A Data-Driven Customer Segmentation Strategy Based on Contribution to System Peak Demand

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***Abstract*—Advanced metering infrastructure (AMI) enables utilities to obtain granular energy consumption data, which offers a unique opportunity to design customer segmentation strategies based on their impact on various operational metrics in distribution grids. However, performing utility-scale segmentation for *unobservable* customers with only monthly billing information, remains a challenging problem. To address this challenge, we propose a new metric, the coincident monthly peak contribution (CMPC), that quantifies the contribution of individual customers to system peak demand. Furthermore, a novel multi-state machine learning-based segmentation method is developed that estimates CMPC for customers without smart meters (SMs): first, a clustering technique is used to build a databank containing typical daily load patterns in different seasons using the SM data of observable customers. Next, to associate unobservable customers with the discovered typical load profiles, a classification approach is leveraged to compute the likelihood of daily consumption patterns for different unobservable households. In the third stage, a weighted clusterwise regression (WCR) model is utilized to estimate the CMPC of unobservable customers using their monthly billing data and the outcomes of the classification module. The proposed segmentation methodology has been tested and verified using real utility data.**

***Index Terms*—Customer segmentation, peak load contribution, observability, machine learning**

I. Introduction

Advent of Advanced metering infrastructure (AMI) has facilitated a deeper understanding of customer behaviors in low-voltage networks for distribution system operators. Individual customers' demand consumption can be recorded by smart meters (SMs) with high temporal resolution, which enables developing novel data-centric grid operation mechanisms. One of these mechanisms is utility-scale customer segmentation [1], which is extremely useful in enhancing system operation and management by intelligently targeting customers for peak shaving programs, AMI investment, and retail price/incentive design. This will help utilities under strict financial constraints to optimize their investment portfolio. However, for small-to-medium utilities, a key barrier against investigating an efficient customer segmentation is the absence of real-time measurements due to financial limitations [2]. Currently, more than half of all U.S. electricity customer accounts do not have SMs to record their detailed consumption behavior [3].

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Several papers have focused on developing customer segmentation strategies using SM data. One of the most common approaches is to leverage clustering techniques for identifying typical load profiles [4]–[6]. In [4], principal component analysis (PCA) is performed to extract the dominant features within customer consumption data and then k-means algorithm is employed to classify consumers. In [5], a finite mixture model-based clustering is presented to obtain distinct behavioral groups. In [6], a C-vine copulas-based clustering framework is proposed to carry out consumer categorization. However, the typical load profile extraction alone is insufficient to assess customers' impacts on system peak demand, which limits utilities' ability to target suitable customers for reducing the operation costs.

Apart from typical load profiles, several customer segmentation methodologies have been developed based on the feature characterization and extraction [7]–[10]. In [7], residential customers are ranked using their appliance energy efficiency to reduce building energy consumption. In [8], the entropy of household power demand is used to evaluate the variability of consumption behavior, which is considered to be a key component in peak shaving program targeting and customer engagement. In [9], a customer's marginal contribution to system cost is obtained using daily demand profiles. In [10], a four-stage data-driven probabilistic method is proposed to estimate the coincident peak demand estimation of new customers for designing new systems. Compared to the clustering approaches, these methods directly quantify customer-level features from SM data and use them to determine the segmentation strategies. Nevertheless, the previously-proposed metrics fall short of considering customers' impact on system peak demand, which is a major problem considering that continuous growth in system peak load raises the possibility of power failure and increases the marginal cost of supply [11]. Furthermore, previous works have only focused on observable customers.

In order to address these shortcomings, this paper proposes a new metric for customer segmentation, which is denoted as coincident monthly peak contribution (CMPC). CMPC is defined as the ratio of individual customer's demand during system daily peak load time over the real-time total system peak demand in a course of a month. Compared with conventional coincident peak demand metrics, which quantify the peak consumption levels of multiple customers based on their empirical diversified maximum demand [10], the proposed CMPC focuses on the impact of individual customer and conveys information on how individual customer's peak time differs from the system's peak demand time. Based on the definition of CMPC, we develop a multi-stage machine learning-based customer segmentation strategy that estimates CMPCs of unobservable customers using only their monthly billing information. The developed method consists of three modules: 1) Using a graph theoretic clustering, a seasonal typical load pattern bank is constructed to classify various customer consumption behaviors. 2) To connect unobservable customers to the seasonal databank, a multinomial classification model is presented which identifies typical load profiles of customers without SMs. 3) According to the outcome of the classification module, a weighted clusterwise regression (WCR) model is trained to map the unobservable customers' monthly energy consumption data to CMPC values. Utilizing our segmentation method, within a certain range of consumption, customers with heavy demand but small contribution to the system peak could be excluded from AMI investment/peak shaving investment portfolios, whereas those with a similar demand level but a larger peak contribution can be targeted in such programs as impactful customers. The main contributions of this paper can be summarized as follows:

- A customer segmentation strategy is developed based on a multi-stage machine learning framework, which enables estimating the contribution of unobservable households to system peak demand using only monthly billing data.
- A new metric, CMPC, is proposed as a measure for customer segmentation strategy, which accurately assesses the individual customer impact on system peak.
- An adaptive data clustering method is integrated into the learning framework to enhance the accuracy of estimating customer impact on peak demand by extracting the seasonal typical load patterns.

