IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 11 June 2022, accepted 11 July 2022, date of publication 14 July 2022, date of current version 19 July 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3190892

RESEARCH ARTICLE

Residential Electricity Rate Plans and Their Selections Based on Statistical Learning

YOUNG MO CHUNG[1], (Member, IEEE), SONGHEE KANG[2], JAEYONG JUNG[3], BEOM JIN CHUNG[4], AND DONG SIK KIM[5], (Senior Member, IEEE)

[1]Department of Electronics and Information Engineering, Hansung University, Seoul 02876, Republic of Korea
[2]StradVision, Seoul 06621, Republic of Korea
[3]School of Computer Science Engineering, Jeonbuk National University, Jeonju-si, Jeollabuk-do 54896, Republic of Korea
[4]Research Center of Electrical and Information Technology, Seoul National University of Science and Technology, Seoul 01811, Republic of Korea
[5]Department of Electronics Engineering, Hankuk University of Foreign Studies, Yongin-si, Gyeonggi-do 17035, Republic of Korea

Corresponding author: Dong Sik Kim (dskim@hufs.ac.kr)

This work was supported in part by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) through the Ministry of Trade, Industry and Energy (MOTIE) of the Republic of Korea under Grant 2021202090028D; and in part by the Basic Science Research Program through the National Research Foundation of Korea (NRF) by the Ministry of Education under Grant NRF-2019R1A6A1A03032119. The work of Young Mo Chung was supported by Hansung University.

ABSTRACT Demand response (DR) is one of the major benefits that utility companies can derive from the advanced metering infrastructure (AMI). In particular, the dynamic rate plan with DR is attracting attention as an electricity rate system suitable for the future power environment. In order for electricity consumers to select an appropriate electricity rate plan, it is necessary to provide information such as whether electricity bills are reduced by the plan and the estimated amount of electricity bill savings. In this paper, we first comparatively analyze the current progressive rate plan and a dynamic rate plan of the time-of-use (TOU). We next propose several prediction methods for households to provide information on whether the electricity bill amount can be reduced in advance when changing to the TOU rate plan from the progressive rate plan by using only the current monthly electricity usages and bills. In order to develop three different prediction methods based on statistical learning, we use the support vector machine, linear regression, and deep neural network techniques. As a ground truth training sequence, we use hourly electricity usages and bills obtained from ten apartment complexes through AMI, and an apartment complex is used for testing the designed methods. The decision accuracy for the test complex was more than 0.98 and the root mean square error of the saving prediction was 1.7%.

INDEX TERMS Advanced metering infrastructure (AMI), deep neural network (DNN), linear regression, support vector machine (SVM), progressive rate, time-of-use (TOU) rate.

NOMENCLATURE

d_i	Annual bill difference of the ith household.
$f(x_i)$	Linear regression estimate of d_i.
$g(x_i)$	DNN estimate of d_i.
p	Feature demension.
x_i	Input vector in $\mathbb{R}^p$ for estimators.
y_i	SVM output in $\{-1, 1\}$.
α, α_0	SVM parameters in $\mathbb{R}^p$ and $\mathbb{R}$.
β, β_0	Regression parameters in $\mathbb{R}^p$ and $\mathbb{R}$.
AMI	Advanced metering infrastructure.
DNN	Deep neural network.
DR	Demand response.
RMSE	Root mean square error.
SVM	Support vector machine.
TOU	Time-of-use.

The associate editor coordinating the review of this manuscript and approving it for publication was Payman Dehghanian.

I. INTRODUCTION

Many electricity utilities around the world are adopting static tariffs or rate plans, such as a flat rate plan and a progressive rate plan for residential electricity. In the progressive rate plan, the unit price per kilowatt-hour increases in stages

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

depending on the amount of electricity used. In the flat rate plans for households, it is enough to read the metering data monthly. Recently, dynamic rate plans have emerged as alternatives to static rate plans for households [1]–[3] in accordance with the expansion of the smart grid and the acceptance of changes in the electric power environment to reduce greenhouse gas emissions. The dynamic rate plan has a purpose to reduce peak electricity usages by reflecting their high wholesale prices of electricity during peak hours in the retail rates [4].

Demand response (DR) has been considered as an important notion in balancing the energy supply and demand, and can be implemented by using the dynamic rate plan. As the proportion of renewable energies, such as solar or wind powers, increases worldwide to respond to climate change, the problem of intermittent power generation becomes worse. To cope with such a problem, further advanced DR systems are being introduced to secure a stable power system [5], [6]. Dynamic rate plans that implement price-based DR systems have been widely applied in large-scale customers, such as factories and buildings, to reduce the power demand during the peak hours or distribute the power demand during the off-peak hours [7]. A general dynamic rate plan for customers is the time-of-use (TOU) rate plan, in which the peak hours of high electricity power consumption have higher rates than the off-peak hours. To reform the long-term behavior of the load demands and renewable energy sources, the TOU rate plan is helpful for efficient power system planning in the electricity generation and transmission [8]. Here, scheduling home electricity usages for the TOU rate plan is also important [9], [10]. In order to apply the TOU rate plan to households, a new metering system such as the advanced metering infrastructure (AMI) is required [11], [12].

Italy has deployed large-scale AMI for more than 30 million households since the early 2000s, and has introduced a TOU rate plan for residential customers since 2007. As of 2018, 56.6% of households adopted the TOU rate plan [13]. Various pilot projects related to TOU rate plans have been attempted in several countries [1], [14] and extensive research is being conducted on effects of the TOU rate plan for households [15]–[20]. To ensure electricity consumers have a choice of electricity rate plans, the EU has recommended that electric power sellers should provide consumers with sufficient information regarding the dynamic rate plan [2]. It is important to inform consumers in advance which rate plan will be advantageous to them so that they can choose an appropriate rate plan [21]–[27]. In addition, utility companies also need to select areas where many consumers can choose the TOU rate plan for an effective AMI deployment.

The current residential rate plans in South Korea have static and progressive properties to restrain excessive electricity usages as summarized in Table 1. This progressive rate plan has three usage ranges, which, for the summer case, are wider than those of other case to provide lower electricity charges or bills as in Table 1 [28]–[31]. A TOU rate plan, which is being considered in South Korea, is summarized in

TABLE 1. Residential low-voltage progressive rate per month for the summer case (July - Aug.) and the other case (Jan. - June, Sep. - Dec.) [31]. The progressive rate has three usage ranges and the basic rate is applied to each household.

Usage range (kWh/month) Other case	Summer	Basic rate (Won)	Usage rate (Won/kWh)
- 200	- 300	910	93.3
201 - 400	301 - 450	1,600	187.9
401 -	451 -	7,300	280.6

As of May 2022, 1,000 Korean Won is approximately 0.798 USD.

TABLE 2. Residential TOU rate per month [31]. The rates of the off-peak and spring/autumn case are lower than the other cases and the basic rate is applied to each household.

