for the time period 1997–1999. Wu [7] conducted productivity and efficiency analysis of bank operations in Australia. DEA was employed in order to investigate the levels of and the changes in the efficiency of Australian banks over the period from1983 to 2001.

A number of studies have applied DEA and the Malmquist TFP index to question the efficiency and productivity change in the Turkish banking system. Zaim [8] analysedthe efficiency of Turkish banks to investigate the effects of post–1980 financial liberalization policies. The intermediation approach is used to select bank inputs and outputs. The inputs included total number of employees, total interest expenditures, depreciation expenditures, and expenditures on materials. The outputs were total balance of demand deposits, total balance of time deposits, total balance of short-term loans and total balance of long-term loans. The years 1981 and 1990 were selected as representative years for pre and post liberalization periods, respectively. The results showed that the financial reforms had a positive effect on efficiency.

Jackson, Fethi and Inal [9] measured the efficiency and productivity growth in the Turkish banking system using the DEA-based Malmquist TFP index. They investigated the efficiency and productivity changes of each bank over the 1992–1996 periods. The value-added method was used to model the bank operations. They used the number of employees and total non-labor operating expenses as inputs. Total loans, total demand deposits and total time deposits were used as outputs. The empirical results showed that except during the financial crisis period of 1993–1994, foreign and private banks were more efficient than their state counterparts owing to the developments in competition and technological advancements. Yildirim [10] analyzed policy and performance in the Turkish banks in response to the financial liberalization after 1980 and the macroeconomic instability. Four inputs (demand deposits, time deposits, interest expenses and non-interest expenses) and three outputs (loans, interest income and non-interest income) were used for the period from 1988 to 1996. The results indicated that the sector did not achieve any sustained efficiency gains in the liberalized period with continuing scale inefficiency. The efficient banks were noted as less profitable. In particular, the less profitable state-owned banks seemed to be more efficient than the others.

Cingi and Tarim [11] examined the efficiency and productivity change in the Turkish banking system using DEA and the Malmquist TFP index. The study covered the period 1989–1996 and two inputs (total assets and total expenses) and four outputs (total income, total loans, total deposits and total non-performing loans/total loans) were used. The results revealed that whereas the four state-owned banks were not efficient, the three private holding banks maintained high efficiency scores over the study period.

DATA ENVELOPMENT ANALYSIS

Data Envelopment Analysis (DEA) is a fractional mathematical programming technique that has been developed by Charnes et al. (1978). It is used to measure the productive efficiency of decision making units (DMUs) and evaluate their relative efficiency. This analysis determines the productivities of DMUs, specified as the ratio of the weighted sum of outputs to the weighted sum of inputs, compares them to each other and determines the most efficient DMU(s). DEA obtains the optimal weights for all inputs and outputs of each unit without imposing any constraints on these weights.

Assuming that there are n DMUs each with m inputs and s outputs the relative efficiency of a particular DMU_0 is obtained by solving the following fractional programming problem:

$$
\begin{aligned}
& w_o = \mathrm{Max}\ \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \\
& \qquad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \quad j = 1, 2, \ldots, n \\
& \qquad u_r \ge 0, \quad r = 1, 2, \ldots, s \\
& \qquad v_i \ge 0, \quad i = 1, 2, \ldots, m
\end{aligned}
\tag{1}
$$

where j is the DMU index, $j = 1, \ldots, n$; r is the output index, $r = 1, \ldots, s$; i is the input index, $i = 1, \ldots, m$; y_{rj} is the value of the r^{th} output for the j^{th} DMU, x_{ij} is the value of the i^{th} input for the j^{th} DMU, u_r is the weight given to the r^{th} output; v_i is the weight given to the i^{th} input, and w_o is the relative efficiency of DMU_0, the DMU under evaluation. In this model, DMU_0 is efficient if and only if $w_o = 1$.

A DMU is considered individually in determining its relative efficiency. This DMU is referred to as the target DMU. The target DMU effectively selects weights that maximize its output to input ratio, subject to the constraints that the output to input ratios of all the n DMUs with these weights are ≤ 1. A relative efficiency score of 1 indicates that the DMU under consideration is efficient whereas a score less than 1 implies that it is inefficient.

This fractional program, well known as CCR model, can be converted into a linear programming problem where the optimal value of the objective function indicates the relative efficiency of DMU_0. Hence the reformulated linear programming problem is as follows:

$$\begin{aligned} & w_o = \mathrm{Max} \sum_{r=1}^{s} u_r y_{ro} \\ & \qquad \sum_{i=1}^{m} v_i x_{io} = 1 \\ & \qquad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad j = 1,\ 2,\ \ldots,\ n \\ & \qquad u_r \ge 0, \quad r = 1, 2,\ \ldots, s \\ & \qquad v_i \ge 0, \quad i = 1, 2,\ \ldots, m \end{aligned} \tag{2}$$

In this model, the weighted sum of the inputs for the DMU_0 is forced to 1, thus allowing for the conversion of the fractional programming problem into a linear programming problem which can be solved by using any linear programming software.

THE PERFORMANCE INVESTIGATION OF A PUBLIC BANK BRANCHES IN TURKEY

The 28 branches of department which is the public bank in the chairman of Adana Religion between the years 2005 and 2012, analyzed for performance investigation through output- DEA. Table 1 indicates the results.

Variables to be used in the present study that we determined:

inputs;

- Number of employees
- Loan loss provisions
- Expense rediscount

outputs;

- Profit
- Consumer loan
- Commercial loan
- Income accrual
- Deposits

- **Table 10: Exchange efficiency score of branches by year**

	branches	2005	2006	2007	2008	2009	2010	2011	2012
1	AD	1	1	1	1	1	1	1	1
2	AN	1	1	1	1	1	1	1	1
3	AT.	1	1	1	1	0,93	0,76	0,71	0,79
4	AY	0,81	1	1	0,73	1	0,98	1	1
5	BA	1	1	1	0,94	1	0,89	0,86	0,87
6	BEI	1	1	0,85	0,66	0,77	0,67	1	0,82
7	BO	1	1	1	1	1	1	1	0,91
8	ÇA	0,79	0,88	0,94	0,41	0,83	0,66	0,89	0,69
9	ÇA	0,82	0,91	0,88	0,84	0,98	0,77	0,84	0,79
10	ERI	0,87	1	1	1	1	1	1	1
11	ESI	0,85	1	1	1	1	1	0,99	1
12	GÜ	0,71	0,97	1	0,88	0,92	0,71	1	0,99
13	İSı	1	1	1	1	1	0,76	1	1
14	KA	1	1	1	1	1	1	1	1
15	KA	0,93	1	1	0,81	1	0,8	1	1
16	KU	0,96	0,97	1	0,66	0,8	0,77	0,94	0,7
17	KU	0,68	0,83	1	0,82	0,81	0,66	0,68	0,76
18	M/	0,78	0,93	0,82	0,7	1	1	1	1
19	MI	1	1	1	1	1	1	1	1
20	MI	0,76	0,85	0,9	0,69	0,85	0,63	0,83	1
21	PO	0,67	0,8	0,79	1	0,72	0,44	0,79	0,61
22	PO	0,85	0,9	0,93	0,87	0,79	0,63	0,62	0,76
23	SEY	0,76	0,89	1	1	1	1	1	1
24	SİL	0,89	1	0,94	0,84	0,91	0,64	0,82	0,93
25	ST/	0,85	0,91	1	1	1	0,91	0,81	1
26	TA	1	1	1	1	1	1	0,87	1
27	TO	0,74	0,94	1	1	0,93	0,94	0,83	1
28	YA	0,89	0,96	0,96	0,96	1	1	1	1

CONCLUSION

Today, performance, profitability and efficiency become indisputable criteria for any company, including money-trading banks and their associates. Banks, establish a trading tie between themselves and their customers, by taking advantage of their branches. Therefore, the more branches banks have, the more profits, yields and prestige they obtain. The state bank, which we have working on, does not consider important efficiency criteria, because they are in construction process. They create targets for their branches in every three months period. Hence, they succeed not only increase their branches power and provide persistency but also they keep their efficiency in tough market area, and maintain their power against their rivals.