II. Data Description and CMPC Definition

A. Data Description

The available data used in this paper is provided by several mid-west U.S. utilities. The data includes the energy consumption measurements of over 4000 residential customers from SMs, and the corresponding supervisory control and data acquisition (SCADA) data. The data ranges from January 2015 to May 2018 [12]. The SM data was initially processed to eliminate grossly erroneous and missing samples. Accordingly, the data points with a z-score magnitude of larger than 5 are marked as "erroneous" and replaced using local interpolation [13]. The empirical distribution and cumulative distribution function (CDF) of customer monthly energy consumption are obtained and presented in Fig. 1. As shown in the figure, the majority of residential customer monthly consumption samples are concentrated around 1000 kWh, and almost 80% of customers have monthly consumption levels below 1000 kWh. Compared to the industrial and commercial customers, the demand level of residential households is distributed within a smaller range. This indicates that using only demand level for customer segmentation can be a difficult task.

B. CMPC Definition

The system peak demand is one of the most important operational factors for utilities due to the high marginal cost of energy procurement at the peak time. Hence, it is obligatory to investigate a customer segmentation methodology based on each load's contribution to system peak demand. However, individual customer's peak demand cannot be employed as a measure to assess this contribution, since individual customer peak demand does not necessarily coincide with the system peak. In order to illustrate this, a statistical analysis is performed on the available SM dataset. Fig. 2 shows the percentage of customers whose peak demand coincides with the system peak load. On average only 6% of customers have the same peak time as the system, with a standard deviation of 12%. This means that a customer's peak demand cannot be relied upon to estimate its contribution to the overall system peak load. Thus, in this paper, we propose a new metric, denoted as CMPC, to accurately quantify the contribution of an individual customer to the system peak demand:

$$F_{j,m} = \frac{1}{n}\sum_{d=1}^{n}\frac{p_{j,m}^{d}(t_d)}{P_m^d(t_d)} \tag{1}$$

where CMPC of the j'th customer at the m'th month is denoted by $F_{j,m}$. Here, $p_{j,m}^{d}(t_d)$ is the customer's demand at time t_d on the d'th day of the month, with n denoting the total number of days in the month. Note that P_m^d and t_d are the value and the time of system peak demand on the d-th day of the m-th month. Hence, CMPC is basically the average customer contribution to the daily system peak demand during a month. A few related but different indices can be found in the literature, such as *coincidence contribution factor*, which is defined as the gap between the aggregate peak demand of a group of customers and their actual consumption at the system peak time [14]. However, the coincidence contribution factor cannot be used as a customer-level metric due to its inability

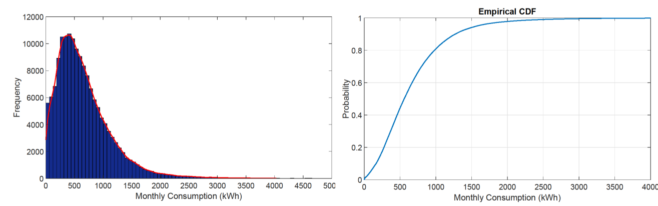


Fig. 1. Monthly consumption distribution: consumption histogram (left), consumption CDF (right).

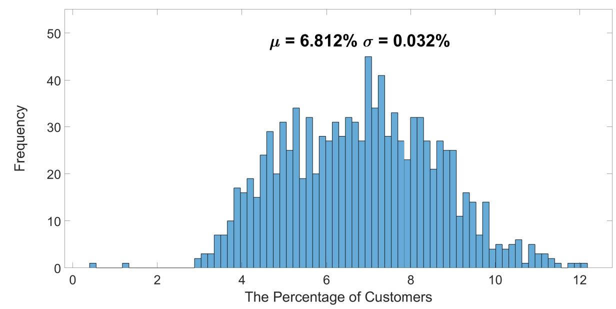


Fig. 2. Percentage of customers whose peak demand coincide with the system peak.