Cases	Basic rate (Won)	Usage rate (Won/kWh)		
		Weekday		
		Peak (9 am - 9 pm)	Off-peak (9 pm - 9 am)	Weekend
Spring/autumn (Mar. - May, Sep. - Oct.)	4,310	140.7	94.1	94.1
Summer/winter (Nov. - Feb., June - Aug.)		188.8	107.0	107.0

Table 2 [31]. Depending on the ranges of peak hours and months, the electricity rates are different so that electricity usages can be efficiently spread. Koo *et al.* [32] studied electricity rate plans according to the consumer power consumption patterns in apartment complexes of South Korea. Based on the rate plans of Tables 1 and 2, Jung *et al.* [31] recently conducted a comparative analysis of electricity bills between the progressive and TOU rate plans for an apartment complex equipped with AMI facilities. Through this analysis, changing the current progressive rate plan to a TOU rate plan for a given household can provide the benefit of reducing the electricity bill depending on the amount and pattern of electricity usage. A guideline in selecting the electricity rate type by observing information on electricity energy usage can be obtained. If hourly electricity usage data are available, then the proper electricity rate plan can be explicitly determined. However, if only the information on monthly electricity usages is available, then further careful analysis on selecting the electricity rate is required.

In this paper, we first analyze the current progressive and the TOU rate plans by comparing them. Here, the TOU rate plan is operated based on hourly electricity usage data collected through AMI instead of the current monthly electricity usage. We next propose several prediction methods for households to provide information on whether to save electricity bills in advance when moving to the TOU rate plan from the progressive rate plan by using only the current monthly electricity usages and bills. In order to develop three different prediction methods based on statistical learning, we use the support vector machine (SVM), linear regression, and deep neural network (DNN) techniques [33]–[35]. Here, as a ground truth training sequence, we use the hourly electricity usages and bills obtained from ten apartment complexes with

AMI, and one apartment complex is used for testing the designed methods.

This paper is organized in the following way. In Section II, we first observe the residential electricity rate plans, and next the progressive and TOU rate plans, using the practical metering data from households of eleven apartment complexes. In Section III, we propose three prediction methods for guidelines in selecting an appropriate electricity rate plan. The paper is concluded in the last section.

II. METERING DATA AND BILL IN EACH RATE PLAN

In this section, electricity usage metering data obtained through AMI built in South Korea are empirically analyzed, and the amount of bills for the progressive and TOU rate plans are compared.

A. METERING DATA OBTAINED THROUGH AMI

AMI is currently under construction in South Korea, and as of 2021, AMI has been installed in 10.2 million consumers, which corresponds to 45% of all consumers. In this study, hourly power usage metering data are collected from a total of 12,155 households in eleven apartment complexes where AMI is installed. The usage metering data used in this analysis are collected at hourly intervals for twelve months. As will be discussed in Section III, ten apartment complexes are used for designing classifiers and predictors, and one apartment complex is used to verify the performances of the classifiers and predictors. Note that a relatively small complex can be enough to verify their performances [36].

The details of the apartment complexes used in the study are summarized in Table 3. The average area of the households in each apartment complex varies from complex to complex, ranging from 75.5 m^2 to 143 m^2. The size of each complex is also different and the number of houses in the complex ranges from 435 to 2,064. The average annual usage of household for each complex together with the average annual bill of household in the current progressive rate plan is also shown in Table 3. Unless stated otherwise in this paper, electricity usage and electricity bills are for each household. The average annual usages are between 2,731 kWh/year and 4,149 kWh/year depending on the apartment complex. The average annual bills range from 314,439 Won/year to 572,760 Won/year, depending on the complex.

The average monthly electricity usages for each complex is shown in Fig. 1. The horizontal axis represents the month and the vertical axis is the average monthly electricity usage in kilowatt-hour per month. In Fig. 1, we observe that Complex 6 has the lowest average usage and Complex 2 uses the most. In particular, we can also observe that the average usage is the highest in August in all complexes, which is due to the fact most of the houses use coolers that consume high power. In winter, the average usage does not increase significantly compared to spring and autumn in all complexes, because gas or district heating is used as the main heating energy source in South Korea.

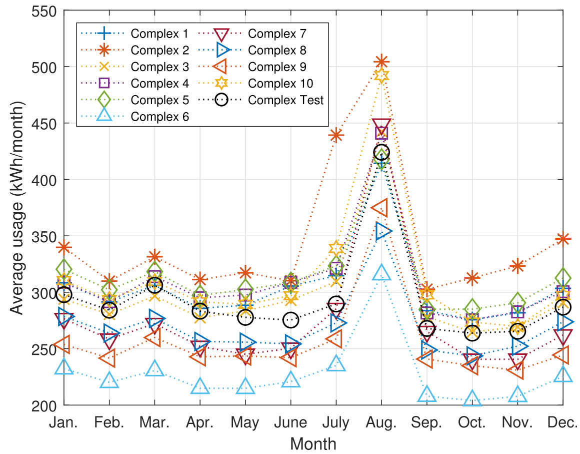

FIGURE 1. Average monthly usage for the apartment complexes of Table 3.

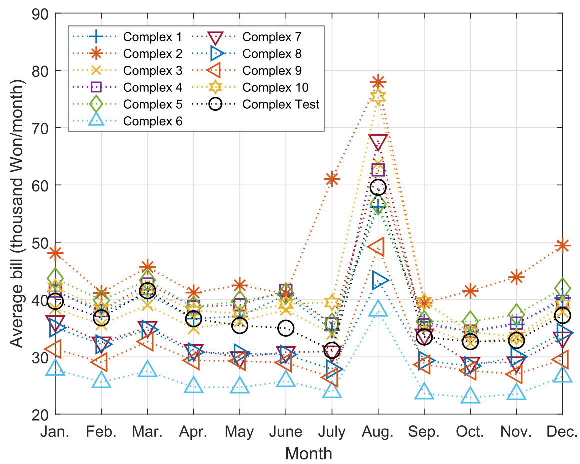

FIGURE 2. Average monthly bill in the progressive rate plan.

B. BILLS BY THE RATE PLANS

When the progressive rate plan is applied to each household, the monthly electricity bills for all households are computed. Fig. 2 shows the result for the average monthly electricity bills with the progressive rate plan for each complex in thousand Won per month. The graph shape of the average bills is similar to that of the average usages of Fig. 1, but due to the characteristics of the progressive rate plan, the following difference is observed. As the electricity usage increases, the electricity bill increases faster than the increase in usage. For example, in Complex 2, the average usage in August is 1.67 times higher than that in September, but the average bill is observed to increase by 1.98 times. This is one of the characteristics of the progressive rate plan shown in Table 1.