In this study, as an input, interest and expenditure rediscount, credit deficient equivalency and optimum number of desired staff have been considered. As an output, personal loan that wanted to be powerful, consumer loan, proficiency, general deposit, interest and accrued income have been used.

According to the results of the study of the presidency Adana region has 4 branches each year, efficient. These branches are b1, b2, b14 and b19. The year 2007 is the highest branches activities. The weakest performance of the year is 2010. As a result, the activities of the branches to be managed effectively in financial term and they will help you to maintain a healthy way.

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TOTAL PRODUCTIVITY GROWTH IN THE FACULTIES OF ANBAR UNIVERSITY USING MALMQUIST PRODUCTIVITY INDEX

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ABSTARCT

The aims of this study is to evaluate the productivity growth of nineteen Faculties of Anbar University (FAUs) in Iraq. The FAUs performance is determined on the change in total factor productivity (TFA) and technical efficiency. We used the output orientated DEA-Malmquist index in estimating the productivity growth from panel data of 19 of FAUs in two periods of time 2010-2011 and 2011-2012 academic years, the model calculated using two educational outputs and two inputs.The results showed that (14) FAUs or or 73.6% are efficient. In terms of total factor productivity, FAUs obtained an index score of 0.879, which means that (7) FAUs or 36.8% remarkable productivity growth. The technological index shows that (2) FAUS or 10.5% only shows a technological progress.

***Keywords**: Total Productivity Growth, Malmquist Productivity Index ,Technological index*

INTRODUCTION

In recent years, Higher Education Institutions (HEIs) have been increasingly studied. In nowadays ‘‘knowledge economy’’ their importance for economic development, social equity, mobility, social cohesion and integration is widely acknowledged (Brennan & Teichler, 2008). Furthermore, given the difficult situation of public finances, considerations about resources allocation have been raised in many countries, calling for more evaluations and accountability (Agasisti et al ,2011)

Productivity management in (HEIs) is one of the major sources of sustainable organizational effectiveness and a systematic understanding of the factors that affecting productivity is very important. The measurement and analysis of productivity change in (HEIs) is always a controversial topic and has enjoyed a great deal of interest among (HEIs) (Mohammadi & Ranaei, 2009).

Productivity growth in (HEIs) is one of the major sources of economic development and a thorough understanding of the factors affecting productivity is very important. In recent years the measurement and analysis of productivity change has enjoyed a great deal of interest among researchers studying firm performance and behavior (Rayeni et al, 2010).

This study aims to measures the productivity growth of nineteen Faculty of Anbar University (FAUs) in Iraq by using the output orientated DEA-Malmquist index in estimating the productivity growth from panel data of 19 of FAUS in two periods of time 2010-2011 and 2011-2012 academic years.

METHOD

DATA ENVELOPMENT ANALYSIS

Data Envelopment Analysis (DEA) has been a technique for measuring the relative efficiency of decision making units (DMUs) with multiple inputs and multiple outputs (Charnes et al., 1978 ; Banker et al., 1984). The method has become popular in university performance measurement (Prichard , 1990; Youn & Park, 2009). In fact, there are literally various kinds of DEA methods such as constant return to scale, variable return to scale, (Cooke & Zhu 2005). DEA is a mathematical linear programming approach based on the technical efficiency concept (TE), it can be used to measure and analyze TF of deferent entities : productive and non productive, public and private, profit and nonprofit seeking firms. It is non parametric approach that calculate efficiency level by doing linear program for each unit in the sample (Al- Delaimi & al-Ani ,2006).

DEA measures the efficiency of the decision making unit (DMUs) by the comparison with best producer in the sample to drive compared efficiency. DEA submits subjective measure of operational efficiency to the number of homogenous entities compared with each other, through a number of samples unit which form together a performance frontier curve envelopes all observations. So, this approach called Data Envelopment Analysis.

DEA-MALMQUIST PRODUCTIVITY INDEX

The Malmquist productivity index, as a kind of consumer price index was first proposed by the Sweden economist and statistician Sten Malmquist (1953). Later it is developed into the index to appraise the department productivity progress for multi-inputs and multi-outputs by Fare et al. (1985). Here after Fare et al. (1994) have consummated this index unceasingly, established the Malmquist productivity index which can be used to estimate the total factor productivity (TFP) growth in 1994, and decomposed this index into the technical change and the technical efficiency change by using the Shephard distance function . The essence of Malmquist index analysis method is to appraise the productivity. The productivity appraisal may analyze the fountainhead of the economic growth (Hu & Liang,2008). The Malmquist index analysis is to utilize the directional output or the input method to define the distance function, and then appraises the efficiency change of each decision-making unit.

The total factor productivity (TFP) approach provides the most comprehensive summary of school's performance. The Malmquist productivity index typically measures the TFP growth change between two data points: period t technology (observation) and the other period t + 1 technology.

Equation 1 shows the Malmquist productivity change index (Fare et. al 1994 p. 71) as stated:

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \text{X} \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right]^{1/2}$$

Where

Mo = Malmquist productivity Index

Do = Distance function

(xt+1, yt+1) = represents the production point of the productivity

(xt, yt) = relative production point of the productivity

t = period of benchmark technology

t+1 = the next period of technology

Equation 1 presents the components of the Malmquist index. The first equation on the right represents the efficiency change, which is the distance function from period *t* technology to period *t+ 1* technology, using input and output quantities. The equation inside the bracket represents the technical change from period *t* to period *t+1*. The Malmquist index is composed of geometric means of two output-based Malmquist index from period *t* to period *t + 1*. Geometric means are used because DEA does not account for measurement noise. In the Malmquist index, all values are ranged from 0 to 1. DEA-Malmquist captures the performance relative to the best practice in a given sample of educational institutions (Castano & Caband,2007) , whose best-practice institutions are operating on the efficient frontier. A value greater than one (>1) using Malmquist index indicates a positive improvement while a value lesser than one (<1) indicates a decline in an institution's performance over the period or denotes deterioration in performance. A constant 1 value means no improvement in performance.

DATA AND RESULTS

The data which have been used in this paper have been taken from the data base of department of planning in Anbar University for the two academic year 2010-2011 and 2011-2012. Input variables used are (1) academic staff, (2) general staff. The output variables are (1) number of graduates, (2) number of research. (appendix 1 & 2). DEAP software has been used for analyzing the information.

DEA-Malmquist (output-orientated) method is employed to decompose the total factor productivity change (TFPCH) into technological change (TECHCH) and technical efficiency (EFFCH). Technical efficiency is further decomposed into scale efficiency (SECH) and pure efficiency change (PECH).