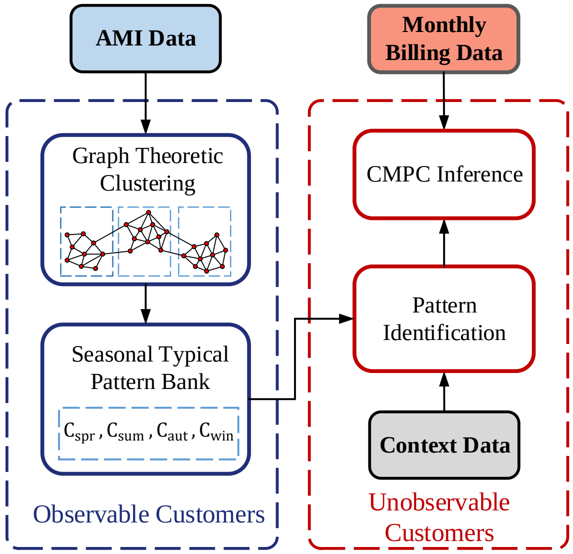
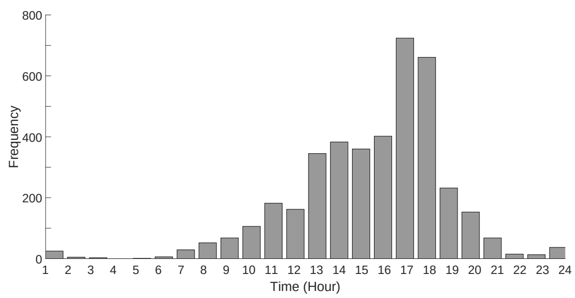
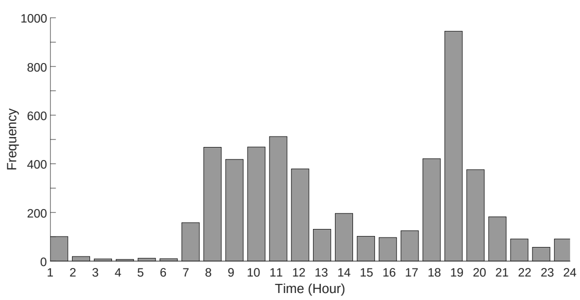


Fig. 3. Proposed data-driven framework.



(a) Summer statistics



(b) Winter statistics

Fig. 4. Seasonal system peak time distribution.

to quantify individual customers' contributions to the system peak load.

CMPC can be directly calculated for observable customers using the real-time SM measurements. Considering that not all customers have SMs in practice, especially for residential households, we propose a multi-stage data-driven method for estimating CMPC. The flowchart of the proposed approach is presented in Fig. 3. (I) In the first stage, the demand profiles of observable customers are utilized to build a seasonal consumption pattern bank, $[\{C_{spr}\}, \{C_{sum}\}, \{C_{aut}\}, \{C_{win}\}]$, using a graph theoretic clustering technique. Here, each $\{C_{(\cdot)}\}$ is the set of the typical daily load profiles for a specific season (detailed in Section III). Seasonal data clustering shows a better load behavior identification performance due to its ability to capture the critical seasonal behaviors of customers [15]. (II) Then, a classification module is developed to infer the likelihood of identified seasonal daily consumption profiles for customers without SM data utilizing sociodemographic information. (III) For each typical pattern, a regression model is trained to provide an inference function to estimate the CMPC from customers' monthly billing data. To take into account the variances of CMPC in different typical patterns, a WCR approach is developed based on the results of classification module. Basically, the proposed customer segmentation approach is able to infer CMPC of customers without SMs using their monthly billing information and limited context information.

III. Graph Theoretical Clustering Algorithm

In this paper, a graph theory-based clustering technique, known as spectral clustering (SC), is adopted. Due to the strong seasonal changes in the customers' behavior, the SC uses seasonal average customer load profiles to identify typical daily load patterns corresponding to different seasons [16], [17]. According to the statistical analysis, both customer behaviors and system peak timing are affected by seasonal changes, as shown in Fig. 4. In Fig. $4(a)$, the peak time distribution in summer is concentrated around evening interval (17:00-18:00 pm). Meanwhile, the peak time probability rises during daytime and falls sharply at night. One possible reason is the increase of air conditioning usage during summer daytime. In contrast, the peak time distribution of winter is presented in Fig. $4(b)$. Compared to the summer, the distribution of peak demand time in winter has two concentration points: one in morning hours (8:00-12:00 am), and the other in the evening (18:00-20:00 pm). Also, the peak time probability shows relatively low values during the afternoon interval (13:00-17:00 pm). Hence, in this work, instead of assigning a single pattern to each customer, various patterns are obtained for different seasons to capture the seasonality of customer behaviors [15].

In each season, the AMI dataset is represented as an undirected similarity graph, $G = (V, E)$. V is the set of vertices in the graph, where the i'th vertex represents the average daily profile of the i'th customer, $V_i = [C_1^i, ..., C_{24}^i]$, with C_j^i denoting the average load value at the j' hour of day for the i'th customer. E is the set of edges in the graph that connect different vertices, where a non-negative weight, $W_{i,j}$, is assigned to the edge connecting vertices i and j. The weight value represents the level of similarity between the two customers' average daily load profiles, with $W_{i,j} = 0$ indicating that the vertices V_i and V_j are not connected. In this paper, the weight $W_{i,j}$ is obtained by adopting a Gaussian kernel function:

$$W_{i,j} = exp(\frac{-||V_i - V_j||^2}{\alpha^2}) \tag{2}$$

where α is a scaling parameter that controls how rapidly the weight $W_{i,j}$ falls off with the distance between vertices V_i

