Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 196 (2017) 302 – 308

Procedia Engineering

www.elsevier.com/locate/procedia

Creative Construction Conference 2017, CCC 2017, 19-22 June 2017, Primosten, Croatia

Bidding model incorporating bid position for determining overhead-cum-markup rate

Li-Chung Chao[a,]*, Shinn-Jye Liaw[a]

[a]*National Kaohsiung First University of Science and Technology, Yanchao, Kaohsiung 824, Taiwan ROC*

Abstract

The direct cost of a construction project constitutes the majority of a contractor's bid, with the remaining part being its overhead cost and markup. Contractors often apply a combined rate of overhead and markup on top of the direct cost for producing a bid. Extending previous researches on overhead rate estimation and bid markup determination, this research aims to develop an improved bidding model incorporating the bid position for determining the minimum overhead-cum-markup rate so as to prevent an inadequate bid. Since factors influencing the overhead rate level may also influence the markup level, it is suggested to build a regression equation from actual bid data for estimating the overhead-cum-markup rate in the winning bid that is used to estimate the probability of winning for a bid. With assessments of probabilities of winning and those of making a loss for various bid levels, fuzzy inference systems that incorporate the bidder's positions in the fuzzy rules regarding the need for work and attitude toward risk are proposed. The model is illustrated using an example involving 406 projects. The suggested bids from the model for two cases of bidding are compared with those from other methods and the actual bids to examine its soundness. The results show that the model can differentiate the bid positions under varying scenarios and suggest minimum bids consistently.

© 2017 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Peer-review under responsibility of the scientific committee of the Creative Construction Conference 2017

Keywords: bid markup; overhead; regression; risk; fuzzy logic.

1. Introduction

The bid for a construction project comprises the contractor's estimated direct cost and overhead cost plus its applied markup, i.e. profit. The contractor's direct cost refers to all expenses for labor, equipment, materials, and subcontracts required for completing the project elements and it constitutes the majority of a bid. The contractor's

* Corresponding author. Tel.: +886-9-28728694; fax: +886-7-6011017.
E-mail address: chaolc@nkfust.edu.tw

1877-7058 © 2017 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Peer-review under responsibility of the scientific committee of the Creative Construction Conference 2017
doi:10.1016/j.proeng.2017.07.203

overhead cost consists of the site overheads for supporting the project and the project's share of the home-office overheads for running the firm. Although the site overheads can be estimated based on a construction program, such detailed estimation is not favored by many contractors, who often use an experience-based rate of the direct cost to cover all site overheads. The project's share of the home-office overheads is usually determined also as a fixed rate according to the ratio of the firm's annual total home-office cost to its annual total revenue. The markup portion of the bid is business-oriented and a higher or lower level may be charged as deemed appropriate, which is usually determined also as a rate based on the conditions of the project, the firm, and the market. Thus, contractors often use an overhead-cum-markup rate on top of the direct cost for producing a bid as in Eq. (1):

$$b = \bar{d} + \bar{o} + p = \bar{d} \times (1 + \frac{\bar{o} + p}{\bar{d}}) = \bar{d} \times (1 + r) \tag{1}$$

where b = bid amount; $\bar{d}$ = estimated direct cost; $\bar{o}$ = estimated overhead cost (site overheads plus project's share of home-office overheads); p = charged profit (markup); r = overhead-cum-markup rate applied in b.

In Eq. (1), $1+r$ equals the $b/\bar{d}$ ratio and, with $\bar{d}$ and r established, b is obtained readily. Such a simple method is naturally prone to inaccuracy, if the applied rate (r) is selected subjectively. Because project owners usually award a construction contract based on the lowest bid, contractors often have to cut their bids to compete but undoubtedly increase the risk of making a loss in completing a job, if the winning bid is exceeded by the actual total cost. Using an overhead-cum-markup rate in competitive bidding without a sound approach certainly involves a greater risk. To avoid suffering an unworthy loss, the bid should achieve a balance between the chance of winning and loss risk according to the bidder's position. Although bidding in construction has attracted much research interest over the years, how to determine the minimum r for a contractor with certain position has not yet been addressed.