Table (1) shows the list of FAUS with five Malmquist indices . fig (1) show total factor productivity change

From the table (1) We see that the mean SECH (1.006) of FAUS is slightly lower than the mean PECH (1.066), but both obtained values greater than one. This result indicates the presence of better management and also operations at optimal scale.

Table (1) Malmquist productivity Index of FAUs

Faculties	TFPCH	TECHCH	EFFCH	SECH	PECH
Education for Girls	1.239	0.622	1.482	0.836	0.77
Education for the Humanities	1	0.507	1	1	0.507
Engineering	1.176	0.807	0.906	1.299	0.949
Sciences	1.223	0.743	1.279	0.956	0.909
Medicine	1.259	0.852	1.418	0.888	1.073
Dentistry	1.756	0.888	1.886	0.931	1.56
Agriculture	1.338	0.921	1.233	1.085	1.232
Administration and Economics - Fallujah	0.896	0.762	0.974	0.92	0.683
Computer	1	1.169	1	1	1.169
Law – Fallujah	0.762	0.803	1	0.762	0.612
Arts	1.181	0.776	1.148	1.029	0.917
Law and Political Science-Ramadi	1.233	0.781	1.307	0.943	0.963
Administration and Economics - Ramadi	0.816	0.847	0.934	0.874	0.691
Islamic Sciences - Ramadi	1.319	0.842	1.042	1.267	1.111
Physical Education	1.512	0.83	1	1.512	1.255
Veterinary Medicine	0.899	1.141	0.828	1.085	1.025
Islamic Sciences - Fallujah	0.777	0.958	0.884	0.879	0.744
Education - Qaim	0.498	0.85	0.44	1.132	0.423
Education for Pure Sciences	1.345	0.693	1.297	1.036	0.932
Geometric Mean	1.076	0.818	1.066	1.009	0.879

Source: The output of DEAP software ver 2.1

The TFPCH index of FAUs (0.879) decomposed into managerial or technical efficiency index (1.076) and technological change index (0.818). The decline in TFPCH was brought about by a decrease in technological change index of 18.2 percent per year. In short, FAUs have managed efficiently their resources (inputs); although, technological innovation is a factor, which has to be improved further to reach the frontier of 1.0. The TFPCH of FAUs was achieved more due to the optimal use of given resources than innovations. On average, FAUs lack more technological innovation and need additional 18.2 percent to reach the technological frontier. The technological change shows that 2 out of 19 FAUS or 10.52 percent scored above the frontier level. The institution, which scored the highest is the Faculty of Computer (1.169).

There are 5 out of 19 FAUs, or 37.6 percent of the educational institutions are technically (managerial) efficient led by faculty of Dentistry. This means that the majority of FAUs have managed their inputs (academic and general staff) efficiently and productively so that there is productive growth in their outputs (graduate students and research). Most of the growth in the FAUs productivity during the period of study stemmed from catching up or best management practices rather than technological progress.

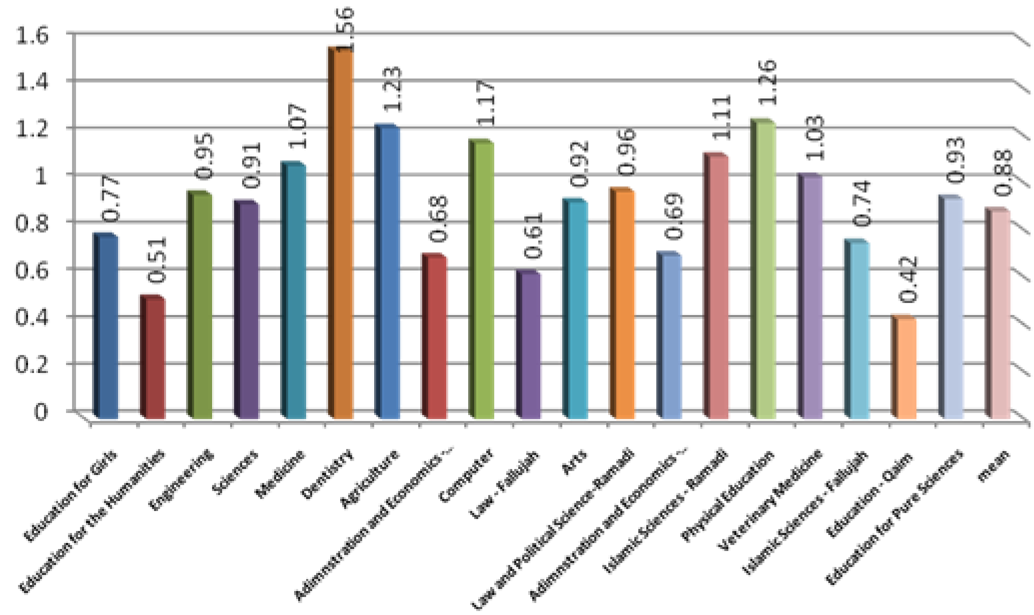

Fig 1: total factor productivity change in FAUs

CONCLUSIONS

The aims of this study is to evaluate the productivity growth of nineteen Faculty of Anbar University (FAUs) in Iraq. The FAUs performance is determined on the change in total factor productivity (TFA) and technical efficiency. using DEA –Malmquist Productivity Model. The results showed that (14) FAUs or 73.6% are efficient. In terms of total factor productivity, FAUs obtained an index score of 0.879, which means that (7) FAUs or 36.8% remarkable productivity growth. The technological index shows that (2) FAUs or 10.5% only shows a technological progress.

The important finding in this paper is that (2) out of 19 FAUS are showing technological progress and the rest are experiencing technological regression. This may call for the FAUs to give considerable attention to technological progress, the enhancement of existing applications and the development of more technology-oriented systems and procedures that will enable the educational institutions to remain effective and competitive. The Ministry Higher Education in Iraq and Anbar University should exert more efforts to provide modern teaching and learning faculties in every college to improve its deteriorating technological performance. Thus, the new findings in this paper may give impetus to Anbar University , and the faculty administrators to adopt measures that would be beneficial to the improvement Faculties of Anbar University in terms of inefficiency and unproductive growth.

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TURKEY AND THE EUROPEAN UNION COUNTRIES EDUCATIONAL PERFORMANCE

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ABSTRACT

Analysis of performance is a concept that has talked about sources of system and circumstance of determining effective and efficient. Efficiency analysis is a method for evaluating of system preformances at recent years. Data Envelopment Analysis (DEA) can handle multiple inputs and multiple outputs makes it an attractive choice of technique for measuring the efficiency of education field. The paper begins by exploring the advantages and drawbacks of the various methods for measuring efficiency in the higher education context. In this study, one of the processes of measuring the effectiveness of systems with DEA activities have used in the field of education in Turkey and European Union countries, the relative total measuring activity is the analysis of technical and scale.

***Keywords**: Data Envelopment Analysis, Education.*

INTRODUCTION

Each system has own objectives. These objectives have usually been expressed in terms of performance indicators such as, high productivity, efficiency, profit maximization and cost minimization, client satisfaction, growth, dignity. Therefore, to understand of system efficiency that reach the desired goals, performance measures need to be calculated.

The methods that are used to measure the system performance are efficiency analysis. In the efficiency analysis, goods and services (output) producing process and systems resources (inputs) are determined how to use that the system be effective and efficient.

PURPOSE AND SCOPE OF STUDY

The purpose of this study is the evaluating of efficiency in the field of education in Turkey and the European Union countries thanks to Data Envelopment Analysis (DEA).