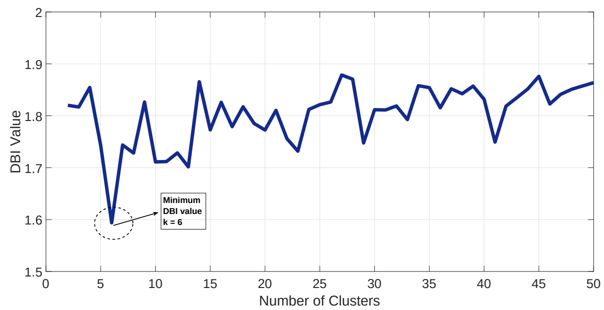


Fig. 5. Cluster validation index performance for summer season.

and V_j. To enhance computational efficiency and adaptability to the dataset, we have adopted a localized scaling parameter α_i for each vertex that allows self-tuning of the point-to-point distances based on the local distance of the neighbor of V_i [18]:

$$\alpha_i = ||V_i - V_\varphi|| \tag{3}$$

where, V_φ is the φ'th neighbor of V_i, which is selected according to [18]. Therefore, the weight between a pair of points can be re-written as:

$$W_{i,j} = exp(\frac{-||V_i - V_j||^2}{\alpha_i \alpha_j}) \tag{4}$$

Given a set of vertices and weight matrix $W = (W_{i,j})_{i,j=1,...,n}$, the clustering process is converted to a graph partitioning problem. In this paper, the objective function of graph partitioning is to maximize both the dissimilarity between the different clusters and the total similarity within each cluster [19]:

$$N(G) = \min_{A_1,...,A_n} \sum_{i=1}^{n} \frac{c(A_i, V \setminus A_i)}{d(A_i)} \tag{5}$$

where, n is the number of vertices, A_i is a cluster of vertices in V, $V \setminus A_i$ represents the nodes of set V that are not in set A_i, $c(A_i, V \setminus A_i)$ is the sum of the edge weights between vertices in A_i and $V \setminus A_i$, $d(A_i)$ is the sum of the weights of vertices in A_i. It has been shown in [16] that the minimum of $N(G)$ is reached at the second smallest eigenvector of the graph's Laplacian matrix, L, which can be determined using the weight matrix W, as demonstrated in:

$$L = D^{-\frac{1}{2}} W D^{-\frac{1}{2}} \tag{6}$$

where, D is a diagonal matrix, which (i,i)'th element is the sum of W's i'th row. The k smallest eigenvalues, $[y_1, y_2, ..., y_k]$, of the Laplacian matrix are extracted in the clustering algorithm (see Alg. 1) to build a new matrix $U \in \mathbb{R}^{n\times k}$, where k ranges from 2 to n. Leveraging the properties of the graph Laplacians, the data point V_i is reconstructed using the i'th row of the U matrix, which enhances the cluster-properties of the data [18]. After data reconstruction, a simple clustering algorithm is able to detect the clusters. In this work, we utilized the k-means algorithm to obtain the final solutions from matrix U.

Compared to conventional clustering techniques, the SC algorithm has two main advantages: (1) it mainly relies on the weight matrix of the dataset rather than using the high-dimensional demand profile data directly. Also, computing the eigenvalues of matrix W for data reconstruction is equivalent to achieving dimension reduction by employing a linear PCA in a high dimensional kernel space; (2) as a basic idea of SC, graph partitioning problem can be solved without making any assumptions on the data distribution. This improves the robustness of SC, and leads to better clustering performance for complex and unknown data structures [18]. The main challenge of SC is that the k value still needs to be determined as a priori. To obtain the optimal k, we employ the Davies-Bouldin validation index (DBI), which aims to maximize the internal consistency of each cluster and minimize the overlap of different clusters [20]. The optimal value of k can be obtained when the DBI is minimized. This is shown in Fig. 5 for summer data subset.

IV. CMPC Estimation for Unobservable Customers

In order to assess the CMPC of unobservable customers, a WCR approach is proposed using only their monthly consumption information, as shown in Fig. 6. This framework includes two stages: the first stage is unobservable customer classification based on the seasonal typical consumption pattern bank, and the second stage is cluster-based CMPC inference.

A. Unobservable customer classification

Since the detailed time-series SM data of unobservable customers is not available, their daily consumption patterns cannot be directly determined beforehand. To link the existing typical load patterns, obtained from the SC technique, to unobservable customers, a pattern classification model is developed. Thus, the goal of this model is to design a classifier that is able to distinguish different behavioral classes based on an input vector that contains sociodemographic information of unobservable customers. The proposed model in this paper maps the sociodemographic information of customers (i.e. working period and dining time) to the typical daily pattern databank. The basic idea is that the typical daily load profiles of customers can be discovered using prior knowledge of their peak consumption timing.

