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RESEARCH ARTICLE

Personalized Electricity Tariff Recommendation Method for Residential Customers Lacking Historical Metering Data Incorporating Customer Profiles and Behavioral Changes

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ABSTRACT Effective energy management from the demand side and smart meters play an important role in achieving carbon neutrality. The government and utilities in South Korea are working to expand the installation of smart meters and develop time-of-use (TOU) tariffs for residential customers. Although these efforts have expanded the selection of tariffs for customers, it has become increasingly difficult to determine electricity tariffs. Therefore, some studies have been conducted to recommend tariffs for residential customers with historical metering data. However, recommending tariffs for customers who have recently installed smart meters or have failed to obtain historical metering data is a challenging task. Therefore, this paper presents a systematic method to estimate energy consumption patterns and incorporate behavioral changes based on the input profiles of residential customers for personalized electricity tariff recommendations. The proposed method attempts to predict bills by estimating energy consumption patterns using customer profiles. It is designed to reflect the behavioral changes in each pattern caused by the TOU tariff in predicting bills. In addition, the bill prediction model uses deep learning-based matrix factorization with the estimated patterns to improve bill prediction performance. The proposed method increases the probability of selecting TOU tariffs that reduce bills. It can be used as an effective tool for recommending tariffs to residential customers, helping them reduce their bills based on the prediction results. An increase in the number of customers selecting TOU tariffs also contributes to improving the stability and reducing the capital investment cost of the power system through peak shaving.

INDEX TERMS Customer profile, energy consumption pattern, time-of-use tariff, K-medoids, random forest, matrix factorization, deep learning, recommendation.

I. INTRODUCTION

Smart metering devices and energy management from the demand side are important research topics for the transition from traditional grids toward smart grids, as they enable efficient energy management for residential customers [1], [2]. Energy management includes components such as demand response (DR) and dynamic pricing, which play crucial roles in energy systems aimed at achieving carbon neutrality [3], [4], [5].

To achieve carbon neutrality, numerous electric utilities have implemented time-based electricity tariff structures

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and flat tariffs [5], [6]. These tariffs consist of real-time price (RTP), critical peak price (CPP), and time-of-use (TOU) tariffs, formed by a combination of static and dynamic structures [7]. The RTP is designed considering hourly energy consumption and fluctuations in hourly prices, and the price charged reflects to the market price of the wholesale electricity market [8]. The CPP tariffs charge a predetermined high energy consumption price for a specific period, which is defined as a peak event [9]. TOU tariffs indicate variations based on time blocks in which the price is generally higher during peak periods than at other times. These time blocks are divided into two or three distinct periods [10].

Smart metering devices are key components of energy management and are used to effectively manage customer energy consumption and collect data [1]. The Korea Electric Power Corporation (KEPCO) is expanding and distributing an advanced metering infrastructure (AMI) in South Korea. This establishes a strong foundation for the implementation of energy policies to activate demand-side energy management. Additionally, the analysis of energy data gathered from AMI offers significant insights into the behavioral patterns of customers in relation to their energy consumption [11].

Residential customers in South Korea typically utilize a single tariff structure known as the progressive (PRG) tariff. It was recognized by residential customers that it charges higher electricity bills than TOU tariffs for industrial and commercial customers [12]. Currently, the South Korean government and its utilities implement TOU tariffs designed for residential customers. Although these efforts have expanded the selection of tariffs for customers, it has become increasingly difficult to determine electricity tariffs. In the retail electricity markets of various nations, customers frequently encounter difficulties when selecting tariffs because of the numerous electricity tariffs [13]. Therefore, electricity tariff recommendation methods are required to support residential customers' decision-making processes.

The recommendation method is extensively utilized across diverse fields, including e-commerce, social networks, YouTube, Netflix, and others, for the purpose of suggesting products to consumers [14], [15], [16], [17], [18]. Numerous personalized recommendation (PR) methods have been developed over the past few decades to provide recommendations for users of various products. PR uses collaborative filtering (CF) to filter and learn from customers with similar interests and preferences, thereby providing recommendations for products and services. CF-based PR utilizes historical rating information from both the target and other users to predict the ratings that the target user assigned to specific items [19].

A CF-based PR method has also been used to make electricity tariff recommendations. Luo et al. proposed an electricity tariff recommendation method based on energy consumption features. They extracted features from energy consumption data collected through smart metering, considering seasons and working times. The customers were grouped using fuzzy c-means clustering based on the extracted features. The electricity bill of the target customer was predicted using the cosine similarity within the same group. The top K tariff was recommended based on the prediction results [20]. Zhang et al. recommended electricity tariffs based on the operating hours of individual household appliances measured using specific devices. They categorized the operating hours of household appliances into five groups based on the cumulative distribution function of each appliance. Five groups were defined based on the features of each household appliance. Customers with similar features were grouped using machine learning. The customer's bills were predicted using weighted cosine similarity. The predicted bills and recommended tariffs for users were also compared [21]. Li et al. utilized non-shiftable energy consumption data to recommend electricity tariffs. They compared the cosine similarity using the average non-shiftable energy consumption vector for each user. The target user was grouped with other users with high cosine similarities. They predicted bills using probabilistic matrix factorization (MF) for each group, analyzed the prediction results, and recommended a tariff to the user [22].