SELECTING ACTIVITY MEASUREMENT METHOD

In the analysis of studying activities in European countries we use the CCR and BCC models to measure total and technical efficiency scores respectively.

In this study, educational levels of 30 countries of European Union (including Turkey) in 2003-2008 have been examined. The data have been taken from EUROSTAT, that is available online at (http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/themes).

SELECTING THE INPUT AND OUTPUT VARIABLES USED IN THE STUDY

Sometimes, many factors that are effective in education studies as inputs and outputs of measuring the efficiency are not possible to reach. The inputs and outputs under these limits that are used in this study have been described below.

Input variables:

X1: Special education spending and public education expenditure

The annual expenditure on public and private educational institutions per pupil/student compared to GDP per capita relates the resources (e.g. expenditure for personnel, other current and capital expenditure) being devoted to education in public and private educational institutions to the overall economic welfare of a country. It is based on full-time equivalent enrolment. The use of GDP per capita allows the comparison of levels of economic activity of different sized economies (per capita) irrespective of their price levels (in PPS).

X2: percentage of the number of students per teacher in each (shown with OOO)

The pupil-teacher ratio is calculated by dividing the number of full-time equivalent pupils by the number of full-time equivalent teachers teaching at ISCED level 1. Only teachers in service (including special education teachers) are taken into account. The pupil-teacher ratio should not be confused with average class size as it does not take into account special cases, like the small size of groups of special needs pupils or specialised/minority subject areas, or the difference between the number of hours of teaching provided by teachers and the number of hours of instruction prescribed for pupils for example in the case a teacher is working in a shift system.

X3: opposite the percentage of early school leavers (shown with ERT)

Early leavers from education and training refers to persons aged 18 to 24 fulfilling the following two conditions: first, the highest level of education or training attained is ISCED 0, 1, 2 or 3c short, second, respondents declared not having received any education or training in the four weeks preceding the survey (numerator). The denominator consists of the total population of the same age group, excluding no answers to the questions "highest level of education or training attained" and "participation to education and training". Both the numerators and the denominators come from the EU Labour Force Survey.

X4: number of Students (shown with OS)

This table includes the total number of persons who are enrolled in tertiary education (including university and non-university studies) in the regular education system in each country. It corresponds to the target population for policy in higher education. It provides an indication of the number of persons who had access to tertiary education and are expected to complete their studies, contributing to an increase of the educational attainment level of the population in the country in case they continue to live and work in the country at the end of their studies.

Output variables:

Y1: higher education, vocational stream (shown with YMK)

This indicator provides information on the percentage of boys and girls in upper secondary education who are enrolled in the vocational stream. It is indicative in the importance of initial vocational education and training in a country, taking into account also the gender dimension.

Y2: Science and technology graduates (shown with BTM)

The indicator "Tertiary graduates in science and technology" includes new tertiary graduates in a calendar year from both public and private institutions completing graduate and post graduate studies compared to an age group that corresponds to the typical graduation age in most countries. It does not correspond to the number of graduates in these fields who are available in the labour market in this specific year. The levels and fields of education and training used follow the 1997 version of the International Standard Classification of Education (ISCED97) and the Eurostat Manual of fields of education and training (1999).

THE ASSESMNET

According to results of CCR and BCC models, calculations for the mentioned 30 countries, 8 of them are relatively efficient and 22 of them are inefficient.

Table 2.2 The results have been showed in table 2-2

KVB	Ülkeler	CCR Girdi Yönlü	CCR Çıktı Yönlü	BCC Girdi Yönlü	BCC Çıktı Yönlü
1	Belgium	0.93	1.08	0.94	1.07
2	Bulgaria	0.63	1.58	0.66	1.31
3	Czech Republic	0.73	1.36	1.00	1.00
4	Denmark	1.00	1.00	1.00	1.00
5	Germany	0.57	1.77	0.58	1.25
6	Estonia	0.63	1.59	0.63	1.10
7	Ireland	0.79	1.26	1.00	1.00
8	Greece	0.68	1.48	0.92	1.48
9	Spain	0.62	1.61	0.76	1.57
10	France	0.58	1.72	0.58	1.20
11	Italy	1.00	1.00	1.00	1.00
12	Cyprus	0.30	3.30	0.67	2.33
13	Latvia	0.63	1.60	0.78	1.52
14	Lithuanian	1.00	1.00	1.00	1.00
15	Hungary	0.47	2.11	0.92	2.06
16	Malta	1.00	1.00	1.00	1.00
17	Netherlands	0.69	1.45	0.72	1.18
18	Austria	1.00	1.00	1.00	1.00
19	Poland	0.94	1.06	0.97	1.06
20	Portugal	1.00	1.00	1.00	1.00
21	Romania	0.74	1.35	0.75	1.08
22	Slovenia	0.80	1.26	1.00	1.00
23	Slovakia	0.75	1.34	0.97	1.00

24	Finland	1.00	1.00	1.00	1.00
25	Swedish	0.85	1.18	0.86	1.17
26	England	0.52	1.93	0.52	1.27
27	Iceland	1.00	1.00	1.00	1.00
28	Norway	0.94	1.07	1.00	1.00
29	Croatia	0.82	1.22	1.00	1.00
30	Turkey	0.27	3.66	0.40	1.91

Denmark, Italy, Lithuania, Malta, Austria, Portugal, Finland and Island are countries that total of relatively efficiency between countries of the European Union that efficiency score is below 1. Totally the lowest efficiency belong to Cyprus is 0.30, while the countries with the highest efficiency are Poland and Norway with 0.94, as well as the efficiency score of Turkey is 0.27.

Table 2.5. Input Oriented Model Case CCR clusters and the density of the reference:

DMU	Ülkeler	Etkin CCR Girdi	Etkinlik sırası	Refrans ve ağırlıklar
1	Belgium	0.93	11	4 (0.13) 11 (0.06) 18 (0.76)
2	Bulgaria	0.63	23	4 (0.12) 16 (0.26) 18 (0.48)
3	Czech Republic	0.73	18	4 (0.48) 16 (0.04) 18 (0.62)
4	Denmark	1.00	1	15
5	Germany	0.57	26	4 (0.36) 11 (0.59) 18 (0.03)
6	Estonia	0.63	22	16 (0.03) 24 (0.09) 27 (0.86)
7	Ireland	0.79	15	14 (0.63) 27 (0.80)
8	Greece	0.68	20	4 (0.59) 24 (0.09)
9	Spain	0.62	24	4 (0.62) 11 (0.18)
10	France	0.58	25	14 (0.49) 24 (0.47)
11	İtalyaa	1.00	1	9
12	Cyprus	0.30	29	16 (0.15) 24 (0.01) 27 (0.28)
13	Latvia	0.63	21	16 (0.36) 24 (0.24) 27 (0.07)
14	Lithuanian	1.00	1	4
15	Hungary	0.47	28	4 (0.23) 11 (0.05) 18 (0.17)
16	Malta	1.00	1	9
17	Netherlands	0.69	19	11 (0.10) 18 (0.76)
18	Austria	1.00	1	11
19	Poland	0.94	9	4 (0.76) 11 (0.21)
20	Portugal	1.00	1	14 (1.16)
21	Romania	0.74	17	4 (0.59) 11 (0.29) 18 (0.23)
22	Slovenia	0.80	14	4 (0.36) 16 (0.84) 24 (0.00)
23	Slovakia	0.75	16	4 (0.66) 16 (0.62) 24 (0.05)
24	Finland	1.00	1	7
25	Swedish	0.85	12	4 (0.59) 11 (0.06) 18 (0.29)
26	England	0.52	27	14 (1.08)
27	Iceland	1.00	1	4
28	Norway	0.94	10	4 (0.05) 16 (0.11) 18 (0.65)
29	Croatia	0.82	13	4 (0.11) 16 (0.82) 18 (0.29)
30	Turkey	0.27	30	4 (0.16) 11 (0.31) 18 (0.14)

Results of the analysis is shown the reference countries, the countries of the efficient and inefficient (that is effective values equivalent 1 is efficient).