Based on the sociodemographic information of customers, the knowledge of customer behavior over a few distinctive intervals in the day can be obtained, namely the morning interval (from 7:00 am to 9:00 am), the afternoon interval (from 12:00 pm to 14:00 pm), and the evening interval (from 18:00 pm to 21:00 pm). This prior information is then used to obtain an approximate probability distribution function of customer peak timing defined as $X^j = \{X_1^j, X_2^j, ..., X_{h-1}^j, X_h^j\}$, where X_i^j is the probability of j'th customer peak demand occurring at time instant i, with h denoting the maximum number of time points. In this work, using the SM measurements of observable customers, X_i^j is determined as follows:

$$X_i^j = \frac{\sum_{d=1}^{n} \Phi(t_d^j)}{n} \tag{7}$$

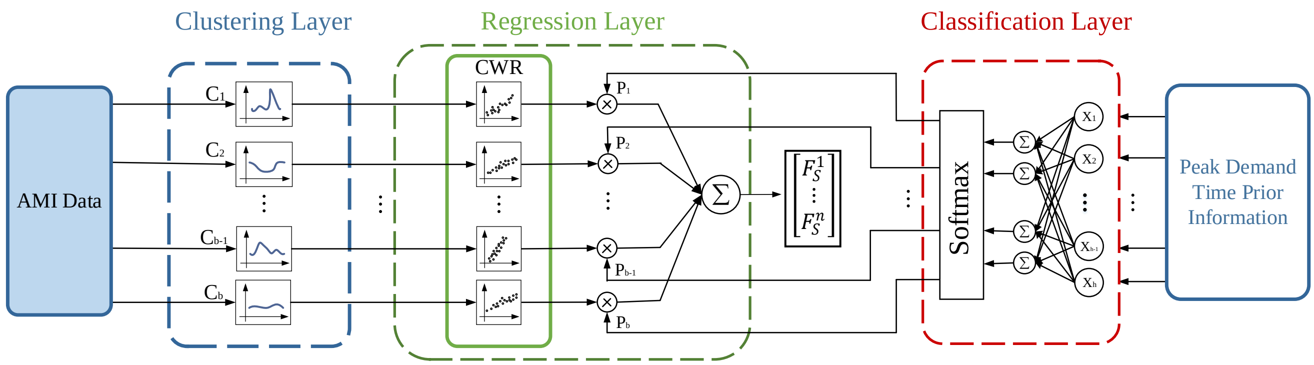
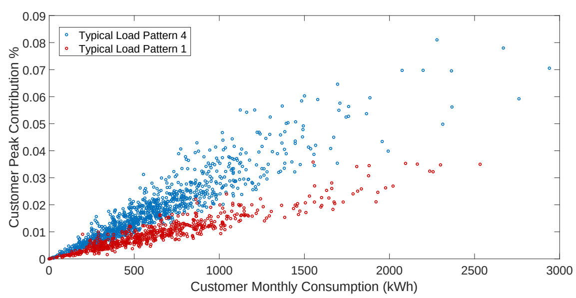
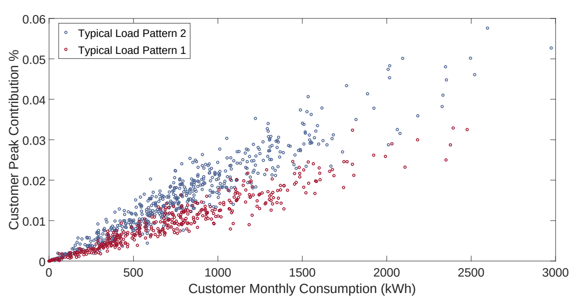


Fig. 6. The structure of WCR model.



(a) Monthly energy and CMPC of different patterns in spring



(b) Monthly energy and CMPC of different patterns in summer

Fig. 7. Performance of clusterwise.

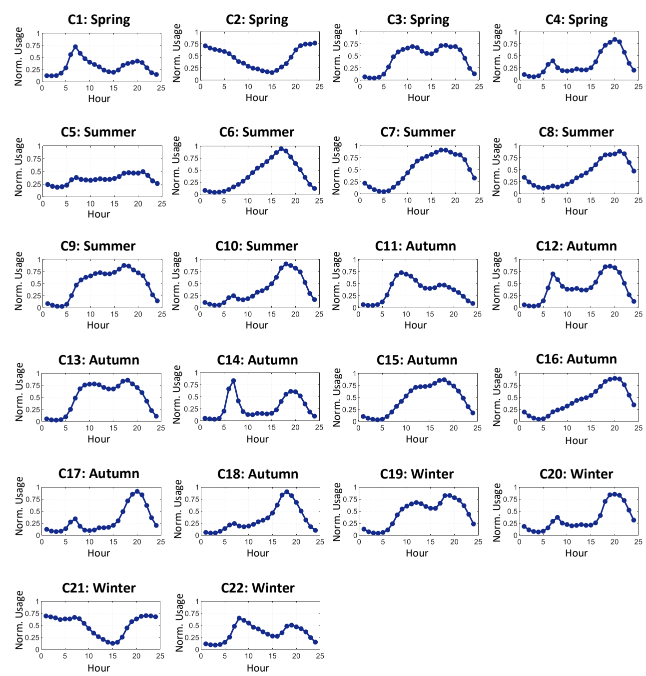


Fig. 8. Seasonal Typical load patterns databank.