However, these previous studies have limitations in recommending electricity tariffs. They primarily recommend electricity tariffs based on metering data, which makes it impossible to recommend electricity tariffs to customers who have recently installed smart meters or have failed to obtain historical metering data. Moreover, the CF-based PR method using only metering data makes it difficult to reflect behavioral changes such as shifting the usage time of household appliances or saving energy consumption to avoid peak periods of TOU tariffs, which might claim high electricity bill. This is because residential customers have different behavioral changes based on their profiles, such as demographic information and whether they are photovoltaic (PV) owners. Therefore, a systematic method for recommending electricity tariffs that considers not only metering data but also customer profiles is necessary.

This paper presents a personalized electricity tariff recommendation method using customer profiles. The proposed method is designed to estimates customers' energy consumption patterns using customer profiles and recommends electricity tariffs incorporating behavioral changes. The main contributions of this paper are as follows:

1) The proposed method estimates energy consumption patterns using customer profiles, such as demographic information, PV owners, and past electricity bills. Consequently, it can use the customer profile to estimate the energy consumption patterns of customers who have recently installed smart meters or have failed to obtain historical metering data. Therefore, it is possible to recommend the electricity tariff through the estimation results of the energy consumption pattern using the customer profile. In addition, utilizing customer profiles to recommend electricity tariffs improves the accessibility

of electricity tariff recommendations and helps increase the number of customers who select TOU tariffs.

2) The proposed method estimates the energy consumption patterns of customers without historical metering data using the data of customers with installed smart meters. Subsequently, it predicts the TOU bills for customers through deep-learning-based matrix factorization using the estimated energy consumption patterns. Consequently, the proposed method shows a lower prediction error than previous studies because it effectively reflects the impact of the behavioral changes of residential customers in predicting TOU bills.

3) The proposed method predicts TOU bills by effectively reflecting the behavioral changes of residential customers and recommends an electricity tariff based on the prediction results. Therefore, it can show customers' electricity bill reductions resulting from behavioral changes. This increases the probability that residential customers will select a TOU tariff that reduces their electricity bills. Consequently, an increase in the number of customers selecting TOU tariffs also contributes to improving the stability and reducing the capital investment cost of the power system through peak shaving.

The remainder of this paper is organized as follows: Section II explains the problems that arise when electricity tariffs are recommended using metering data. Section III introduces the proposed method. Section IV presents the results of applying the proposed method to residential consumers in South Korea. Section V concludes the study.

II. PERSONALIZED ELECTRICITY TARIFF RECOMMENDATION

During the transition from a traditional grid to a smart grid, various changes occurred in the electricity industry. Among these changes, the installation of smart meters and the implementation of various electricity tariffs led to studies on electricity tariff recommendations. However, many of these studies have inherent limitations arising from the dependence on utilized data from smart meters.

Electricity tariff recommendations have been actively studied due to the introduction of competition in the retail electricity market. Electricity tariffs are charged based on customer energy consumption. Therefore, previous studies primarily focused on recommending electricity tariffs using energy consumption data collected from smart meters.

However, the traditional electricity tariff recommendations suffer from problems arising from the use of metering data. The biggest problem is that without historical metering data, it is impossible to recommend electricity tariffs for customers. These customers do not have historical metering data because they have recently installed smart meters or have failed to obtain metering data because of network obstacles.

The next problem is that there is a limitation to reflecting the behavioral changes of residential customers using metering data. Residential customers have different behavioral changes depending on their profiles and the metering data. For example, PV owners show little change in behavior owing to TOU tariffs, as they show low energy consumption during the daytime. However, families with babies are more likely to stay at home during peak periods of the TOU tariff, making it easier to change their behavior.

In this study, the aforementioned problem is resolved using an enhanced CF-based personalized electricity tariff recommendation method that uses customer profiles.

The proposed method can suggest electricity tariffs using customer profiles even to customers without past metering data. Using customer profiles reflects changes in the behavior of residential customers better than using existing methods.

III. PERSONALIZED ELECTRICITY TARIFF RECOMMENDATION METHOD INCORPORATING BEHAVIOR CHANGES USING CUSTOMER PROFILES FOR RESIDENTIAL CUSTOMER WITHOUT HISTORICAL METERING DATA

This section introduces a method for recommending electricity tariffs by using customer profiles without metering data. In the proposed method, the target customer is one without historical metering data, and the training customers are those who install smart meters to obtain historical metering data. The proposed method consists of three steps: estimating the energy consumption pattern using the profiles of the target customer; predicting the TOU bills through deep-learning-based matrix factorization using the estimated energy consumption patterns; and recommending an electricity tariff using the prediction result. Fig. 1 shows an overview of the proposed method.

A. ENERGY CONSUMPTION PATTERN ESTIMATION USING THE PROFILES OF THE TARGET CUSTOMER WITHOUT HISTORICAL METERING DATA

This study estimates the energy consumption pattern of a target customer using two types of customer training features: the extrema selected from the metering data and the customer profile. The estimation of energy consumption patterns consists of clustering and classification.

First, clustering uses the extrema and their profiles. In this study, the extrema represent the maxima and minima of the metered data. The maxima are the highest values, and the minima are the lowest values within a specific range, respectively. Residential customers have different energy consumptions depending on the time of day. Therefore, this study uses the maxima and minima as features representing the energy consumption at four specific times: morning, afternoon, evening, and night. Further technical details regarding the process of selecting the energy consumption features of residential customers at specific times from metering data are provided in [23].