Using electricity usage data metered and collected at hourly intervals through AMI, we can apply the TOU rate plan to each household and calculate the corresponding bill. Fig. 3 shows the average electricity bills when the TOU rate plan is applied to all households of each complex. Comparing this result with the electricity usage in Fig. 1, we observe

TABLE 3. Apartment complexes for the analysis. Metering data are collected from the ten complexes of Complexes 1 - 10 with 10,865 households. Complex 11 is the test complex to verify the analysis.

Apartment complexes	Average area (m^2)	Number of households	Average usage (kWh/year)	Average bill (Won/year)
Complex 1	115	593	3,659	471,737
Complex 2	126	605	4,149	572,760
Complex 3	136	1,299	3,578	458,969
Complex 4	143	477	3,344	423,887
Complex 5	117	1,049	3,764	494,920
Complex 6	75.5	1,710	2,731	314,439
Complex 7	108	435	3,297	419,699
Complex 8	99.9	2,064	3,231	386,879
Complex 9	100	1,858	3,068	368,943
Complex 10	116	776	3,760	498,505
Complex 11 (Test)	127	1,289	3,522	451,968

The maximal and minimal values are underlined.

that the average bills in the summer/winter case are relatively higher than those in the spring/autumn case, even for the case of similar average usages. This is because the usage rate in the summer/winter case is higher in the TOU rate plan as shown in Table 2. Compared to the result of the progressive rate plan in Fig. 2, the average bills in August for the complexes that consumed the most electricity energy (e.g., Complexes 2 and 10) decreased further under the TOU rate plan. Note that the progressive rate plan sharply increases electricity rates in the third range as shown in Table 1, while the TOU rate plan applies a constant electricity rate regardless of usage. On the other hand, in the case of Complex 6, which consumes the least amount of electricity, we observe that the average bill by the TOU rate plan is higher in every month than the bill by the progressive rate plan. This is due to the fact that the basic rate of the TOU rate plan is higher than that of the progressive rate plan in the first and second ranges in Table 1.

In general, we can state that the progressive rate plan is more advantageous when the electricity usage is relatively low, and the TOU rate plan is more advantageous when the electricity usage is relatively high. However, we notice that in the TOU rate plan, even if the electricity usages are the same, the electricity bills can be different depending on the time of the day and the month of electricity usages. In addition, the rate increases rapidly as more electricity is used in the progressive rate plan. Thus, it is difficult to determine which rate plan gives the lower electricity bill for each household if only the amount of electricity consumption is considered.

C. CHANGES IN HOUSEHOLD ELECTRICITY BILLS WITH THE RATE PLANS

The curves of Figs. 2 and 3 present the average monthly electricity bills of households for each complex but not the electricity bills for each individual household. In terms of the average bills, for example, Complex 6 has a lower electricity bill using the progressive rate plan in Fig. 2 than the case of the TOU rate plan in Fig. 3. However, if we consider the electricity bills of individual households, then there exist households that have lower electricity bills with the TOU rate plan.

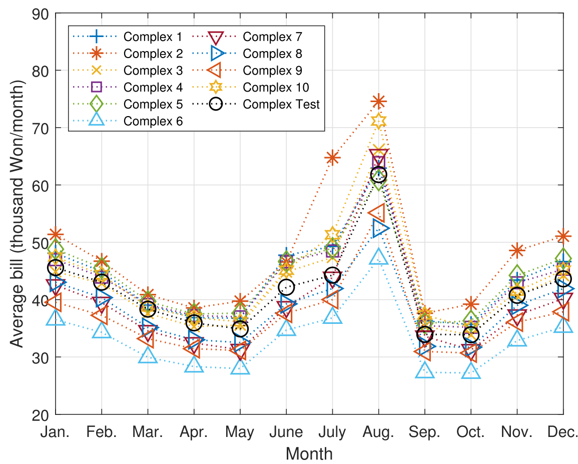

FIGURE 3. Average monthly bill when the TOU rate plan is applied.

We now compute and analyze the monthly electricity bill difference between the TOU rate plan and the progressive rate plan. We assume that each household changes the electricity rate plan from the progressive to TOU rate plan. Positive bill differences imply increases in the electricity bills due to changing to the TOU rate plan. If the bill difference is negative, then the corresponding household can reduce the amount of electricity bill by adopting the TOU rate plan. In Fig. 4, the monthly bill differences for the entire 12,155 households during twelve months are shown. Figs. 4(a) and (b) represent the results of the spring/autumn and summer/winter cases, respectively. Here, the horizontal axis represents the monthly electricity usage, and the vertical axis represents the monthly bill difference due to the change of the rate plans to the TOU rate plan. The results of each household are represented by different symbols depending on the month.

We observe from Fig. 4 that the bill difference values appear as three piecewise lines, which is due to the three rate ranges of the progressive rate plan shown by Table 1. In Fig. 4(a), the bill difference increases as the electricity usage increases up to 200 kWh/month because the TOU rate plan has higher rates than the progressive case.

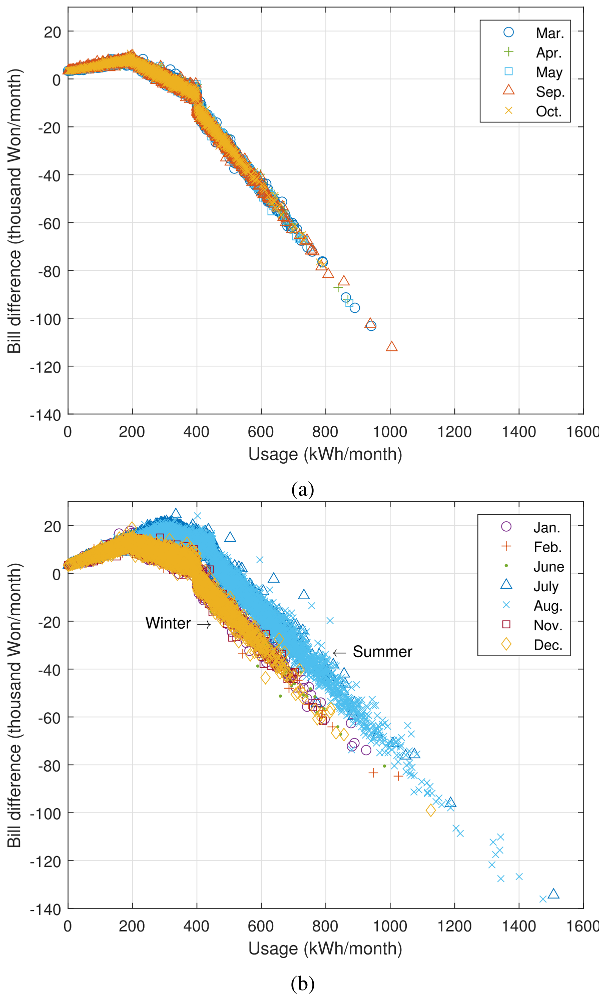

FIGURE 4. **Monthly bill differences of the households in all apartment complexes. (a) Scatter diagram of the spring/autumn case. (b) Scatter diagram of the summer/winter case.**