$$\Phi(t_d^j) = \begin{cases} 1 & \text{for } t_d^j = i \\ 0 & \text{for } otherwise \end{cases} \tag{8}$$

where, t_d^j is the peak demand time of j'th customer at the d-th day. Thus, the peak timing likelihood distribution, $\{X_1^j, X_2^j, ..., X_{h-1}^j, X_h^j\}$, is utilized as the input of the classification model. This classification model for unobservable customers is developed using the multinomial logistic regression (MLR) algorithm. Compared to other binary classification methods such as random forests, MLR is able to obtain the likelihood of different typical profiles for customers rather than picking a single consumption pattern from the databank [20]. The probability that the j'th customer follows the z'th typical load profile can be written as [21]:

$$P(C_j = z|X^j) = \frac{exp(w_z^T X^j)}{\sum_{j=1}^{b} exp(w_j^T X^j)} \tag{9}$$

where, C_j represents the class of the j'th unobservable customer, b is the total number of consumption patterns, T is the transposition operator, and w_z is the weight vector corresponding to pattern z. The learning parameters w_z are obtained by solving $\nabla_{w_z} J = 0$ over the training set, where J is the classification risk function, defined as follows [22]:

$$J = \sum_{j=1}^{M} [\sum_{z=1}^{k} c_j^z (w_z)^T X^j - \log \sum_{z=1}^{k} \exp\big((w_z)^T X^j\big)] \tag{10}$$

where, c_j^z is the j'th element of c^z, which is a binary string representing customer class membership. To maximize the log-likelihood function, J, with respect to w_z, an iterative reweighted least squares (IRLS) training mechanism was implemented [22].

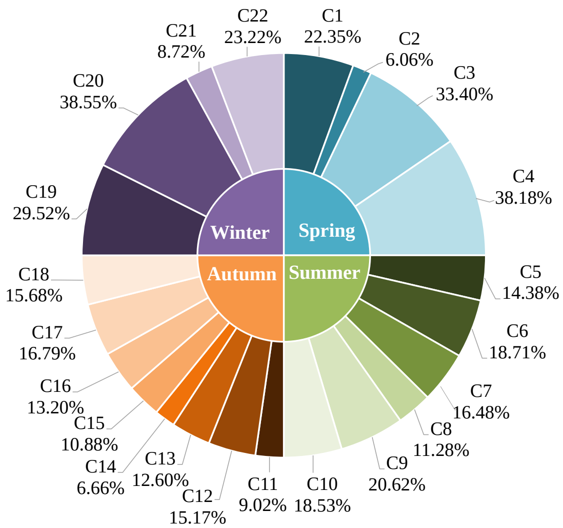


Fig. 9. Proportion of typical load patterns for different seasons.

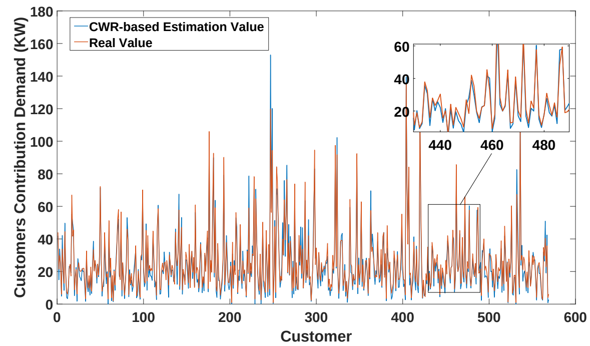


Fig. 10. Comparison of WCR-based estimation value and real value.

B. Estimation of CMPC for Unobservable Customers

To infer the CMPC for unobservable customers, a WCR model is developed by combining two variables: daily load profile and demand level. The basic idea of WCR approach is to utilize the linear nature of the relationship between the CMPC and monthly energy consumption when the load profiles of customers are similar. This is demonstrated in Fig. 7, where the CMPC and monthly energy consumption of customers in different clusters are shown. As depicted in Fig. 7, the correlation between monthly energy consumption and the CMPC is largely different for customers with two distinct behavioral patterns in the same season. Hence, for z'th typical pattern, a linear regression model is trained to infer linear regression coefficients: W_z and b_z, from the corresponding observable customers data using ordinary least squares (OLSs) [23]. After training, all regression models are then merged into a WCR to estimate the CMPC for unobservable residential customers. Using the cluster probability values obtained from the classification model, $P(C_j = z|X^j)$, the estimated CMPC for the j'th customer at the m'th month, $\hat{F}_{j,m}$, is determined as follows:

$$\hat{F}_{j,m} = \sum_{z=1}^{k} P(C_j = z|X^j)(W_z E_{j,m} + b_z) \tag{11}$$

where, $E_{j,m}$ is the customer's monthly consumption level. Hence, the proposed WCR is able to estimate the CMPC of unobservable customers using only their measured monthly consumption within a probabilistic classification setting.