In this study, customer profiles include data on family composition, the age of the householder, and the PV owner. Family composition includes data on the number of family members: babies (six years old or younger),

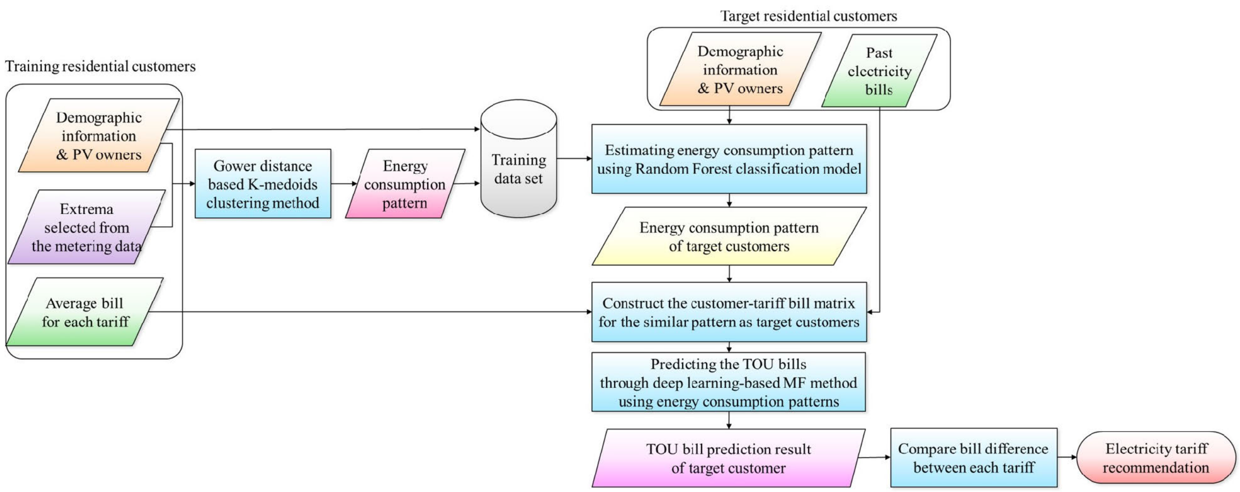

FIGURE 1. **Overview of the enhanced CF-based personalized electricity tariff recommendation method using customer profiles for residential customers without historical metering data.**

students (over six years old), workers, and unemployed adults. This study classifies the age of householders into groups of people in their 30s or younger, 40s, 50s, and 60s or older. The PV owner indicates by 'Yes' or 'No.'

This study describes a Gower distance-based K-medoid clustering method that groups energy consumption patterns using a mixed dataset that includes profiles and extrema. Gower distance calculates the pairwise distance between each customer. The pairwise distance is computed using the weighted average of the distances for each feature. In this study, the continuous feature is the extrema, and the categorical feature is the profile. The distance for continuous features is the normalized value of the Manhattan distance, as follows [24] and [25]:

$$d_{n,m}^{CNT} = \frac{|CNT_n - CNT_m|}{max\,(CNT) - min\,(CNT)}, \tag{1}$$

where $d_{n,m}^{CNT}$ denote the pairwise distances between customers n and m for continuous features. CNT_n and CNT_m denote the values of the continuous features for customers n and m, respectively.

The distance for categorical features is zero if the features between customers are in the same category and one if they are in different categories, as follows [24] and [25]:

$$d_{n,m}^{CAT} = \begin{Bmatrix} 0, CAT_n = CAT_m \\ 1, CAT_n \neq CAT_m \end{Bmatrix}, \tag{2}$$

where $d_{n,m}^{CAT}$ denotes the pairwise distances between customers n and m for categorical features. CAT_n and CAT_m denote the values of the categorical features for customers n and m, respectively.

The Gower distance is the weighted average of the distance for each feature, as follows [24] and [25]:

$$GD_{n,m} = \frac{\sum_{f\in F} w_f d_{n,m}^f}{\sum_{f\in F} w_f}, \tag{3}$$

where $GD_{n,m}$ indicates the Gower distance between customers n and m, and $d_{n,m}^f$ denotes the pairwise distances between customers n and m for feature f. F denotes a set of features in a mixed dataset that includes continuous and categorical features. w_f denotes the weighted value of feature f. The weighted value can be set differently for each feature, and the sum of the weighted values needs to equal 1. Typically, the weighted values are set to the same value [24].