Existing bidding models focus on bid markup determination. In traditional models such as Carr [1], the optimum markup is suggested as one with the maximum expected profit, where the expected profit for a markup is defined as the product of it and its probability of winning. However, the bid thus produced tends to give too low a chance of winning for contractors who sacrifice profit to compete. Meanwhile, various multi-criteria markup models have been proposed, e.g. the multi-attribute utility model by Dozzi et al [2] and the case-based reasoning model by Chua et al [3]. They offered various methods for producing an optimum markup for a project, yet they did not determine how low a bid could be and provide a rational solution under intense competition.

Chao and Liou [4] developed a probabilistic approach to determining the minimum markup based on minimization of overall loss risk. Chao [5] proposed a fuzzy logic model for determining the minimum markup that incorporates the position of the bidder. These two models considered the chance of winning versus the risk of making a loss in evaluating various bid levels, but they did not include the contractor's overhead cost in the scope and neither did they establish a connection between project attributes and the probability of winning for a bid. A case-based reasoning model for supervision cost estimation was developed by Chen et al [6], but it did not cover other overheads. Chao [7] developed a decision support system approach for estimating the overhead rate from project attributes, but it did not cover the markup to be applied in a bid.

Clearly, there exists a gap among existing models. The present research aims to develop an improved bidding model that incorporates the bid position for determining the minimum overhead-cum-markup rate $r^{\#}$ for a project in competitive bidding so as to prevent an inadequate bid. The proposed model is built upon previous researches by Chao [5] on fuzzy logic for bid markup determination, Chao [7] on overhead rate estimation, and Chao and Kuo [8] on the probabilistic approach to determining the overhead-cum-markup rate. The reason for using fuzzy logic is that it is tolerant of imprecise and uncertain data and appears potentially useful for modeling consistently the difficult and risky overhead-cum-markup rate decision, in which the bidder's position plays a large part.

2. Description of proposed model

The first step of the model is to estimate the probabilities of winning (P_w) for various r applied in the bid for a project. One estimating method is based on assuming a normal probability distribution for the ratio of the winning bid (b^*) to $\bar{d}$. The estimate of P_w for r applied on top of $\bar{d}$ can be made as a parallel to that of the probability of

winning for a markup rate applied on top of total project cost. By collecting a sample of recent local projects and using the sample mean and standard deviation of $b^* / \bar{d}$ as the estimated parameters of the distribution, P_w for a bid b with $b/\bar{d}$ = 1+r can be estimated without considering influences of project attributes.

In order to give more accurate estimates of P_w, the estimation can be connected with project attributes by a multi-input model. Chao [7] developed a model using project size, duration, location, and type of work, as inputs for estimating the overhead rate in bidding. Since factors influencing the overhead level may also influence the markup level, it is proposed to build a regression equation establishing the relationship of the expected overhead-cum-markup rate in the winning bid for a project ($\bar{r}$) to the same inputs. The equation can be built from the perceived overhead-cum-markup rates in the winning bids ($\hat{r}$), calculated as $\hat{r} = (b^* - \bar{d})/\bar{d} = b^*/\bar{d} - 1$, and the attributes of collected projects. The root of mean squared error (*RMSE*) defined below is used as error measure for the regression equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{r}_i - \hat{r}_i)^2} \tag{2}$$

where n = number of projects; $\bar{r}_i$ = $\bar{r}$ from the equation for project i; $\hat{r}_i$ = $\hat{r}$ for project i.

The obtained $\bar{r}$ for a project is used to estimate the mean of $b^* / \bar{d}$ as 1+$\bar{r}$. Next, assuming that $\hat{r}$ is normally distributed around $\bar{r}$ and since the variance of $\hat{r}$ is equivalent to that of 1+$\hat{r}$, the standard deviation of $b^* / \bar{d}$ is estimated using the *RMSE* of the model. Therefore, P_w for a bid with $b / \bar{d}$ = 1+r can be estimated using the Excel function below.

$$P_w = 1 - \text{NORMDIST}(1+r,\ 1+\bar{r},\ RMSE,\ \text{TRUE}) \tag{3}$$

If the contractor wins with a bid b, there is a probability of making a loss in completing the project (P_l) because the actual project cost c is higher than b. To evaluate P_l for b, we start by estimating project cost ($\bar{c}$) using Eq. (4) in the following:

$$\bar{c} = \bar{d} + \bar{o} = \bar{d} \times (1 + \frac{\bar{o}}{\bar{d}}) = \bar{d} \times (1 + \bar{r}_o) \tag{4}$$

where $\bar{d}$ = estimated direct cost; $\bar{o}$ = estimated overhead cost; $\bar{r}_o$ = estimated overhead rate.