V. Numerical Results

The real distribution system provided by our utility collaborator is equipped with SMs, thus fully observable. This enables us to calculate the exact CMPC of each customer. To test the proposed customer segmentation method for partially observable systems, we assume that 40% of customers are unobservable and then compare the estimation results with the actual CMPCs. Thus, the data of observable customers (the remaining 60% of the total data) is divided into 4 subsets corresponding to different seasons of the year for model training.

A. SC Algorithm Performance

For every subset, the optimal cluster number is determined using DBI and typical load patterns are obtained employing the SC algorithm (detailed in Section III). Fig. 8 and Fig. 9 present the 22 typical load shapes, namely C_1, C_2, ..., C_{22}, and the distribution of population of customers belonging to each cluster during all the seasons. As shown in the figures, the number of typical load profiles in different seasons is not the same and the SC approach is able to capture the critical seasonal consumption patterns. In spring, around 22% of customers show typically higher consumption levels during the morning (around 7:00 am). In contrast, more than 38% of customers have higher energy consumption during the evening (around 20:00 pm). Meanwhile, more than half of customers present low energy consumption value during the afternoon period. The typical load profiles in summer are different from spring. Except for C_5, the typical load patterns of 85% of all customers show similar behavioral tendencies. This could be due to air-conditioning load consumption during time intervals with higher temperature. Based on the typical load patterns, the majority of peak demand occurs during the evening interval. For around 74% of customers in summer, the peak time ranges from 17:00 pm to 19:00 pm. In fall, the number of typical load patterns is relatively larger rather than other seasons due to variability of customer behavior. Compared to summer, when peak demand barely happens in the morning, more than 40% of customers have high consumption at around 7:00 am in fall, such as C_{11}, C_{12}, C_{13} and C_{14}. Also, around 23% of customers provide almost zero consumption from 10:00 am to 15:00 pm, and nearly one-third of customers show two peaks in the morning and evening periods. The winter typical daily patterns are similar to the results of spring since these two seasons have similar weather in mid-west U.S.

B. WCR Performance

When the seasonal consumption pattern bank is developed using the SM data of observable customers, the WCR models are utilized to infer the CMPC of unobservable customers.

TABLE I
PERFORMANCE OF SEASONAL WCR MODELS WITH R^2 AND MAPE.

Season	Average R^2	Average MAPE
Spring	0.9446	12.44%
Summer	0.9071	14.24%
Fall	0.9384	13.18%
Winter	0.9204	13.7%

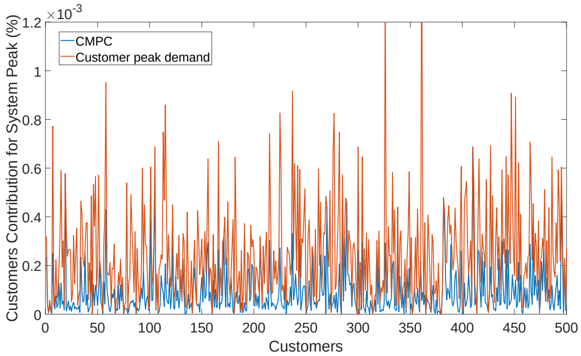


Fig. 11. Comparison of CMPC and customer peak demand.

1) Classification Performance Analysis: For the classification part, the Area under the Curve (AUC) index is employed to assess the performance of MLR model [24]. AUC is determined as follows:

$$\gamma = \int_0^1 \frac{TP}{TP+FN} d\frac{FP}{FP+TN} = \int_0^1 \frac{TP}{P} d\frac{FP}{N} \qquad (12)$$

where, TP is the True Positive, TN is the True Negative, FP is the False Positive, FN is the False Negative, and N is the number of total Negatives. Compared to the commonly-used metric, accuracy, the AUC does not depend on the cut-off value that is applied to the posterior probabilities to evaluate the performance of a classification model [25].

The meaningful range of AUC is between 0.5 to 1. In order to avoid the overfitting problem, the k-fold cross-validation method is applied to the MLR to ensure the randomness of the training set [26]. Based on the prior information on customer peak timing distribution, the MLR achieves an AUC value of 0.7 when assigning daily load patterns to unobservable customers.

2) Regression Performance Analysis: Based on the WCR approach, the CMPC of unobservable customers can be estimated using the monthly billing data. Fig. 10 shows the performance of WCR. As can be seen, the estimated values are able to accurately track the unobservable customer's real contribution to system peak demand. To assess the performance of the model, the goodness-of-fit measure, R^2, and the mean absolute percentage error (MAPE) are utilized in this paper. These two indices are presented in Table I for all seasons. Based on these results, the regression model has a good performance for estimation of CMPC of unobservable customers in this case.