The Gower distance-based K-medoid clustering method groups customers according to the Gower distance between specific and other customers. The specific customer is a medoid customer, the centroid of each cluster. The clustering method performs a swapping process to identify the medoid customers with the smallest Gower distance between customers. The swapping process compares the total cost, which is the sum of the Gower distances for each cluster. After the swap, if the total cost decreases, the medoid customers swap. However, if the total cost increases, medoid customers will not swap. This process is repeated until the medoid customers in each cluster no longer swap. The swapping process of the Gower distance-based K-medoids clustering method is as follows [26], [27], and [28]:

$$TC_{before} = \sum\nolimits_{k=0}^{K} \sum\nolimits_{f_n\in C_k} GD(f_n, MDI_k^{before}) \tag{4}$$

$$TC_{after} = \sum\nolimits_{k=0}^{K} \sum\nolimits_{f_n\in C_k} GD(f_n, MDI_k^{after}), \tag{5}$$

$$MDI_k^{swap} = \begin{Bmatrix} MDI_k^{before}, TC_{before} < TC_{after} \\ MDI_k^{after}, TC_{before} > TC_{after} \end{Bmatrix}, \tag{6}$$

where TC_{before} and TC_{after} denote the total costs before and after the medoid-swapping process, respectively. C_k denotes the set of customers in the k-th cluster. f_n denotes the features of customer n in C_k. MDI_k^{before} denotes the medoids for C_k before the swapping process, and MDI_k^{after} denotes the medoid customers for C_k after the swapping process, excluding MDI_k^{before}. MDI_k^{swap} denotes the medoid customer determined by the swapping process.

The Gower distance-based K-medoids clustering method uses the Davies–Bouldin index (DBI) to determine the optimal value of K. The DBI calculates as follows [29]:

$$DBI = \frac{1}{K}\sum\nolimits_{(k,k')\in K} max_{k\neq k'}\left(\frac{D_k^{CH}+D_{k'}^{CH}}{D_{k,k'}^{SP}}\right), \quad (7)$$

where D_k^{CH} and $D_{k'}^{CH}$ indicate the average between the centroid of the cluster and data points that are part of the same cluster. $D_{k,k'}^{SP}$ represents the distance between the center points of cluster k and another cluster k'. Low DBI indicates that each cluster can be distinguished sufficiently.

This study estimates the energy consumption patterns of target customers using a Random Forest (RF) classification model. In the RF classification model, the input is the customer profile, and the output is the energy consumption pattern. The RF generates several different decision trees and estimates the energy consumption pattern of the target customer through the aggregate voting of these decision trees [30], [31]. RF aims to minimize impurities at each node. In this study, impurities are calculated using the Gini index (GI) [32], [33], [34]:

$$GI = 1 - \sum\nolimits_{k=1} p_k^2, \quad (8)$$

where p_k indicates the probability of a feature belonging to the k-th cluster in a decision tree node. The minimum value of the GI is zero, which means that all features of the set belong to the same cluster.

B. TOU BILLS PREDICTION THROUGH DEEP LEARNING-BASED MF REFLECTING THE BEHAVIORAL CHANGES

This study describes a deep learning-based MF (DMF) method that uses energy consumption patterns for the prediction of TOU bills. The proposed method constructs a customer-tariff bill matrix with a set of training customers and an energy consumption pattern that is similar to the estimated energy consumption pattern by customer profile. It predicts TOU bills by performing DMF using a customer tariff bill matrix. Therefore, behavioral changes according to the customer profiles are reflected in the TOU bill prediction. DMF is a neural collaborative filtering (NCF)-based prediction method that combines the generalized matrix factorization (GMF) of linear characteristics with the multilayer perceptron (MLP) of nonlinear characteristics [35]. DMF comprises layers of different forms (input, embedding, hidden, and output), as shown in Fig. 2. The input is a vector derived from the one-hot encoding of customer N_u and tariff T_v indices. For example, customer N_2 is encoded into $\overrightarrow{N_2} = [0100\ldots]$, and T_3 is encoded into $\overrightarrow{T_3} = [0010\ldots]$. The embedding layer is a fully connected layer that transforms a sparse input vector into a dense latent factor vector. This study identifies potential customer and tariff factors using an embedding process [36]. The embedding process includes

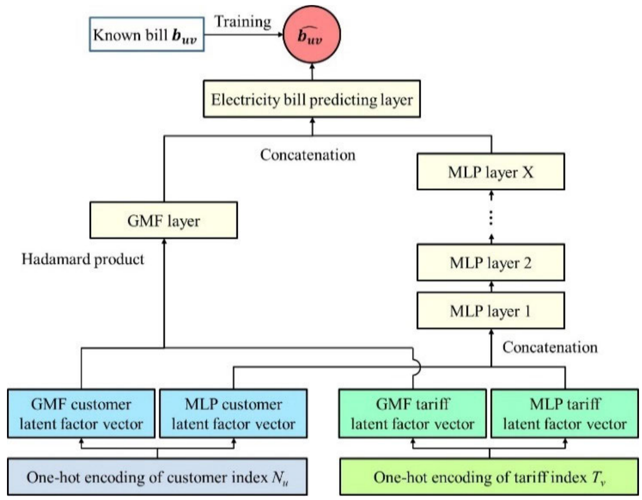

FIGURE 2. Deep learning-based MF for the prediction of TOU bills.

the utilization of backpropagation to update the randomly initialized dense vectors. The dense latent factor matrix is calculated using the weight matrix as follows:

$$\overrightarrow{h_u} = w_{HL}^{N}\overrightarrow{N_u}, \quad (9)$$

$$\overrightarrow{h_v} = w_{HL}^{T}\overrightarrow{T_v}, \quad (10)$$

where $\overrightarrow{h_u}$ and $\overrightarrow{h_v}$ are dense latent factor vectors for each customer N_u and tariff T_v, respectively. H indicates the length of the customer and tariff indices, and L denotes the length of the latent factors. w_{HL}^{N} represents the customer weight matrix, and w_{HL}^{T} represents the tariff weight matrix.