Efficient countries that are given as references to an inefficient country, they can be used also in improving the inefficient one.

Inefficient units for change to efficient unite with calculate of target value will be available in recommendations to the management. α values has been given for calculation of the target values.

WINDOWS ANALYSIS

According to Windows analysis results, effective value with 30.32% is lowest in Cyprus in 2008 and 30.47% in 2003. Non significant different is not observed in this country in six years that it was between 30% among eight countries, Denmark is seen active, in 2003 and 2008, but in actively decreasing is seen in 2005-2006 and also is shown active in 2008 again. For Turkey is observed 20% between 2003 and 2008.

CONCLUSIONS

The aim of the universities is grow human resources that have sufficient knowledge of business life which needs to train in various fields and to contribute by researching in different fields of science. However, both of state and private universities have contribution in realizing these objectives that facing the number of personnel, financial resources, as there are different constraints. For effective higher education in universities using of the limited resources in the most efficient manner is extremely important. In recent years, the Data Envelopment Analysis has been started to use in resources allocated for education increasingly for better deployment and efficiency. Total of relatively inactive among countries of European Union, with value of activity below 1 are Denmark, Italy, Lithuania, Malta, Austria, Portugal, Finland and Izland. Total value of relative activity among the countries with lowest non-active countries, Cyprus is 0.30, while the countries with highest countries are Poland and Norway with 0.94, as well as the activity value in Türkey is 0.27. Denmark has been achieved these and all countries could shown it as a reference.

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TURKISH DECISION SUPPORT SYSTEM FOR PERFORMANCE ANALYSIS WITH C# PROGRAMMING LANGUAGE

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ABSTRACT

Data Envelopment Analysis, one of the methods of Performance Analysis, is the non-parametric method in which relative efficiency is measured by using observance values of variables belonging to decision making units. Different types of computer packet programmes may be used for Data Envelopment Analysis. However, there are some deficiencies in these packet programmes prepared in foreign languages. In this study, a completely Turkish performance analysis package program has been developed with Microsoft Visual C# programming language covering each of the various features such as the input-oriented and output-oriented CCR (Charnes Cooper Rhodes) - BCC (Banker Charnes Cooper) models in order to overcome the deficiencies. This packet programme is thought to bring added value to our country (Turkey) as it is more useful than its equivalents and it is a domestic product.

***Keywords**: Data Envelopment Analysis, Performance, Efficiency, C# Programming Language*

INTRODUCTION

Nowadays large companies such as banks, hospitals and insurance agencies are seeking excellence in their sectors. However, it’s only possible to reach this excellence when they measure their actual competitive power and take the necessary precautions on time. Thus they have to use their resources most efficiently and productively. Performance Analysis methods are the only way to use resources efficiently and productively.

Although there are many methods for Performance Analysis, Data Envelopment Analysis (DEA) method is the most preferred method in the literature. DEA based on the principles of linear programming, evaluating relative efficiencies, of Decision Making Units (DMU) using the same type of inputs that produce the same type of outputs is a non-parametric method. DEA can be used with different types of computer software packages. However, some programs in this package in a language other than Turkish lacks in some aspects such as receiving data from different databases, importing analysis results different data bases, window analysis and limited sensitivity. In this study, a new Decision Support System (DSS) prepared by Microsoft Visual C # programming language has been developed to overcome this deficiencies partially at least. While DSS was being developed, firstly linear programming methods have been investigated in order to solve DEA models and Simplex Method, one of the Linear Programming Methods, has been preferred both for computer coding and for being more sensitive to other methods. In DSS coding, Microsoft Visual C# programming language which is equal to both machine language and human perception and includes a similar with syntax programming languages such as Java, C and C++ was preferred.

DATA ENVELOPMENT ANALYSIS

DEA is a non-parametric method for evaluating relative efficiencies of similar units in point of view of the produced product and service which was developed firstly by Charnes, Cooper and Rhodes [1]. Charnes, Cooper and Rhodes who developed Farrel's (13) idea extended the single-output/input ratio measure of efficiency to the multiple output / input measure of efficiency. Then the relative efficiency of any DMU is calculated by forming the ratio of a weighted sum of outputs to a weighted sum of inputs, where the weights for both outputs and inputs are to be selected in a manner that calculates efficiency measure of each DMU subject to the constraint that no DMU can have relative efficiency score grater than unity.

In DEA there are many models which can be used to measure of efficiency and these models are derived from the ratio models in which the weighted sum of efficiency outputs are measured as the ratio to the weighted sum of inputs [1]. Considering as n units each of which has m inputs denoted by x_{ij} $(i = 1,2,\ldots,m$ and s outputs denoted by y_{rj} $(r = 1,2,\ldots,s)$, the mathematical programming problem of ratio form can be given as follows:

$$max \sum_{r=1}^{s} \mu_r Y_{r0} \Big/ \sum_{i=1}^{m} v_i X_{i0}$$

$$\sum_{r=1}^{s} \mu_r Y_{rj} \Big/ \sum_{i=1}^{m} v_i X_{ij} \leq 1 \quad j = 1, \ldots, n$$

$$\mu_r, v_i \geq 0$$

If the sum of weighted inputs of DMU whose efficiency is measured is made equal to 1(i.e. $\sum_{i=1}^{m} v_i X_{i0} = 1$), then the CCR model is obtained as follows.

$$max \sum_{r=1}^{s} \mu_r Y_{r0}$$

$$\sum_{r=1}^{s} \mu_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \quad j = 1,2, \ldots, n$$

$$\sum_{i=1}^{m} v_i X_{i0} = 1$$

$$\mu_r, v_i \geq 0$$

While it has been measured efficiency of DMUs by this model, it is necessary to solve model n -times for each DMU. The optimum value of objective function gives the efficiency score of the interested DMU in the model. Different set of weights μ_r, v_i will be selected for each DMU. Therefore, the set of optimum weight identifies a hyperplane for each DMU. Any DMU whose efficiency score equals to one is defined as efficient, otherwise inefficient [2,3,4,5]. In this study, it's used input oriented CCR model, output oriented CCR model, input oriented BCC model, output oriented BCC model and these models's dual forms.

SIMPLEX METHOD

Simplex Method is based on the process of algebraic recurrence (iteration) Firstly, the initial table is created. Then procedures are maintained with repetitive operations in a particular calculation method moving towards developing solutions until it reaches the optimal solution.

In the Simplex Method, while trying to reach the best solution, different points in the solution space is tested during its implementation simplex method. During this trial successive solutions developed in the same standart calculations are renewed until the best solution is reached. It is quite easy to computerize due to repetition of the property and the standard ways of calculation [6].