In Eq. (4), $\bar{r}_o$ is to be produced from the model in Chao [7] that maps overhead rates from project attributes, so as to obtain $\bar{c}$. Consider the actual direct cost (d) and the actual overhead rate (r_o) for a project as random numbers with the relation to c as $c = d \times (1+r_o)$. To obtain a probability distribution for c, probabilistic estimating methods such as Diekmann [9] are used. The probability distribution for d is aggregated from the distributions for all work items. As a project comprises many items in various trades, the central limit theorem applies generally, the distribution of d is approximately normal, and so are that of c. The mean of c (μ_c) can be estimated using $\bar{c}$ from Eq. (4). Since d and r_o usually are not linearly correlated, the variance of c (σ_c^2) can be obtained using Eq. (5).

$$\sigma_c^{\ 2} = \mu_d^{\ 2}\sigma_{1+r_o}^{\ \ 2} + \mu_{1+r_o}^{\ \ 2}\sigma_d^{\ 2} + \sigma_d^{\ 2}\sigma_{1+r_o}^{\ \ 2} = \mu_d^{\ 2}\sigma_{r_o}^{\ 2} + (1+\mu_{r_o})^2\sigma_d^{\ 2} + \sigma_d^{\ 2}\sigma_{r_o}^{\ 2} \tag{5}$$

where μ_d = mean of d; σ_{ro}^2 = variance of r_o; μ_{ro} = mean of r_o; σ_d^2 = variance of d.

In Eq. (5), μ_d can be estimated at $\bar{d}$ using the sum of mean direct costs for all work items and σ_d^2 can be estimated using the sum of variances of direct cost for all items (*SV*). For each item, the minimum, most likely, and maximum estimates can be used to form a triangular distribution, from which its mean and variance can be solved. Next, μ_{ro} can be estimated at $\bar{r}_o$ from the overhead rate model and σ_{ro}^2 can be estimated using the mean squared error of it (MSE_o). By standardizing c against $\bar{d}$, P_l for a bid with $b / \bar{d}$ = 1+r can be estimated using the Excel function below:

$$P_l = 1\text{- NORMDIST}(1+r,\ 1+\bar{r}_o,\ (\frac{\bar{d}\text{^}2 * MSE_o + (1+\bar{r}_o)\text{^}2 * SV + SV * MSE_o}{\bar{d}\text{^}2})\text{^}0.5,\ \text{TRUE}) \quad (6)$$

The next step of the model is to setup the if-preconditions-then-consequences fuzzy rules and membership functions representing the bid position. The bidder's degree of need for work and attitude toward risk will be the basis for the rules that reflect his/her priorities. The need-for-work degree and the risk attitude are implied by the ranks assigned to different levels (in linguistic values) of chance of winning and chance of making a loss in the rules' preconditions, respectively. The Gaussian and triangular membership functions are considered appropriate for the fuzzy variables "chance" and "rank", respectively.

Then, the developed fuzzy inference system is used to evaluate various bid levels for a project. The prepared pairs of the estimated probabilities of winning and making a loss for various $b/\bar{d}$ ratios are fed into the fuzzy inference system to produce a score as output for each corresponding *r*. A fuzzy inference is achieved by selected mathematical operations of the formulated membership functions on the if-then rules. The inference process includes fuzzifying the crisp inputs of probabilities, calculating the rules' firing strengths, weighing the rules' consequences (ranks), aggregating the weighed consequences, and defuzzifying the result into a crisp output (score). The minimum overhead-cum-markup rate $r^{\#}$ is determined as one with the highest score from evaluation. Chao [5] can be consulted for details on the above. The model is illustrated using the example below.