The hidden layer consists of the GMF and MLP. The GMF is the result of calculating the Hadamard product of the latent factor matrices obtained from the input and embedding. The Hadamard product is a mathematical function that defines the product of corresponding elements in two matrices of equal dimensions. In this study, the GMF using the Hadamard product is calculated as follows [35]:

$$Z_{GMF} = \overrightarrow{h_u^{GMF}} \odot \overrightarrow{h_v^{GMF}}, \quad (11)$$

where $\overrightarrow{h_u^{GMF}}$ and $\overrightarrow{h_v^{GMF}}$ represent the dense latent factor vectors for the GMF of customer N_u and tariff T_v, respectively. Z_{GMF} represents the result of the Hadamard product.

The MLP is a multilayer input of the latent factor matrix that concatenates the embedding results of the tariff and customer. The activation function and the number of layers determine the structure of the MLP. The MLP is calculated as follows:

$$Z_X(Z_{X-1}) = F_{act}(w_X Z_{X-1} + \sigma_X), \quad (12)$$

$$Z_{MLP} = Z_X(\ldots Z_2(Z_1(F_{concat}(\overrightarrow{h_u^{MLP}}, \overrightarrow{h_v^{MLP}})))\ldots), \quad (13)$$

where Z_X indicates the multilayer. F_{act} refers to the activation function, and F_{concat} refers to the concatenated function. w_x represents the weight vectors for each layer. σ_x is biased for each layer. $\overrightarrow{h_u^{MLP}}$ and $\overrightarrow{h_v^{MLP}}$ represent the dense latent factor vectors for the MLP of customer N_u and tariff T_v, respectively. Z_{MLP} represents the result by the MLP.

The output layer trains to reduce the difference in losses between the known and prediction of TOU bills. The output layer predicts TOU bills by concatenating the results of the GMF and MLP through the final hidden layer. The prediction of the TOU bills is calculated as follows [35]:

$$\widehat{b_{uv}} = Z_{pred}(F_{concat}(Z_{GMF}, Z_{MLP})), \tag{14}$$

where Z_{pred} indicates the output layer for predicting the TOU bills. $\widehat{b_{uv}}$ indicates the prediction for the TOU bill.

This study evaluates the TOU bill prediction of DMF using the mean absolute percentage error (MAPE).

$$MAPE = \frac{100}{|N_{test}|} \sum\nolimits_{(u,v)\in N_{test}} \left| \frac{b_{uv} - \widehat{b_{uv}}}{b_{uv}} \right| \tag{15}$$

where N_{test} is the test dataset, and $|N_{test}|$ is the length of the test dataset. b_{uv} denotes known TOU bills in test dataset.

C. ELECTRICITY TARIFF RECOMMENDATION USING THE PREDICTION OF TOU BILLS

This study estimates energy consumption patterns using customer profiles without historical metering data and predicts TOU bills through DMF using estimated energy consumption patterns. The proposed method recommends electricity tariffs by comparing past electricity bills with the prediction results of TOU bills.

The proposed method recommends electricity tariffs based on the bill difference between past electricity bills and the prediction results of TOU bills. The recommendation for the electricity tariff suggests maintaining the PRG tariff if the bill difference is positive and changing to the TOU tariff if it is negative. The bill differences are calculated as follows:

$$b_{diff}^{prediction} = \widehat{b_{uv}} - b_{past} \tag{16}$$

$$T_{recommend} = \left\{ \begin{matrix} PRG, b_{diff} > 0 \\ TOU, b_{diff} < 0 \end{matrix} \right\}, \tag{17}$$

where $b_{diff}^{prediction}$ denotes the bill difference between the prediction of TOU bills and past electricity bills. b_{past} denotes past electricity bills using the PRG tariffs. $T_{recommend}$ denotes the result of a recommendation based on bill differences.

In addition, this study compares the bill differences caused by structural differences in electricity tariffs to analyze whether the proposed method reflects behavioral changes according to customer profiles. The bill differences caused by structural differences in electricity tariffs are the difference between the electricity bill calculated based on the TOU tariff and the electricity bill calculated based on the PRG tariff. The bill differences caused by the structural differences in electricity tariffs are calculated as follows:

$$b_{diff}^{structure} = b_{TOU} - b_{past} \tag{18}$$

where $b_{diff}^{structure}$ denotes the bill differences caused by the structural differences in electricity tariffs. b_{TOU} is the electricity bill of the target customer which is calculated based on the TOU tariff. This is the calculated electricity bill when only the electricity tariff is changed from the PRG tariff to the TOU tariff without considering the target customer behavioral changes.

Consequently, the main steps of the proposed method in this research can be described as follows:

Step 1: Select features using the profile and metering data of the training customers, and calculate the Gower distance between the training customers using Equations (1), (2), and (3). Train for customer clustering using the Gower distance-based K-medoid. The profile of the training customers and the clustering results are then used to train the RF classification model to estimate the energy consumption pattern of the target customer.

Step 2: Construct the customer-tariff matrix with the set of training customers, the same group as the estimated energy consumption pattern, using the profiles of the target customer. TOU bills are predicted by performing DMF using a customer-tariff matrix.

Step 3: Recommend electricity tariffs through the bill difference calculated using Equations (16) and (17).