The bill difference then decreases because the TOU rate plan has lower rates than the progressive case exceeding 200 kWh/month. We also observe the bill difference values bending at the monthly usage of 400 kWh/month, where the highest rate of the third range of the progressive rate plan begins to apply. We observe a jump of the bill difference values because there is a big step increase of the basic rate for the progressive rate plan as shown in Table 1. The ratios of usages in peak and off-peak (or weekend) hours affect the bills under the TOU rate plan of Table 2 and can be different depending on households. We notice that the bill differences are not the same even for the cases of the same electricity usages. Therefore, the markers are widely spread even when the electricity usages are the same. The dispersion of the markers at the same usage is seen more in the summer/winter case of Fig. 4(b) than the spring/autumn case of Fig. 4(a). Note that home appliances, which consume high electric energies, are usually used in the summer/winter case (especially in July and August), and a small usage change of those appliances between the peak and off-peak hours can

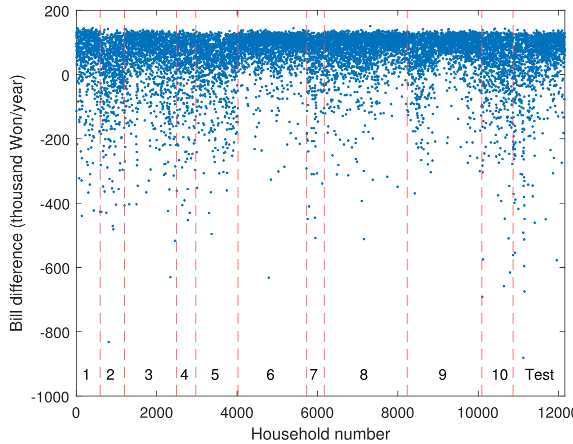

FIGURE 5. **Annual bill differences in thousand Won per year. The eleven apartment complexes are indicated as their complex number at the lower part of the graph and the whole households of the complexes are designated as the household number below the graph.**

make a large change in the ratio of usages in peak and off-peak hours.

For the summer/winter case in Fig. 4(b), the monthly bill difference values can be divided into two groups. The upper one is the summer result group and the lower is the winter result group. This seasonal distinction is due to the fact that the summer and winter rate ranges are different in the progressive rate plan. In particular, the reason that the summer results are in a higher position for the same electricity usage is because the progressive rate plan offers a lower electricity rate in the summer case than the other case.

Meanwhile, in South Korea, the electricity rate plan is contracted by each household on an annual basis. Therefore, we need the total billing amount of twelve months for progressive and TOU rate plans, and compare them in selecting an appropriate electricity rate plan to save electricity bills. Fig. 5 shows the annual bill differences obtained when the rate plan is changed from the progressive to TOU rate plan based on the bills summed over twelve months for each household in the eleven complexes. The horizontal axis represents the household number, and the vertical axis represents the annual bill difference in thousand Won per year. An annual bill difference greater than zero means an increase in the bill when changing to the TOU rate plan, and thus it is advantageous to just stay with the current progressive rate plan. If the annual bill difference is less than zero, then the electricity bill can be saved after the plan change to the TOU rate plan. We observe increases of bills in many households, but the value of increase is 151,013 Won/year at most. Although the decrease of the annual bill difference is less frequent than the increase case, we observe that the value of decrease is large enough to reach the minimum of −881,063 Won/year, of which magnitude is much larger than the progressive case.

D. SAVINGS AND DIFFICULTY IN SELECTING THE BEST RATE PLAN

In this subsection, we discuss methods in appropriately selecting the electricity rate plan for each household.

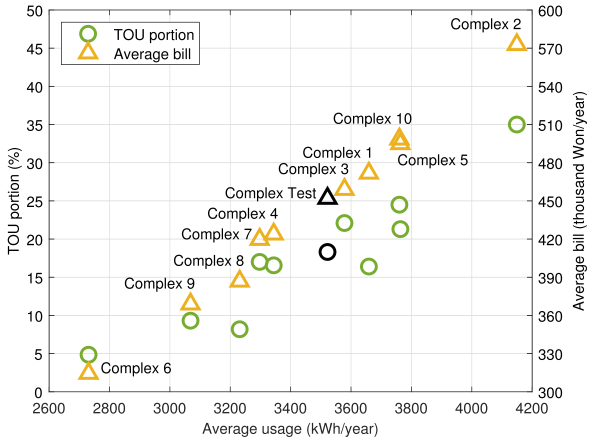

FIGURE 6. Portion of the TOU rate plan and the average annual bill under the progressive rate plan with respect to the average annual usage for the apartment complexes of Table 3.

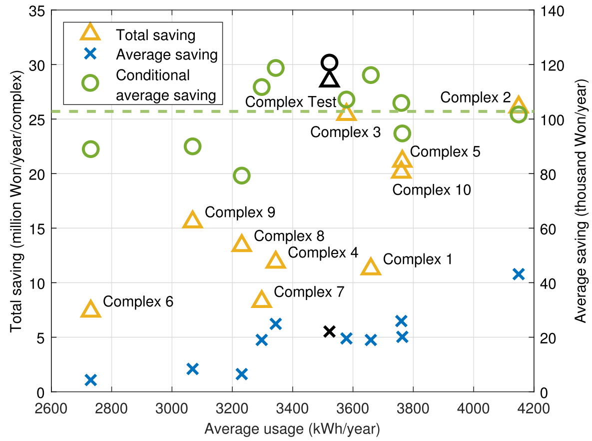

FIGURE 7. Total and average annual savings for each complex.

If the annual bill difference is positive for a household, then it is better to keep the progressive rate plan without changing the rate plan because the positive value implies applying the TOU rate plan increases the electricity bill. On the other hand, for households whose annual bill differences are negative, it is better to change the rate plan to the TOU rate plan because the electricity bill will decrease.

The portion of households, which can save electricity rates by changing the progressive to TOU rate plan, to the entire households in each complex is shown as the circle marks ("◯") in Fig. 6. Here, the horizontal axis represents the average annual electricity usage in each complex, and the left vertical axis represents the TOU portion in percentage. In addition, Fig. 6 also shows the average annual electricity bills with the progressive rate plan in each complex as the triangle marks ("△") along with the apartment complex name. The vertical axis on the right represents the annual electricity bill. As we can expect, both the average bill and the TOU portion increase as the average usage increases. For example, the complex with the lowest portion of households for which it is advantageous to change to the TOU rate plan is Complex 6, and the TOU portion is 4.85%, while the highest TOU portion is shown in Complex 2 as 35.0%. In addition, we observe from Fig. 6 that the TOU portion and the average bill of the test complex are placed approximately in the middle of the complexes.