3. Illustrative example

In this research, bid data for 431 recent public construction projects in Taiwan were collected from government procurement web sites and it was used to build a regression equation for estimating $\bar{r}$ using four project attributes: size indicated by estimated direct cost ($\bar{d}$), duration (*D*), location, and type of work. The winning bid (b^*) of a project and the project's $\bar{d}$ based on the owner's budget were used to calculate the perceived overhead-cum-markup rates in the winning bid, $\hat{r} = (b^* - \bar{d})/\bar{d} = b^*/\bar{d} - 1$, for use as the target value. With respect to location as well as type of work, a classification scheme was developed and binary representation was used. Then, a regression analysis was carried out on the projects and the obtained R^2 of 0.183 shows poor explanation of variation of $\hat{r}$. An examination of the errors reveals 25 projects with very large deviations from their target values, indicating existence of factors unique to them, and so one with unusually large size, ten with duration less than one month, and 14 with very low winning bids ($\hat{r}$ <-0.2) were discarded, resulting in a sample of 406 usable projects. Then, statistical analyses were carried out on the 406 projects, including descriptive statistics and correlations among the variables, and the results are shown in Tables 1 and 2 for quantifiable variables ($\bar{d}$, *D*, and $\hat{r}$) as well as Tables 3 and 4 for categorical variables ($\hat{r}$ by location and $\hat{r}$ by type of work). Compared to the data in Chao and Kuo [8], the present sample has more small projects reflecting the nature of the local construction market in general, because the present study did not obtain the sample from the bids of a large contractor as the previous study did.

Table 1. Statistics of $\bar{d}$, *D*, and $\hat{r}$ for the 406 projects (note: NT$1≈US$0.03).

	Mean	Standard deviation
$\bar{d}$ (NT$ 10 million)	4.7	10.2
D (working day)	185	138
$\hat{r}$	0.142	0.132

Table 2. Coefficients of correlation among $\bar{d}$, *D*, and $\hat{r}$.

	$\bar{d}$	*D*	$\hat{r}$
$\bar{d}$ (NT$ 10 million)	1		
D (working day)	0.625	1	
$\hat{r}$	0.076	0.260	1

Table 3. Statistics of $\hat{r}$ by location

Location	Number of projects	Mean	Standard deviation
Taipei area (*TP*)	55	0.187	0.118
Other cities (*OC*)	162	0.125	0.139
Counties (*CO*)	189	0.144	0.127

Table 4. Statistics of $\hat{r}$ by type of work.

Type of work	Number of projects	Mean	Standard deviation
Buildings (*BL*)	83	0.251	0.070
Bridges (*BR*)	19	0.152	0.113
Roads (*RD*)	76	0.050	0.148
Site works (*ST*)	120	0.127	0.115
Pipelines (*PP*)	97	0.139	0.122
Ports (*PR*)	11	0.126	0.107

The statistics in Tables 1-4 show that the projects vary widely in size, duration, and $\hat{r}$ with large standard deviations and that projects in Taipei area have a higher mean $\hat{r}$, so do projects of the types of buildings and bridges. While $\bar{d}$ and D are positively and strongly correlated, $\hat{r}$ correlates with $\bar{d}$ and D weakly, probably because larger projects in the sample tend to be more complex. The above appear reasonable from the viewpoint of construction management and economics principles. The 406 projects were then used to build a regression equation for estimating $\bar{r}$. The obtained equation shown below achieves a higher R^2 of 0.269 and an *RMSE* of 0.113, which is lower than the sample standard deviation of 0.132 in Table 1.

$$\bar{r} = 0.104 - 0.0006\bar{d} + 0.0002D + 0.0032TP - 0.0133OC + 0.1097BL + 0.0046BR - 0.0721RD - 0.0021ST + 0.0049PP \quad (7)$$

The two case projects in Chao and Kuo [8], called Project A and Project B, were used again herein for simulation of bidding. With their attributes ($\bar{d}$ = 15.4 and 8.3, D = 432 and 400, location = TP and OC, type of work = BR and PP), $\bar{r}$ are obtained from Eq. (7) at 0.187 and 0.169 for Projects A and B, respectively. Next, for each project, P_w for various levels of r are estimated using Eq. (3). Meanwhile, the standard deviation of direct cost is estimated at $0.05\bar{d}$ for Project A and at $0.04\bar{d}$ for project B, so the *SV* for the two projects are $(0.05\bar{d})^2$ and $(0.04\bar{d})^2$. The overhead rates for each project are estimated using the model in Chao [7] with an MSE_o of 0.0244^2=0.0006 and the obtained $\bar{r}_o$ are 0.087 and 0.064 for the two projects. Then, for each project, P_l for various levels of r are estimated using Eq. (6).