If a equation system is m equations and n variables also the number of variables is greater than the number of equality, finding a complete solution is mathematically impossible. In this situation, any value is assigned to (n-m) one variable and the rest of the n one the variables is found the value. If such a situation is encountered, one variables n basic variables and the remaining one variable (n-m) non-basic variable which by the value of one variable is zero are determined. For a basic solution eligible to be the value of all the basic variables must be greater than zero.

Simplex method begins with an appropriate solution and progresses by finding better solution at each stage. When it is not possible to find a better solution, the optimal solution will have been found in this systematic process [7].

DECISION SUPPORT SYSTEM

Both the users are familiar with it and now that it's used by many package programs such as SPSS, Excel is preferred as the data input interface. So, exchange data with other platforms can be provided easily and adopted more quickly by the users. It's possible to import data from "xls", "xlsx" (MS Excel 97-2010) and "txt" (Notepad) file extensions for data entry interface. In addition it's also possible to manually input data via the keyboard.

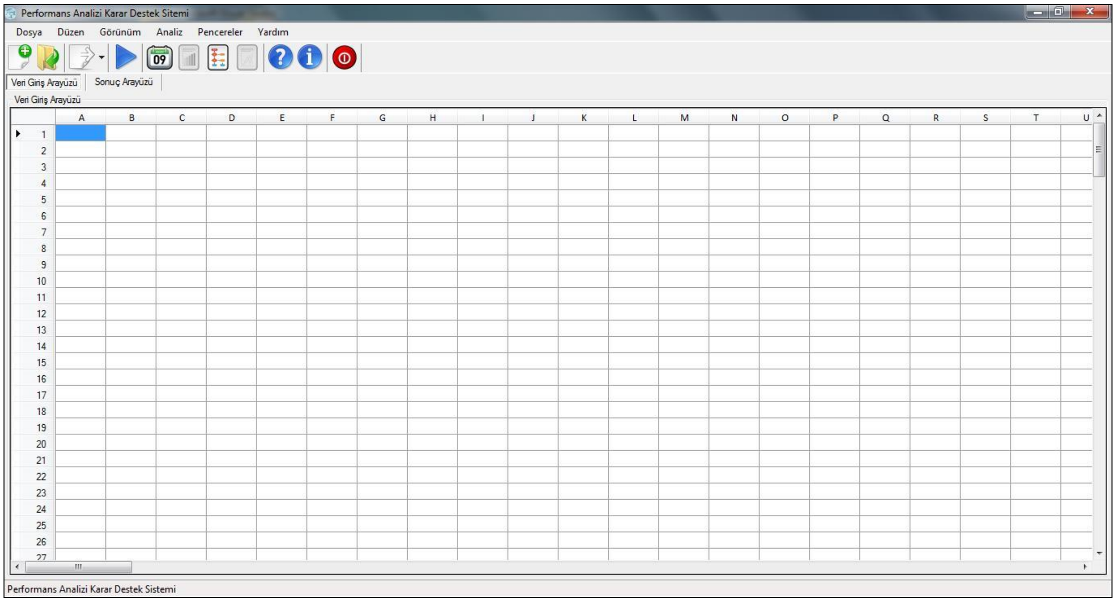

Figure 1: Screenshot of the data entry interface

As if they are manually entered data imported from the Excel and Notepad and if inaccurate, can be manually corrected. Besides there are six menu of DSS now, some of the inactive menus which are thought in advance to be placed in the next versions of it are added.

Figure 2. Screenshot of DSSs menus

Analysis of the data imported different platforms or manually, are entered performed by analysis interface are shown in Figure 3. It will be analyzed after the algorithms of model selected by the user run automatically. After the analysis, as shown in Figure 4, the report screen which will show efficieny scores will be presented to the user.

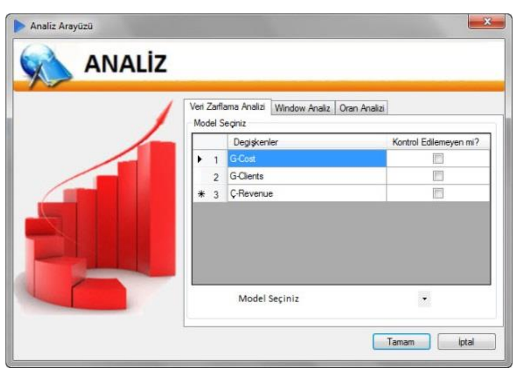

Figure 3. Screenshot of DSSs analysis menus

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Karar Verme Birimleri :	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14
2	Etkinlik Değerleri :	0.7429	0.9907	0.9587	1	0.8945	0.929	0.796	1	0.7648	1	0.9771	0.9214	0.9723	0.9844
3	Referanslar Olma Sıklığı :				6				5		6				
4	Referanslar :	F4 (1.51)	F8 (0.02)	F4 (1.62)		F8 (0.05)	F8 (0.36)	F4 (0.77)		F4 (0.63)		F4 (1.57)	F8 (0.1)	F8 (0.3)	F4 (1.24)
5			F10 (1.87)			F10 (1.15)	F10 (0.72)					F10 (0.93)	F10 (0.93)	F10 (0.54)	
6															
7															
8															
9															
10															
11															
12															
13															
14															
15															
16															
17															
18															
19															

Figure 4. Screenshot of DSSs report interface

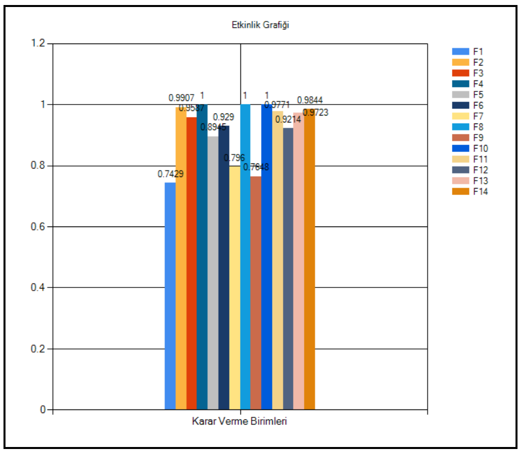

Figure 5. Analysis result of the efficiency graph

Each column in the report interface shown in Figure 4 shows DMUs efficiency scores and reference sets. These values presented are open to user's comment. At the same time, the graph of efficiency scores as shown in Figure 5 is displayed to the user.

In order to test the accuracy of the developed DSS, comparison of analysis results is preferred with non-commercial Efficiency Measurement System (EMS 1.3.0) package program. As a result of the comparison results, DMUs efficiency scores, reference sets and reference frequency have been found to be equal both in the package program. The superior characteristics of DSS are as follows. Although there is no manual data input interface in EMS, it is available at KDS. EMS is only supported version of MS Office 97-2003 Excel (xls) whereas DSS is supported even all version of MS Office Excel (97-2003-2007-2010) (xls, xlsx). EMS isn't able to import data from Notepad while DSS can. There are differences between these two packet program in terms of platforms presented of the analysis. EMS only can export to Excel results of the analysis while DSS can export to different platforms such as Word, Adobe PDF, Excel and Notepad.

Conclusions

Concepts such as efficiency and productivity have always been important in the world where resources are limited and will continue to be. Necessity of using resources efficiently is required to measure performance of the production of goods and services. Getting a high level of performance for organizations is key to success. So, improving the present performance and understanding why the organization doesn't work efficiently are the ultimate goals at the present time. DEA, one of the methods of performance analysis, is a non-parametric method using value observation of the various input and output variables of DMU.