In Fig. 7, we illustrate the total bill saving of a complex that can be obtained by changing the electricity rate plan to the TOU rate plan, where the horizontal axis represents the average annual usage in each complex. The total annual bill savings in million Won per year per complex are shown as the triangle marks with the apartment complex numbers in Fig. 7 when each household selects the best rate plan. Note that this total amount of savings depends on the number of households in the corresponding complex. The average annual savings per household in each complex are also shown as the cross marks ("×") in Fig. 7 with the right vertical axis in thousands Won per year. We observe from Fig. 7 that both total saving and average saving tend to increase as the average annual usage per household increases.

In fact, not all households will benefit from the rate plan changes. For each apartment complex, we now compute a conditional average annual savings only for the households that could lower their electricity bills by changing the rate plan. These conditional annual bill savings are also depicted as circle marks in Fig. 7 with the right vertical axis. They are between about 79,000 Won and 121,000 Won with their average of 102,808 Won, which is presented as a horizontal dotted line. We can find that there are no significant correlations between the conditional saving and the average usage, in other words, the average savings calculated conditionally for the households that benefit are similar independently of the complex.

In order to evaluate the annual savings as shown in Fig. 7, electricity usage metering data collected at hourly intervals through AMI are required as described in Subsection II-B. For calculating the bills in the TOU rate plan, information on the time of electricity usage as well as the amount of usage are required. However, currently, all the households in South Korea are provided with electricity bill reports that contain only their monthly electricity usage and bill. With such reports, it is not easy for a household to determine which rate plan is better, and the accuracy of the determination cannot be guaranteed. In the following section, we will describe methods for determining the better rate plan between the progressive and TOU rate plans for each household using only the monthly electricity usages and bills in the current progressive rate plan.

III. SELECTION OF THE ELECTRICITY RATES

In this section, under the assumption that only monthly usages and bills are available, we design classifiers and predictors to provide guidelines in determining an appropriate rate plan between the progressive and TOU rate plans. By training metering data of the ten complexes for various input

TABLE 4. Various inputs for the classifier and predictor designs.

Method	Input $x \in \mathbb{R}^p$	p
Usage (1)	Annual usage	1
Bill (1)	Annual bill	1
Usage+Bill (2)	Annual usage and bill	2
Usage (12)	12 monthly usages	12
Bill (12)	12 monthly bills	12
Usage+Bill (24)	12 monthly usages and bills	24

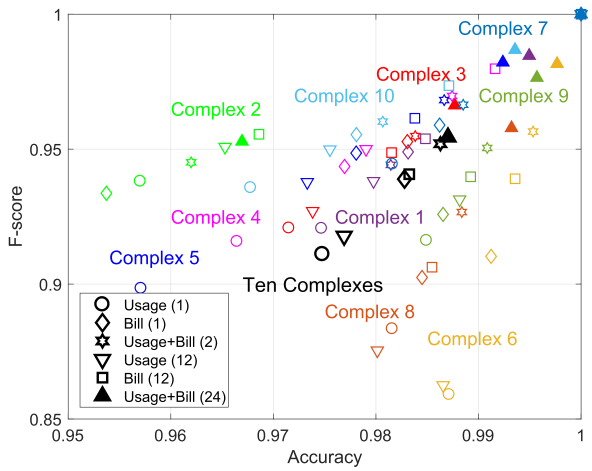

FIGURE 8. Accuracies and F-scores of the SVM classifiers designed for the ten complexes as well as each complex of Table 3.

features, different classifiers are designed based on SVM, linear regression, and DNN, respectively. Here, the techniques of the linear regression and DNN can additionally provide predictions of the bill differences or expected average savings from changing the rate plan from the progressive to TOU rate plans. Statistical properties of the designed classifiers and predictors are next analyzed as selection guidelines for an appropriate electricity rate plan.

A. SUPPORT VECTOR CLASSIFIERS

The training sequence consists of N pairs (x_i, y_i), for $i = 1, \cdots, N$, where $x_i \in \mathbb{R}^p$ and $y_i \in \{-1, 1\}$. For the ith household, the input vector x_i can be composed of the monthly or annually usages or bills as summarized in Table 4. Define a hyperplane by

$$\{x \ : \ x^{\mathsf{T}}\alpha + \alpha_0 = 0, x \in \mathbb{R}^p\}, \tag{1}$$

where α is a unit vector as $||\alpha|| = 1$ and $\alpha_0 \in \mathbb{R}$. Note that the input vectors of x_i can be classified by the hyperplane of (1). The hyperplane of (1) can be found based on SVM using the training sequence (x_i, y_i) [33], [34, p. 417]. A rate plan selection for the ith household can then be conducted by checking the sign of $x_i^{\mathsf{T}}\alpha + \alpha_0$. If this quantity is negative, then moving to the TOU rate plan can save the electricity bill and thus selecting the TOU rate plan is recommended.

In order to construct a training sequence, we use the ten complexes of Table 3 and use the test complex to verify the designed classifier. Using the hourly metering data of the ten complexes through AMI, we prepared ground truth selections between the progressive and TOU rate plans and constructed a training sequence of (x_i, y_i). In the training sequence, the output y_i is determined as $y_i = -1$ if the bill difference is negative and $y_i = 1$ otherwise. Among the total $N = 10,865$ households of the ten complexes, 1,556 households should choose the TOU rate plan and other 9,309 households should stay on the progressive rate plan in terms of minimizing their annual electricity bills.

Using the training sequence of (x_i, y_i), the coefficients of α and α_0 in (1) are determined based on SVM. In designing the SVM classifiers, we considered various combinations of the usages and bills as the SVM input as summarized in Table 4. "Usage (1)" uses the annual sum of the electricity usage and "Bill (1)" uses the annual sum of the electricity bill. By combining these two features as "Usage+Bill (2)" we can also design an SVM classifier. In a similar manner, we can use 12 monthly usages and 12 monthly bills as "Usage (12)," "Bills (12)," and "Usage+Bill (24)" in Table 4.

The accuracies and F-scores of the SVM classifiers designed using the ten complexes are illustrated as black symbols "Ten Complexes" in Fig. 8. Here, as shown in Fig. 6 regarding the TOU portion, the classes of the progressive and TOU rate plans have imbalance properties. Hence, the F-scores can have further significant meaning than the accuracy values. In Fig. 8, we observe that using 24 features as "Usage+Bill (24)" shows the best accuracy and F-score values, and using the bill data is more advantageous than the usage data case. Interestingly, the result using two features of "Usage−Bill (2)" is very similar to the result using 24 features of "Usage−Bill (24)." Hence, using 2 or 24 features for designing a classifier is recommended in terms of maximizing both the accuracy and F-score as the solid black triangle ("▲‘’). In Fig. 8, trained SVM results for each apartment complex are also illustrated to show different accuracy properties depending on the complexes. We observe that as the TOU portion increases the location of the accuracies versus F-scores move to the left.