IV. CASE STUDY

This study recommends TOU tariffs to residential customers in South Korea using the proposed method and analyzes the results. Fig. 3 shows a representative single-line diagram of residential customers in South Korea. Residential customers comprise 1,031 TOU and 985 PRG customers. In this study, TOU customers are used to train the model, and PRG customers are the target customers. TOU customers use PRG tariffs until September 2019, and TOU tariffs from October 2019 to September 2020. PRG customers use only PRG tariffs.

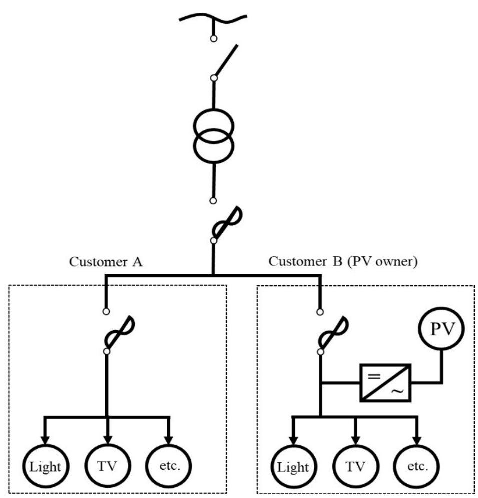

FIGURE 3. Single-line diagram for residential customers in South Korea.

In this study, the Pearson correlation coefficient is used to analyze the similarity of energy consumption patterns between TOU and PRG customers. The correlation coefficient is 0.986, and the energy consumption pattern between

TABLE 1. PRG tariff table for residential customers [12].

Tier	Total energy consumption [kWh]		Fixed price [$]	Energy price [$/kWh]
	Another season	Summer		
1	≤200	≤300	0.61	0.07
2	201~400	301~450	1.05	0.12
3	401≥	451≥	5.07	0.18

TABLE 2. TOU tariff table for residential customers [12].

Classification		Energy price [$/kWh]	Period
TOU A			
Summer	Peak	0.16	13:00~17:00
	Mid-peak	0.13	09:00~13:00 17:00~23:00
	Off-peak	0.07	23:00~09:00
Spring/Fall	Peak	-	
	Mid-peak	0.09	09:00~23:00
	Off-peak	0.07	23:00~09:00
Winter	Peak	0.13	09:00~12:00
	Mid-peak	0.12	12:00~23:00
	Off-peak	0.08	23:00~09:00
TOU B			
Summer	Peak	0.26	15:00~17:00
	Mid-peak	0.13	09:00~15:00 17:00~23:00
	Off-peak	0.06	23:00~09:00
Spring/Fall	Peak	-	
	Mid-peak	0.09	09:00~23:00
	Off-peak	0.06	23:00~09:00
Winter	Peak	0.22	09:00~11:00
	Mid-peak	0.12	11:00~23:00
	Off-peak	0.08	23:00~09:00

TOU and PRG customers has a high similarity, so an effective case study is possible.

The PRG tariff consists of a fixed price and an energy price per kWh. The PRG tariffs in South Korea are three-tiered, as listed in Table 1. The TOU tariff comprises two types: TOU A and TOU B, as shown in Table 2. The TOU tariff uses the same fixed price as the PRG tariff. However, energy prices differ according to the season and period. TOU A and TOU B differ in terms of the period and energy price. This study examined the average exchange rate during the period when TOU customers used TOU tariffs. Therefore, prices are calculated at 1194.5 KRW per USD.

A. ANALYSIS OF ENERGY CONSUMPTION PATTERN ESTIMATION USING CUSTOMER PROFILES

This study analyzes the results of clustering energy consumption patterns using the profiles and historical metering data of TOU customers. To determine optimal number of the cluster, this study compared DBI value of 2 to 10 clusters.

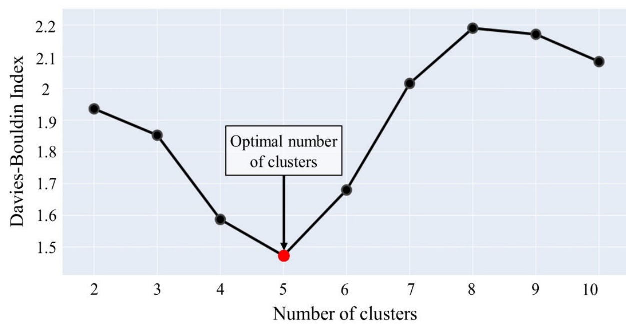

FIGURE 4. Comparison of DBI results by number of clusters using the Gower distance-based K-medoids.

TABLE 3. Customer profile analysis based on energy consumption patterns of TOU customers.

Customer profiles	Proportion [%]				
	Class 1	Class 2	Class 3	Class 4	Class 5
Babies					
0	31.73	21.35	31.36	3.62	11.94
1	5.52	28.96	5.52	55.17	4.83
≥2	7.02	10.53	1.75	77.19	3.51
Students					
0	32.26	0.42	35.62	18.10	13.60
1	24.17	51.65	7.14	13.74	3.30
≥2	0.74	94.12	1.47	0.00	3.67
Worker					
0	1.57	1.57	74.81	0.79	21.26
1	14.61	24.72	27.87	21.79	11.01
2	36.66	29.65	11.86	14.55	7.28
≥3	81.82	3.41	6.82	2.27	5.68
Unemployed					
0	36.10	32.49	3.97	18.41	9.03
1	25.49	25.05	19.44	20.95	9.07
2	17.67	6.43	59.44	2.41	14.05
≥3	30.95	7.14	47.62	0.00	14.29
Age of householder					
≤30s	1.58	11.81	0.00	84.25	2.36
40s	10.25	66.08	0.35	16.61	6.71
50s	75.30	8.10	8.50	0.00	8.10
≥60s	15.51	0.80	66.04	0.00	17.65
PV owner					
Yes	0.00	2.68	0.00	0.89	96.43
No	29.92	24.16	29.27	16.65	0.00

Fig. 4 shows the DBI results by the number of clusters. Consequently, the number of clusters K for the Gower distance-based K-medoids method is determined to be 5 with the lowest DBI.