Three sets of fuzzy rules (shown in Tables 5-7) are formulated to address three possible scenarios of bid position regarding risk attitude and need-for-work degree: a risk-taking bidder with urgent need for work, a risk-averse bidder with normal need for work, and a risk-neutral bidder with slight need for work. The rules in Table 5 are interpreted as “the higher the chance of winning, the better the bid, as long as its loss risk is not very high”, those in Table 6 are interpreted as “the lower the loss risk, the better the bid, as long as its chance of winning is not low”, and those in Table 7 are interpreted as “the bid is not too bad, as long as its chance of winning is not very low and its loss risk is not very high”. The fuzzy variables “chance of winning”, “chance of making a loss, and “rank” each can take five linguistic values, whose membership functions are shown in Fig. 1. Note that adding “Not” to a linguistic value produces a membership function complementary to that for it. The mathematical operations in fuzzy inference are: maximization for “OR” connector, minimization for weighing consequences, maximization for aggregating weighed consequences, and centroid for defuzzification to produce the score. MATLAB’s fuzzy logic toolbox was used to develop the fuzzy inference systems [10].

Then, for each project, the obtained pairs of P_w and P_l for various ratios of $b/\bar{d} = 1 + r$ are inputted into the developed fuzzy inference systems to obtain corresponding scores. The minimum overhead-cum-markup rates $r^{\#}$ suggested for each scenario above are determined as those achieving the highest scores. The $\hat{r}$ perceived in the

actual lowest bids, $r^{\#}$ suggested for the three scenarios using the proposed model, $r^{\#}$ suggested by the approach in Chao and Kuo [8] with average prospect, and $r^{\#}$ suggested by the traditional model are compared in Table 8.

Table 5. Example fuzzy rules for risk-taking bidder with urgent need for work (first scenario)

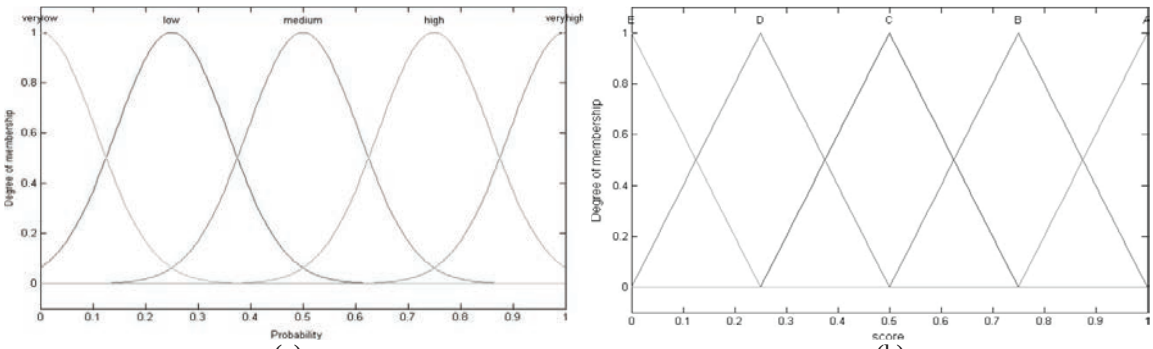
No.	Chance of winning	Connector	Chance of making a loss	Rank
1	Very high	-	-	A
2	High	-	-	B
3	Medium	-	-	C
4	Low	-	-	D
5	Very low	OR	Very high	E

Table 6. Example fuzzy rules for risk-averse bidder with normal need for work (second scenario)

No.	Chance of winning	Connector	Chance of making a loss	Rank
1	-	-	Very low	A
2	-	-	Low	B
3	-	-	Medium	C
4	Low	OR	High	D
5	Very low	OR	Very high	E

Table 7. Example fuzzy rules for risk-neutral bidder with slight need for work (third scenario)

No.	Chance of winning	Connector	Chance of making a loss	Rank
1	Very low	OR	Very high-	E
2	-	-	Not very high	Not E



(a) (b)

Fig. 1. Membership functions for fuzzy variables (a) “chance of winning” and “chance of making a loss” (b) “rank”

Table 8. Overhead-cum-markup rates for projects A and B

	Project A	Project B
$\hat{r}$ perceived in actual winning bid	0.162	0.080
$r^{\#}$ suggested for risk-taking bidder with urgent need for work	0.059	0.042
$r^{\#}$ suggested for risk-averse bidder with normal need for work	0.172	0.147
$r^{\#}$ suggested for risk-neutral bidder with slight need for work	0.156	0.137
$r^{\#}$ suggested by risk-minimizing approach with average prospect	0.136	0.116
$r^{\#}$ suggested by traditional model based maximum expected profit	0.151	0.146