For the ten complexes, scatter diagram examples of the annual electricity bill versus the annual usage is illustrated in Fig. 9. The households of the triangle (blue) marks of "TOU" in the upper right are preferred to select the TOU rate plan (1,556 households). The households of the circle (red) marks of "Progressive" should stay at the progressive rate plan to reduce the annual electricity bill (9,309 households). Fig. 9 also shows SVM results of "Usage (1)," "Bill (1)," and "Usage+Bill (2)" of Table 4 with the corresponding hyperplanes. The accuracies of "Usage (1)" and "Bill (1)" are 0.9748 and 0.9828, respectively. The accuracy of "Usage+Bill (2)" increases to 0.9863. If we consider only one feature as an input of SVM, the threshold of "Bill (1)" shows a better accuracy than the case of "Usage (1)" [31]. For the case of "Usage+Bill (2)," we observe a different hyperplane as shown in Fig 9 and the accuracy is further increased.

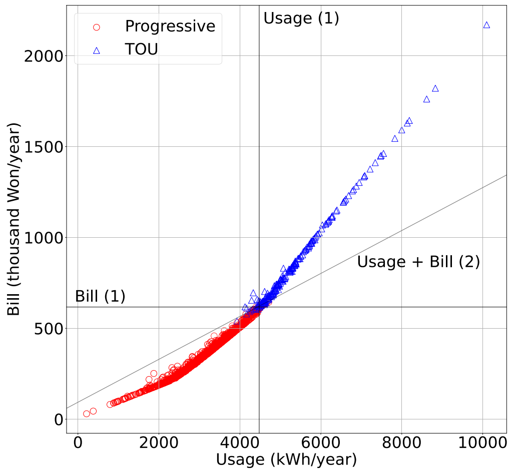

FIGURE 9. Scatter diagram of the annual bill (progressive rate plan) with respect to the annual usage and SVM design examples for the ten complexes. The SVM hyperplanes of "Usage (1)," "Bill (1)," and "Usage+bill (2)" are illustrated.

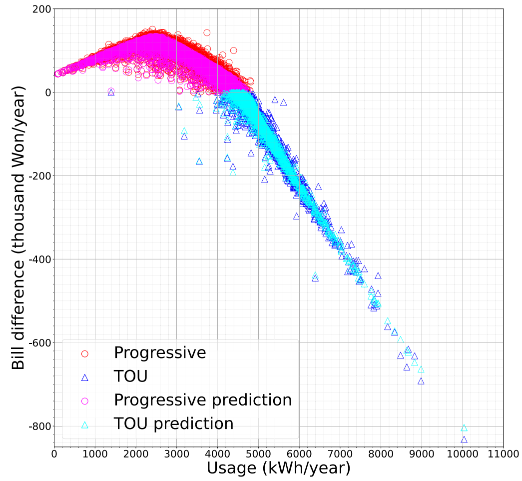

FIGURE 10. Predictions of the annual bill difference based on the linear regression with inputs of "Usage+Bill (24)" ($p = 24$) for the ten complexes.

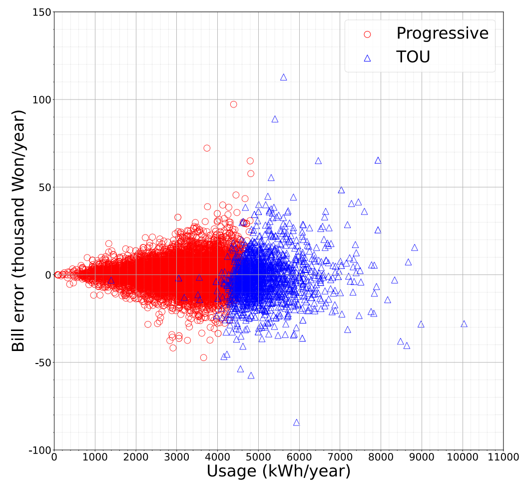

FIGURE 11. Prediction errors for the annual bill difference in Fig. 10. The root mean square error is 8,785 Won/year.

B. PREDICTIONS BASED ON LINEAR REGRESSION

The bill difference can be approximated by a hyperplane based on a linear regression analysis. We consider a training sequence that consists of N pairs (x_i, d_i), for $i = 1, \ldots, N$, where $x_i \in \mathbb{R}^p$ and d_i is the annual bill difference. A linear regression

$$f(x) := x^\top \beta + \beta_0, x \in \mathbb{R}^p \tag{2}$$

is optimized by using the training sequence (x_i, d_i) to minimize a sum of the square errors as $[f(x_i) - d_i]^2$, where $\beta \in \mathbb{R}^p$ and $\beta_0 \in \mathbb{R}$. From the optimized regression function f, we can estimate saved electricity bills as well as learn preferred rate plan between the progressive and TOU rate plans by observing the sign of f in a similar manner to the SVM case.

For the households of the ten complexes, the prediction values $f(x_i)$ from the linear regression are depicted in Fig. 10 ("Progressive prediction" and "TOU prediction") with the true bill difference values, where f was trained for the ten complexes with $p = 24$. The prediction errors of $f(x_i) - d_i$ are also depicted in Fig. 11. We observe that the prediction values faithfully follow the bill difference values. The root mean square error (RMSE) value was 8,785 Won per year. From the trained f, we can predict a saving amount of the electricity bill when we move to the TOU rate with a 95% confidence interval of $f(x_i) \pm 17,570$ Won per year assuming a normal probability distribution on the prediction errors.

C. PREDICTIONS BASED ON DEEP NEURAL NETWORK

DNN can be used to predict the bill difference as well as design a classifier for an electricity rate plan selection.

In order to design a DNN, we use the training sequence (x_i, d_i) of the linear regression case. Here, the input x_i contains 24 features ("Usage+Bill (24)", $p = 24$) without normalizations and seven hidden layers are added to the DNN architecture. As shown in Fig. 12, an input x of 24 features goes to 32, 64, 128, 256, 128, 64, and 32 nodes, and the last layer yields one output as the bill difference prediction $g(x)$. For the outputs of the hidden layers, activation functions and normalizations are not applied. In order to design a DNN for the training sequence, the loss function is the mean square error (MSE), where the batch size is 128, training epoch is 300, and the learning rate is 0.0005. The decreasing loss is illustrated in Fig. 13 and the final RMSE is 8,983 Won per year.