Software package program for performance analysis that is completely Turkish complements the deficiencies of similar programs and is encoded with Microsft Visual C # programming language has been developed in this study. In order DSS to run on the computer, .NET Framework 4 should be installed. For example, DEAP, one of the performance analysis package programs, does not work in windows operating system so it is just a program that runs in MS-DOS. Considering the lack of this kind of a program, a package program running in windows operating system has been developed. Even though there is no manual data input interface in Efficiency Measurement System (EMS) package program, it is available in DSS. Namely, it is not possible changing data imported from Excel before analyzing it to see if there are any errors and inaccuracies at EMS. However, it is only possible at DSS. Window Analysis for panel data is also available in DSS. Whereas the average value for the periods in many studies which included window analysis is calculated in different ways, the immediate calculations are presented to the user during the analysis at DSS.

This software package program developed (DSS) is thought to increase awareness issue of performance particularly in health, education, banking, industry, transport and agriculture sectors in our country and contributes to Turkey's economy nation-wide due to its domestic production.

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TWO-STAGE ANALYSIS OF BANKING EFFICIENCY IN NIGERIA

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ABSTRACT

This paper establishes the efficiency scores of the Nigerian banking industry, and subsequently identifies important variables determining the efficiency level. Data Envelopment Analysis (DEA) is used to measure the efficiency and Panel Data Analysis is used to explain the determinants. Using total deposits and operating expenses as inputs and loans and other investments as output in the DEA across a panel of 17 banks over 5-year period to 2009, it was observed that efficiency improved during the sampled period. In general, old generation banks are more efficient as exhibited by their progressive approach to the frontier benchmarks. It is also found that the result based on Hausman test selection and some statistical criteria shows that a market specific factor (shareholders' networth-SHN) and a firm specific factor (Loan loss provision- LLP) are the two most common factors that determine the efficiency. This paper therefore recommends that LLP and SHN be given top priority in understanding the variations in the Deposit Money Banks' efficiency.

***Keywords**: Efficiency, Data Envelopment Analysis, Panel Data Analysis*

INTRODUCTION

Research interest in banking efficiency in developing countries has increased over the past years especially post reform periods seeking to evaluate the efficiency gains of deregulation. However, for sub-Saharan African countries like Nigeria, such research remains thin and inconclusive. This weakens growth potentials especially given the structural dominance of banking firms in their financial systems. Banks are almost the sole determinants of financial intermediation with the capital markets being near absent.

Sweeping economic reforms that engulfed these markets raised expectations of increased efficiency of the intermediation process. This expectation is more positive in improved functioning of the markets given the fact that the changes are policy responses to the inherent government inefficiency in managing the intermediation process. In this streak, bank consolidation with identification of improved capital base, is a critical condition to propel efficiency growth.

However, the effect of the capital boost on the efficiency gains is unclear. On one hand, expansion in bank capital may enhance efficiency by providing alternative source of funding and raise the obligor limits. On the other hand, strengthening bank capital may generate wasteful investment instead of translating into higher efficiency performance. To this end, researchers should be interested in assessing the levels of efficiency gains; and what determine the efficiency.

It is the feasible bi-dimensional market response to the consolidation exercise that motivated this study. The research is an attempt to provide information on the sizes of efficiency of the Nigerian banking sector since the consolidation exercise under a two-stage analysis. Efficiency scores will be generated through the Data Envelopment Analysis technique while the causality dictum is achieved through econometric panel data analysis. Two main questions are addressed in this study: What efficiency scales have been achieved by individual banks in Nigeria post consolidation? What determines the efficiency- is it banking internal characteristics, market/industry characteristics or macroeconomic conditions or some sort of combination?

METHODS

Farrel's (1957) seminal work was the first to propose the concept of productive efficiency by arguing that overall efficiency can be decomposed to generate "price efficiency" separate from traditional "technical efficiency". Farrel's definition of technical efficiency stimulated development of different methods for estimating relative efficiencies of productive units. Since then, two strands of frontier estimation methodologies were developed in consonance with the assumptions (especially about the error term) and model specification: parametric (stochastic) -the stochastic frontier approach (SFA and non-parametric (linear programming) - Data Envelopment Analysis (DEA).

One of the qualities of the DEA methodology is that it does not explicitly make any assumptions about the functional form of the frontier being estimated. Instead it empirically builds a best-practice frontier from observed inputs and outputs. Numerous studies have generated EA efficiency scores which were further regressed on some environmental variables in a second stage analysis based on the work of Banker and Natarajan (2008). This method is adopted in seeking information of what determine efficiency in the Nigerian banking since consolidation in 2005.

Important variables are identified (see Hesse (2007), Ajao & Ogunniyi (2010), David & Poloamina (2012) and Haruna (2011b)); these are deposits and operating expenses as inputs, while loans & advances and Investments are outputs. Central to meeting the expectation of financial reforms are what determines the efficiency changes. Haruna (2011a) classifies these determinants into three: internal organizational structure of the bank; the market and industry structure; and the macroeconomic structure.

Table 1: Definition of Determinants

Classifications	Variables	Definitions	Significance/A Priori Expectations
Firm-Specific	Operating Expenses (OE)	Non-interest Exp/ Total Earning Assets	Requires more spread to cover. It is expected to have direct effect on Spread.
	Loan Loss Provisions (LLP)	Provision for bad debt/Total loans & Advances	Banks would tend to push this cost to customers. In ex-post analysis, LLP on the income statement decreases spread. Hence inverse relationship is anticipated.
Market-Specific	Financial Intermediation (IMED)	Total Loans/Total Deposit Liabilities	Active intermediation indicates high IMED. Competitive environment decreases spread; hence an inverse relationship.
	Shareholders' Networth (SHN)	Shareholders' Funds/ Total Assets	Requires more spread to accumulate. It is expected to have a positive relationship with Spread.
	Exchange Rate Depreciation (ERD)	$[(fxr)_t-(fxr)_{t-1}]/(fxr)_{t-1}$ where (fxr) = periodic exchange rate and $_{t-1}$= annual time-lag.	Proxied by its annual average rate of growth/depreciation. It is expected to have direct effect on Spread.

Macroeconomic	Treasury Bill (TRB)	Average Annual Treasury Bill rates	Proxy for marginal cost of funds; a bench mark for interest rate decisions by banks. As a cost indicator, it should generate a positive relationship with spread.
	Annual Inflation Rate (IFL)	$[(CPI)_t - (CPI)_{t-1}]/(CPI)_{t-1}$ where $_{t-1}$= annual time-lag.	This is to capture business cycle effects. Inflation can also affect spread if monetary shocks are not passed wholly to deposits and lending rates, or adjustment occurs at different speed and time.

Source: Haruna (2011c)

Given the perception of the role played by banks, the intermediation approach is adopted. That is, the financial institutions are regarded as intermediaries between savers and borrowers. They transform and transfer financial assets through their intermediation services (i.e. converting deposits and other liabilities to earning assets, such as risk assets, securities and other investments). In this approach both operating expenses, and deposits are ideal for inputs, whereas all earning assets should count as outputs. Consistent with this logic, the chosen inputs in the DEA model are deposits and operating expenses; while the outputs are loans and other investments. Details on DEA approaches can be found in Das and Ghosh (2005) and Favero and Papi (1995), among others.