The suggested $r^{\#}$ from the proposed model for the first scenario is the lowest for either project, lower than that perceived in the actual winning bids. On the other hand, the suggested $r^{\#}$ for the second scenario are the highest and those for the third scenario are in the middle. The above are due to the effects of the rules in Tables 3-5. While the approach based on minimization of overall loss risk gives more competitive bids than the traditional model based on maximization of expected profit, the fuzzy inference systems produce a wider range of bids. Note that $\hat{r}$ in the actual lowest bids, one very high and the other very low, reflect the random nature of bids received. The results show that the model is sound generally, as it can differentiate the bid positions under varying scenarios and suggest minimum overhead-cum-markup rates in competitive bidding consistently.

4. Conclusions

In bid preparation, contractors commonly focus on direct cost estimation and apply an overhead-cum-markup rate on top of the estimated direct cost for producing a bid. Since contractors often have to cut their bids to compete, determining an overhead-cum-markup rate subjectively without a sound approach certainly involves a greater risk. For a contractor, the maximum risk it can take and the degree of its need for work, which both are subjective and fuzzy, will determine the minimum overhead-cum-markup rate for it. In order to prevent an inadequate bid, the applied rate should achieve a balance between the chance of winning and loss risk according to the bidder's position. The proposed bidding model in the present research is firstly based on building a regression equation that relates the perceived rate in the winning bid to project attributes and is used to obtain more accurate estimates of chance of winning for various bid levels. Then, using the chance of winning and the chance of making a loss as the evaluation criteria, the model incorporates a contractor's bid position on its degree of need for work and attitude toward risk in the fuzzy rules and membership functions. It determines the minimum overhead-cum-markup rate for a project as the one achieving the highest fuzzy score.

As shown by the illustrative example, the proposed fuzzy logic model can differentiate the possible bid positions of a contractor in varying scenarios and suggest minimum overhead-cum-markup rates consistently. The model generally reflects fuzzy logic's flexibility, manageability, and robustness and fills a gap among existing models. The principal findings of this research and its contribution to the body of knowledge on bid decision in construction are that by formulating appropriate fuzzy rules contractors' bid positions can be distinguished and incorporated in the model, thereby suggesting consistent overhead-cum-markup rates for contractors in bidding.

Acknowledgements

Support for the research herein from Ministry of Science and Technology, R.O.C., Grant No. 105-2221-E-327-008, is gratefully acknowledged.

References

[1] R.I. Carr, General bidding model, Journal of Construction Division, ASCE, 108(CO4) (1982) 639-650.
[2] S.P. Dozzi, S.M. AbouRizk, S.L. Schroeder, Utility-theory model for bid markup decisions, Journal of Construction Engineering and Management, 122(2) (1996) 119-124.
[3] D.K.H. Chua, D.Z. Li, W.T. Chan, Case-Based Reasoning Approach in Bid Decision Making. Journal of Construction Engineering and Management, 127(1) (2001) 35-45.
[4] L.-C. Chao, C.-N. Liou, Risk-minimizing approach to bid-cutting limit determination. Construction Management and Economics, 25(8) (2007) 835-843.
[5] L.-C. Chao, Fuzzy logic model for determining minimum bid markup. Computer-Aided Civil and Infrastructure Engineering, 22(6) (2007) 449-460.
[6] J.-H. Chen, L.-R. Yang, W.H. Chen, C.K. Chang, Case-based allocation of onsite supervisory manpower for construction projects. Construction Management and Economics, 26 (2008) 805–814.
[7] L.-C. Chao, Estimating project overhead rate in bidding: DSS approach using neural networks. Construction Management and Economics, 28(3) (2010) 287-299.
[8] L.-C. Chao, C.-P. Kuo, Probabilistic approach to determining overhead-cum-markup rate in bid price. Procedia Engineering, 164 (2016) 243-250.
[9] J.E. Diekmann, Probabilistic estimating: mathematics and applications. Journal of Construction Engineering and Management, 109(3) (1983) 297-308.
[10] MATLAB (2014). *Fuzzy Logic Toolbox for Use with* MATLAB R2014a, *User's Guide*, The Math Works, Inc., Natick, MA.