D. EXPERIMENTS ON THE SELECTION METHODS

We first compare the classifiers designed based on SVM, linear regression, and DNN in terms of their accuracies and F-scores. For the SVM case, the accuracies and F-scores of the test complex are illustrated as "Test (SVM)" in Fig. 14. The maximal accuracy and F-score are 0.9791 and 0.9413,

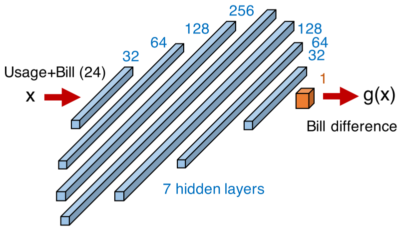

FIGURE 12. DNN architecture for a prediction of the bill difference. The input x has 24 features of the monthly usages and bills ($p = 24$) without normalizations.

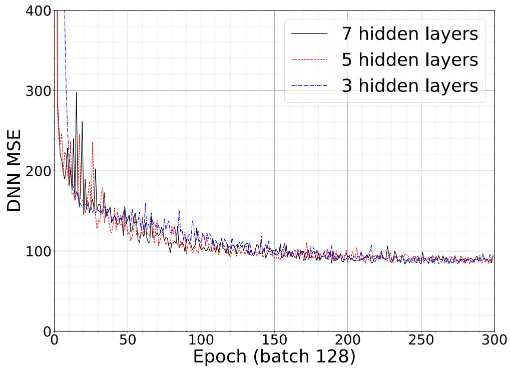

FIGURE 13. Training MSE curves with respect to the epoch for the ten complexes based on the DNN architectures with different sizes of hidden layers.

respectively, when the input is "Usage+Bill (2)" ($p = 2$). The results for the test complex are similar to the case of the ten complexes. Note that the training ratio, which is the ratio of the total number of households to the number of parameters in α and α_0, is relatively high to provide a good training performance [36]–[38]. The accuracies and F-scores from the classifiers designed based on the linear regression and DNN are also shown in Fig. 14 ("Regression" and "DNN"). Here, the classifications for the ith household are conducted by checking the signs of $f(x_i)$ and $g(x_i)$, respectively. For the 2 features "Usage+Bill (2)" and the 24 features "Usage+Bill (24)" show similar results of the SVM case. For "Usage+Bill (24)," the results of SVM, regression, and DNN, shown by the triangle marks ("△"), are similar. If the electricity bills are only available as "Bill (12)," then the results of regression and DNN are considerably worse than the SVM case. These results are shown by the solid squares ("■"). For the test complex, the results are also similar to the SVM case. However, if we consider the features of $p = 1$ or $p = 12$, then using the SVM classifier in selecting the electricity rate plan is further advantageous than the linear regression or DNN case.

We next compare the predictions from the methods of linear regression and DNN. Prediction values of the test complex by the linear regression $f(x_i)$ of (2) are illustrated in Fig. 15. We observe that the prediction values can successfully follow the ground truth values of the bill difference with RMSE=7,846 Won/year. Several example households of the test complex are shown in Table 5. For the training of the methods, inputs of "Usage+Bill (24)" in Table 4 are used from the training sequences of the ten complexes. The SVM

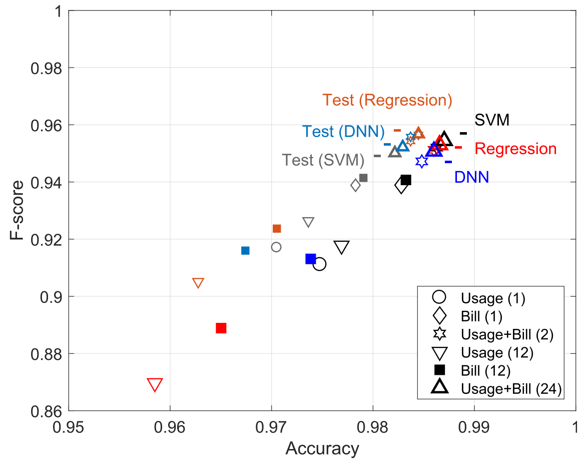

FIGURE 14. Accuracies and F-scores of the test complex using the SVM, regression, and DNN classifiers designed for the ten complexes.

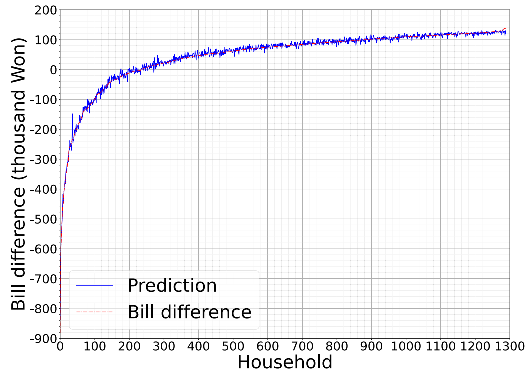

FIGURE 15. Predictions of the annual bill differences with respect to the households of the test complex by using the trained linear regression of Fig. 10. The root mean square error is 7,846 Won/year.

TABLE 5. Examples of the electricity rate plans and predictions of the bill difference d_i (thousand Won) for the test complex of Fig. 15. The input is "Usage+Bill (24)" of Table 4.

Household	Usage (kWh/year)	Ground truth Progressive (thousand Won/year)	Ground truth d_i (thousand Won/year)	Prediction of d_i Regression (thousand Won/year)	Prediction of d_i DNN (thousand Won/year)
A	2073	193.9	115.4	121.5	120.5
B	4642	654.4	-26.77	-9.393	-17.38
C	5761	978.9	-208.5	-203.3	-201.8
RMSE				8.785	8.983

results can only provide a selection between the progressive and TOU rate plans. On the other hand, the methods of the linear regression and DNN can provide predictions of saving bills when the rate plan moves to the TOU rate. In Table 5, Household A should stay at the current progressive rate plan to save the electricity bill. Households B and C should change their electricity rate plan to the TOU rate plan to save bills and predicted savings can be obtained from the methods of the linear regression or DNN as summarized in Table 5.

Prediction precisions of the linear regression and DNN methods are illustrated in Fig. 16. We observe that both linear regression and DNN methods can provide similar saving electricity bills with similar standard deviations. Hence, by using the linear regression or DNN method, we can predict amounts

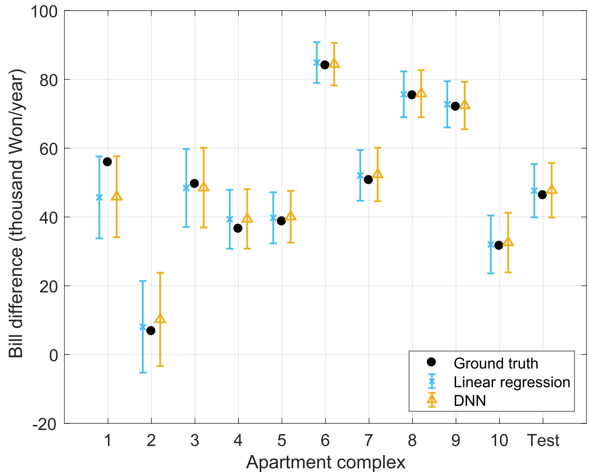

FIGURE 16. Prediction precisions of the bill differences with respect to the apartment complexes with the prediction means and standard deviations, in which the length of the error bar is the twice the standard deviation.

of annual electricity bill savings if we move to the TOU rate plan.