Panel data econometric analysis is used in the second stage for the determinants in order to mitigate the impact of the heterogeneity of banks. In the model, it is hypothesized that the efficiency score is a function of the three (3) broad classifications of variables: bank internal characteristics, market/industry specific characteristics, and the macroeconomic environment as tabulated in Table 1 above:

$$EFFSCORE_{it} = \alpha_0 + \beta_1 LLP_{it} + \beta_2 OE_{it} + \beta_3 IMED_{it} + \beta_4 SHN_{it} + \beta_5 ERD_{it} + \beta_6 TBR_{it} + \beta_7 IFL_{it} + w_i + \varepsilon_{it}$$

Where

ω_i = Variables that vary across banks but do not vary over time

ε_{it} = error terms over cross section and time

The population of the study was the 24 banks in Nigeria at the time of consolidation in 2005 classified as either "New Generation" (NGB) or "Old Generation" (OGB) based on their age and level of efficiency. Perception of efficiency levels between the OGB and the NGB are different. As such in order to avoid sample concentration or bias, 17 sample points taken were stratified into OGBs and NGBs. Thus, the total sample size covering 2005 to 2009 with distribution per stratum are as follows: (12) New Generation[3] and (5) Old Generation banks[4].

RESULTS AND DISCUSSION

The Performance Information Management (PIM) software version 3.1 is used to generate the efficiency scores. The Panel regression result is evaluated using the EViews 7.1 software.

[3] Access Bank, Diamond Bank, Ecobank, Fidelity bank, Firstcity Monument Bank, Guaranty Trust Bank, Intercontinental Bank, Oceanic Bank, Skye Bank, Stanbic-IBTC Bank, Sterling Bank, and Zenith Bank.
[4] First Bank, Union Bank, UBA, Afribank , and Wema Bank.

Considering our pre-determined categorical variables as regards efficiency, the OGBs stood alone since they consolidated by transferring their investment in subsidiaries without need to inject new capital or merge/acquire other banks, except UBA. This invariably kept their culture unchanged. On the other hand, the NGBs have three (3) categories: Group one composed of banks that acquired other banks fusing a new culture that is expected to improve performance; if and only if the fusion generated a better culture. Within the merger category, the direction of performance is a function of the weight of a new culture. Finally, for the banks that resorted to pure capital boosting, they are expected to present significant causality between their improved efficiency and increased capital.

The technical efficiency score is computed with the VRS 'pure' technical efficiency in the output orientation specification taking advantage of the findings of Haruna (2011b) and is contained on Tables 2 and 3. Under the VRS assumption, the average efficiency of the seventeen banks is oscillatory both intra and inter groups. Overall however, all the groups have registered significant efficiency improvement. Such improvement is well noticed with the OGBs that are known to be conservative and resistant to change. The pure merger in the exercise shows a good hybrid of cultures as the group appears to be the most efficient within the NGBs. The banks with pure capital boosting are known to be the industry efficiency leaders; as such they remain on the frontier from the start of the exercise even though Ecobank registered a decline in 2009. Overall, the technical efficiency of Nigerian deposit money banks is approximately 93%.

Table 2: Individual Bank Efficiency VRS

Name	2005	2006	2007	2008	2009
ACCBANK01	54.28	62.49	100	100	100
AFRIBANK02	44.95	69.49	77.67	92.88	79.03
DIAMBANK03	84.69	79.02	73.39	75	90.92
ECOBANK04	100	94.12	88.52	48.24	50.6
FIDEBANK05	43.27	69.45	64.37	82.69	64.4
FIRSTBANK06	100	100	77.8	86.4	100
FCITBANK07	100	100	100	100	100
GTBANK08	100	98.7	82.47	100	100
INTERBANK09	77.92	100	100	100	100
OCEABANK10	100	100	100	100	100
SKYEBANK11	55.78	77.23	72.21	99.21	67.56
STANBANK12	100	100	100	100	72.79
STERBANK13	32.41	58.58	63.44	54.14	55.86
UBNBANK14	72.99	69.86	62.49	50.53	56.79
UBABANK15	61.89	100	100	100	99.48
WEMABANK16	100	100	82.98	100	100
ZENITHBANK17	100	100	76.28	72.01	100

Source: Authors' computation

Table 3: Average Bank Efficiency VRS

	2005	2006	2007	2008	2009

Old Generation Banks	93	98	100	100	94
New Generation Banks- Acquisition	95	100	98	100	100
New Generation Banks- Merger	80	87	89	99	100
New Generation Banks- Capital	100	100	100	100	100
Total Sample	74	84	81	98	93

Source: Authors' computation

At the second stage analysis, this study adopted the two widely panel data regression models (fixed effect and random effect panel data estimation techniques). The difference in these models is based on the assumptions made about the explanatory variables and cross sectional error term.

In table 5, the two panel data estimation techniques (fixed effect and random effect) for the two models based on Hausman test selection are presented. The results show that about 53% of the systematic variations in the efficiency score in the selected Nigerian banks was explained jointly by firm and market specific factors in the Fixed Effect model**.** Whereas the Random Effect shows that less than 11% variation could be explained by the model.

It is also observed that **LLP** and **SHN** were the key determinants of efficiency in the selected banks in Nigeria with the Fixed Effect model. This is consistent with the capital increase impact and enhanced culture of loan management after the consolidation. However, in line with the poor explanatory power of the Random Effect model, only the **LLP** is statistically significant. The F-statistic of the Fixed Effect model shows that the model is statistically significant at 1% level and the Hausman test selected the fixed effect panel data estimation as more appropriate when compared to the random effect approach that failed the F-test.

Table 4: Panel Data Result

	C	LLP	OE	IMED	SHN	TBR	ERD	IFL	Adj.R2	F-stat	Hausman test
Eff. Score	77.294	-52.466	-14.568	-11.334	72.961	92.516	-55.138	-18.048	0.529	5.109	19.67
FIXED EFFECT MODEL	(3.682)	(-2.631)	(-0.829)	(-0.691)	(1.812)	(1.330)	(-1.092)	(-0.202)			
	[0.001]	[0.011]	[0.411]	[0.493]	[0.075]	[0.188]	[0.279]	[0.841]			[0.01]
Eff. Score	82.740	-40.963	-22.570	-0.924	26.766	83.926	-61.856	-22.602	0.104	2.389	5.35
RANDOM EFFECT MODEL	(3.973)	(-2.497)	-1.373)	(-0.077)	(1.417)	(1.210)	(-1.240)	(-0.254)			
	[0.000]	[0.015]	[0.174]	[0.939]	[0.161]	[0.230]	[0.219]	[0.800]			[0.7]

Note: (1)Parentheses ( ) are t-statistic while brackets [ ] are p-values

Source: Authors' computation

Following the above in identifying the determinants of efficiency in Nigerian commercial banks, it is observed that LLP and SHN were the two most common factors that determine the efficiency. This therefore means that market specific factor (shareholders' networth (SHN)) and firm specific factor (Loan loss provision (LLP)) are the most relevant in understanding the variations in the efficiency.

CONCLUSIONS

The investigation of the efficiency and the determinants used seventeen banks drawn from the quoted banks on the Nigerian Stock Exchange. The study establishes overall increase in efficiency post consolidation. In identifying the determinants of the efficiency, we estimated the two popular panel data regression models (fixed and random effects). The result based on Hausman test selection and some statistical criterion shows that LLP and SHN were the most common determinants. This study therefore recommends that Loan loss provision (LLP) and shareholders' networth (SHN) be given top priority in understanding the variations in the Deposit Money Banks efficiency.

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