C. Metric and Method Comparison

In this section, we demonstrate that the proposed segmentation strategy can target suitable customers, which cannot

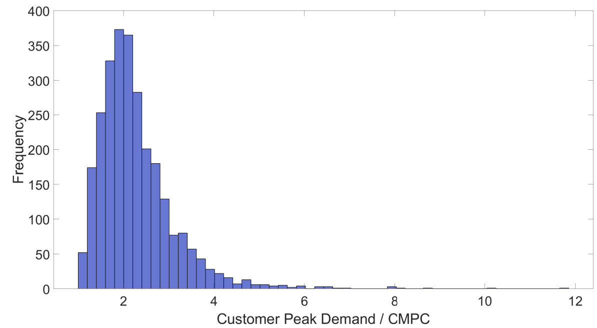


Fig. 12. The histogram of customer peak demand over CMPC ratio.

be classified by existing method in the literature, including customer peak demand-based and load profile entropy-based segmentation strategies [6], [8]. Furthermore, to validate the performance of our multi-stage machine learning framework, we have compared the peak contribution estimation MAPE of the proposed learning-based framework with previous method [27].

1) Comparing customer peak demand-based strategy and proposed method: Customer peak demand is a conventional index to describe the potential impact of individual customers on the overall peak demand, which is commonly-used by utilities to perform customer segmentation [8]. In Fig. 11, the difference between the proposed CMPC and customer peak demand values are presented. It can be seen that the customer peak demand values are generally much higher than CMPC values due to the diversity of load behaviors. According to Fig. 12, the customer's peak demand can reach five times the customer's actual contribution to the system peak. This considerable difference shows that compared to the proposed method, customer peak demand-based strategy is a very conservative method of quantifying the actual impact of customers, which could lead to unnecessary over-investments in AMI expansion.

2) Comparing load profile entropy-based strategy and proposed method: Entropy is a measure of the variability and uncertainty of customer demand, which has been used to develop customer segmentation approach for peak shaving program targeting [6]. Customers with lower entropy levels have stable consumption behaviors, which makes them higher priority candidates for peak reduction. In Fig. 13, the relationship between CMPC and entropy is presented. It is observable that customers with high CMPC do not necessarily have low entropy values. This indicates that these two concepts are almost uncorrelated and do not contain mutual information. Hence, unlike the proposed method, the entropy-based strategy does not provide information about customers' impact on system peak demand, and thus, cannot be used as a generic strategy for guiding peak shaving/AMI planning.

3) Comparing the performance of the proposed multi-stage machine learning-based framework with an existing method: The performance of the proposed multi-stage machine learning framework is compared with an existing baseline method [27] in terms of estimation accuracy. The baseline method uses

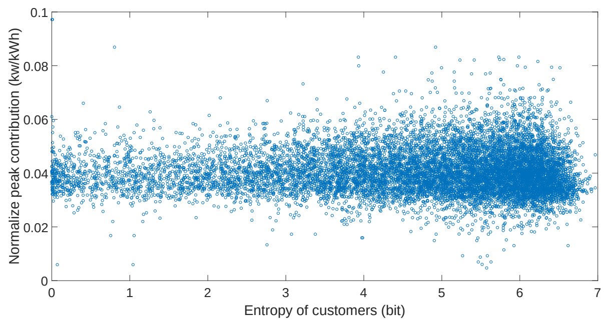


Fig. 13. The relationship between CMPC and entropy.

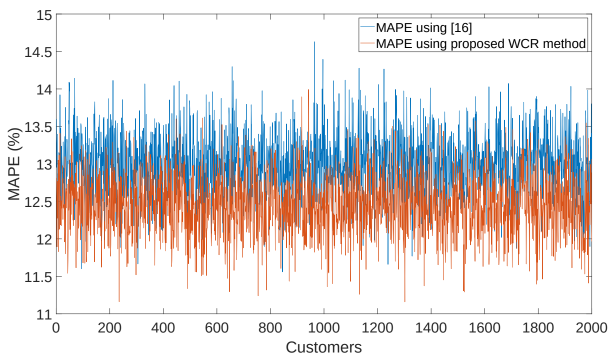


Fig. 14. Comparison of proposed method and existing method.

ordinary least square regression to determine the peak demand based on the periodic energy consumption. As shown in Fig. 14, the estimation MAPE values for our proposed method are generally lower than the results obtained from the previous method in [27]. Our framework has been able to improve the estimation MAPE by 5% on average. Furthermore, a maximum point-wise improvement level of 19% has been achieved over the previous baseline method. Hence, based on this AMI dataset, the proposed method shows a better estimation accuracy compared to the previous work.

VI. Conclusion

In this paper, we have presented a new metric, CMPC, to quantify the contributions of individual loads to system peak demand. Moreover, using the proposed data-driven framework, CMPC can be accurately estimated for unobservable residential customers using only their monthly billing data. It is demonstrated that CMPC provides utilities with additional actionable information for customer segmentation, which can then be employed to guide investment decisions for active energy management and AMI expansion. The proposed method is successfully validated using real SM data.

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