Table 3 shows the results of the analysis of customer profiles based on energy consumption patterns. Fig. 5 shows the energy consumption patterns of TOU customers clustered using the Gower distance-based K-medoids method.

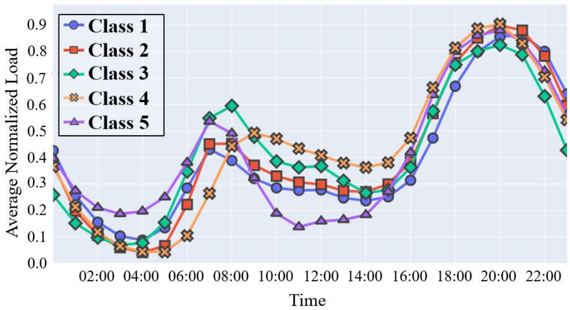

FIGURE 5. Energy consumption patterns of TOU customers clustered using the Gower distance-based K-medoids.

Class 1 includes 81.82% of the customers with three or more workers. Therefore, the characteristic of Class 1 defines as the workers' families. In addition, Class 1 indicates that the house is empty during the daytime because all family members go to work. Consequently, Class 1 shows a relatively low energy consumption pattern during the morning and afternoon compared with the other classes. Class 2 includes 94.12% of the customers with two or more students. Therefore, the characteristic of Class 2 defines as the students' parents. In addition, Class 2 shows a relatively lower energy consumption pattern during the morning and afternoon compared to the other classes because the children went to school. The characteristics of Class 1 and Class 2's profiles lead to differences in their energy consumption patterns at specific times. Comparison of the changes in energy consumption between Class 1 and Class 2 from 14:00 to 17:00, Class 1 shows a 0.24 increase, whereas Class 2 shows a 0.30 increase. This distinction arises from the different times at which workers and students return home. This is because workers' work schedules are from 9:00 to 18:00, but students return home between 15:00 and 17:00. Class 3 has a higher proportion of unemployed individuals than the other classes. Class 3 includes 66.14% of the householders in their 60s or older. Therefore, the characteristic of Class 3 defines as the old couples. Moreover, Class 3 shows a relatively high energy consumption pattern during the morning and afternoon compared to the other classes, especially during the morning. In addition, Class 3 indicates that the time for increasing energy consumption is 04:00, one hour earlier than other classes. Their energy consumption increases relatively significantly compared to other classes. Such differences indicate that the behavior patterns of the old couples differ from those of other classes. Class 4 includes 77.19% of customers with two or more babies. Therefore, the characteristic of Class 4 defines as newlyweds with babies. In addition, Class 4 shows relatively high energy consumption and less change in energy consumption during the morning and afternoon compared to other classes because these customers have to take care of their babies. Class 5 includes 96.43% of the customers who are PV owners. Therefore, the characteristic of Class 5 defines as the PV owners. Consequently, Class 5 shows a similar energy consumption at night and during the daytime owing to PV.

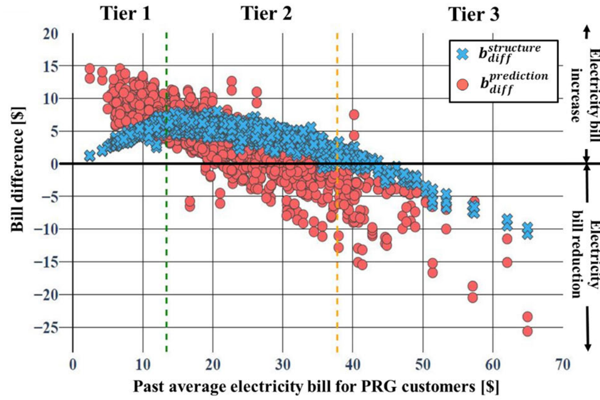

FIGURE 6. Analysis of bill differences based on electricity bills of PRG tariff for PRG customers.

RF classification model using the profiles and energy consumption patterns of TOU customers to estimate the energy consumption patterns of PRG customers. It evaluates the accuracy by splitting TOU customer data into training and test data. Consequently, the accuracy of the energy consumption pattern estimation is 92.35%. Therefore, the proposed method can estimate the energy consumption patterns of PRG customers using their profiles without historical metering data.

B. TOU BILL PREDICTION AND ELECTRICITY TARIFF RECOMMENDATION RESULTS

This study predicts the TOU bills of PRG customers using a set of TOU customers, which is the same group used to estimate the energy consumption pattern of PRG customer profiles. Furthermore, this study uses a 5-fold validation method that minimizes MAPE to determine the optimal number of latent factors and layers for the DMF model. In addition, it compares the mean absolute percentage error (MAPE) of the prediction methods used in the metering data-based electricity tariff recommendation method.

Fig. 6 shows the $b_{diff}^{structure}$ and the b_{diff} based on the past average electricity bill for the PRG customers. $b_{diff}^{structure}$ is negative from Tier 3 of the PRG tariff, and $b_{diff}^{prediction}$ is negative from Tier 2 of the PRG tariff. Therefore, the proposed method recommends TOU tariffs to a greater number of PRG customers. This increases the probability that residential customers will select the TOU tariff, which can reduce their electricity bills.

Table 4 presents the prediction results of TOU bills for each method. As indicated in Table 4, the MAPE of the proposed method is 13.7%, indicating superior performance compared to the other methods. Therefore, effective electricity-bill prediction for residential customers should include not only metering data but also customer profiles. This is because residential customers indicate different behavioral changes depending on their profiles.

This study analyzes the TOU tariff recommendation results by comparing the bill differences calculated using Equations (16) and (18). Table 5 presents the average bill

TABLE 4. Comparison of the MAPE of TOU bill prediction by each method.

Method	MAPE [%]
Cosine similarity-based prediction method using energy consumption feature extracted by metering data [20]	15.67
Probabilistic MF-based prediction method using non-shiftable energy consumption vector extracted by metering data [22]	19.82
Deep learning MF-based prediction method using customer profiles in the absence of historical metering data	**13.7**

TABLE 5. Analysis of the average electricity bill differences customers recommending TOU tariffs to PRG customers.

Classification	Average electricity bill difference [$]	
	$b_{diff}^{structure}$	$b_{diff}^{prediction}$
TOU A	+2.08	-3.60
TOU B	+2.74	-3.94

TABLE 6. Proportion of customers who recommend the TOU tariffs by energy consumption patterns.

Classification	Proportion [%]	
	TOU A	TOU B
Class 1	9.24	4.62
Class 2	33.33	7.69
Class 3	2.99	14.94
Class 4	4.35	34.78
Class 5	15.08	0.00

difference of customers recommending TOU tariffs to PRG customers according to Equation (17). The $b_{diff}^{structure}$ is positive, so the bill increases when PRG customers change to TOU tariffs. This is because PRG tariffs below Tier 2 are less expensive than TOU tariffs. However, $b_{diff}^{prediction}$ is negative because it reflects the behavioral changes of residential customers. In addition, TOU B has higher prices than TOU A; therefore, the increase in bills owing to structural differences is significant. In comparison with b_{diff}, TOU B indicates a larger reduction in bills than TOU A. Therefore, it can be inferred that TOU B has a greater potential to influence behavioral changes than TOU A.

This study analyzes the TOU tariffs recommended to PRG customers based on their estimated energy consumption patterns. Table 6 shows the proportion of customers who recommend TOU tariffs based on their energy consumption patterns. Classes 1 and 2 have more customers who are recommends to TOU A than TOU B. This is because Classes 1 and 2 each have characteristics of workers and students' parents, making it difficult to change their behavior during peak periods. Classes 3 and 4 have more customers who are recommends to TOU B than TOU A. This is because Classes 3 and 4 each have characteristics of old couples and families with babies, making it easy to change their behavior during peak periods. Class 5 demonstrated the lowest energy consumption during the morning and afternoon because of the PV. Therefore, a TOUA with a long peak period is recommended for Class 5.

The results indicate that the proposed method recommends TOU A for customers who have difficulty changing their behavior because they do not stay at home during peak periods, and TOU B for customers who can easily change their behavior because they stay at home.

V. CONCLUSION

In this paper, a systematic method for recommending personalized electricity tariffs based on customer profiles is proposed. The proposed method estimates the energy consumption pattern using customer profiles and predicts TOU bills through DMF using the estimated energy consumption patterns. Finally, the proposed method recommends an electricity tariff based on the prediction results.

Consequently, the proposed method effectively recommends personalized electricity tariffs even to residential customers without historical metering data. Therefore, it improves the accessibility of electricity tariff recommendations and increases the number of customers who select TOU tariffs. Moreover, the proposed method shows a lower prediction error than the existing methods because it effectively reflects the impact of the behavioral changes of residential customers in predicting TOU bills. Finally, the proposed method recommends TOU tariffs to more customers because they effectively reflect changes in customer behavior. This increases the probability that residential customers will select a TOU tariff that reduces their electricity bills. Consequently, an increase in the number of customers selecting TOU tariffs also contributes to improving the stability and reducing the capital investment cost of the power system through peak shaving.

Furthermore, while this paper categorizes residential customers into five classes based on their characteristics, certain customers may have multiple characteristics at the same time, such as students' parents with PV owners, families of workers with babies, and so on. Future research is required to recommend tariffs to these customers by optimizing the weighted value of the Gower distances of each feature in accordance with the tariff structure. In addition, future research should focus on developing an operation schedule for an energy storage system using the recommended results, as well as developing DR participation strategies for residential customers. This will be useful for designing a residential microgrid to achieve carbon neutrality.

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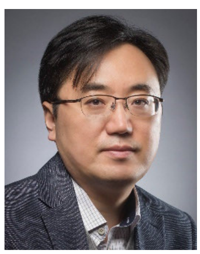

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