IV. CONCLUSION

Using only monthly electricity usage and bill data based on the current progressive rate, we could accurately conduct decisions on appropriate electricity rate plan between the progressive and TOU rate plans. If a small number of monthly bill or usage data are available, then choosing the SVM technique is preferable. On the other hand, if we want to know the amount of savings from changing the rate plan, then we should use the linear regression or DNN technique to predict the savings. Based on the framework of the simulations on the apartment complexes, we can extensively conduct electricity bill calculations for different scenarios of electricity energy consumptions as a future work. By moving the electricity usage duaring the peak hour to the usage duaring the off-peak hour, households can further reduce the electricity bills. Explicit calculations of the achievable savings can be obtained from a mathematical modeling as well as empirical simulations.

REFERENCES

[1] A. Faruqui and S. Sergici, "Household response to dynamic pricing of electricity: A survey of 15 experiments," *J. Regulatory Econ.*, vol. 38, no. 2, pp. 193–225, Oct. 2010.
[2] J. So, "Reform of the progressive electricity tariff system and the new and renewable energy market," Korea Energy Econ. Inst., Ulsan, South Korea, Res. Rep. 17-25, Dec. 2017.
[3] Y. J. Jung, "Deriving a task for reforming the electricity rate system through case studies in major overseas countries and studying implications," Korea Energy Econ. Inst., Ulsan, South Korea, Res. Rep. 20-01, vol. 20, no. 1, Dec. 2020, pp. 6–7.
[4] G. Dutta and K. Mitra, "A literature review on dynamic pricing of electricity," *J. Oper. Res. Soc.*, vol. 68, no. 10, pp. 1131–1145, Oct. 2017.
[5] S. Impram, S. V. Nese, and B. Oral, "Challenges of renewable energy penetration on power system flexibility: A survey," *Energy Strategy Rev.*, vol. 31, Sep. 2020, Art. no. 100539.
[6] J. Wellinghof and D. L. Morenoff, "Recognizing the importance of demand response: The second half of the wholesale electric market equation," *Energy Law J.*, vol. 28, no. 2, pp. 389–419, 2007.
[7] *Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them*, U.S. Dept. Energy, Washington, DC, USA, Feb. 2006.
[8] M. S. Javadi, K. Firuzi, M. Rezanejad, M. Lotfi, M. Gough, and J. P. S. Catalao, "Optimal sizing and siting of electrical energy storage devices for smart grids considering time-of-use programs," in *Proc. 45th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Oct. 2019, pp. 4157–4162.
[9] M. S. Javadi, A. E. Nezhad, P. H. J. Nardelli, M. Gough, M. Lotfi, S. Santos, and J. P. S. Catalão, "Self-scheduling model for home energy management systems considering the end-users discomfort index within price-based demand response programs," *Sustain. Cities Soc.*, vol. 68, May 2021, Art. no. 102792.
[10] T. Yu, D. S. Kim, and S.-Y. Son, "Optimization of scheduling for home appliances in conjunction with renewable and energy storage resources," *Int. J. Smart Home*, vol. 7, no. 4, pp. 261–272, Jul. 2013.
[11] D. S. Kim, B. J. Chung, and Y. M. Chung, "Statistical learning for service quality estimation in broadband PLC AMI," *Energies*, vol. 12, no. 4, p. 684, Feb. 2019.
[12] D. S. Kim, B. J. Chung, and Y. M. Chung, "Analysis of AMI communication methods in various field environments, *Energies*, vol. 13, no. 10, p. 5185, 2020.
[13] "Italian regulation authority for energy, networks and environment (ARERA)," Summary Annu. Rep. 2019, Italy, 2019.
[14] J. M. Potter, S. S. George, and L. R. Jimenez, "Smart pricing options final evaluation," U.S. Dept. Energy, Sacramento, CA, USA, Sep. 2014.
[15] M. A. R. Muzmar, M. P. Abdullah, M. Y. Hassan, and F. Hussin, "Time of use pricing for residential customers case of Malaysia," in *Proc. IEEE Student Conf. Res. Develop. (SCOReD)*, Dec. 2015, pp. 589–593.
[16] K. H. Tiedemann and I. M. Sulyma, "Modeling the impact of residential time of use rates," BC Hydro, Burnaby, BC, Canada, 2009.
[17] E. Salies, "Real-time pricing when some consumers resist in saving electricity," *Energy Policy*, vol. 59, pp. 843–849, Aug. 2013.
[18] C. Schlereth, B. Skiera, and F. Schulz, "Why do consumers prefer static instead of dynamic pricing plans? An empirical study for a better understanding of the low preferences for time-variant pricing plans," *Eur. J. Oper. Res.*, vol. 269, no. 3, pp. 1165–1179, Sep. 2018.
[19] L. Zhao, Z. Yang, and W. J. Lee, "The impact of time-of-use (TOU) rate structure on consumption patterns of the residential customers," *IEEE Trans. Ind. Appl.*, vol. 53, no. 6, pp. 5130–5138, Nov./Dec. 2017.
[20] S. Sergici, A. Faruqui, and N. Powers, "PC44 time of use pilots: Year one evaluation," Brattle Group, Baltimore, MD, USA, Sep. 2020.
[21] M. Jang, H. Jeong, T. Kim, and S. Joo, "Load profile-based residential customer segmentation for analyzing customer preferred time-of-use (TOU) tariffs," *Energies*, vol. 14, no. 19, p. 6130, Sep. 2021.
[22] S. V Oprea and A. Bara, "Setting the time-of-use tariff rates with NoSQL and machine learning to a sustainable environment," *IEEE Access*, vol. 8, pp. 25521–25530, 2020.
[23] A. Khalid, N. Javaid, A. Mateen, M. Ilahi, T. Saba, and A. Rehman, "Enhanced time-of-use electricity price rate using game theory," *Electronics*, vol. 8, no. 1, p. 48, Jan. 2019.
[24] K. S. Cho and S.-Y. Son, "Design and impact analysis of time-of-use pricing based on progressive pricing," *J. Korea Inst. Inf., Electron., Commun. Technol.*, vol. 13, no. 2, pp. 159–168, Apr. 2020.
[25] R. Carmichael, J. Schofield, M. Woolf, M. Bilton, R. Ozaki, and G. Strbac, "Residential consumer attitudes to time-varying pricing," Imperial College, London, U.K., Tech. Rep. A2, Sep. 2014.
[26] A. Ozbafli and G. P. Jenkins, "Estimating the willingness to pay for reliable electricity supply: A choice experiment study," *Energy Econ.*, vol. 56, pp. 443–452, May 2016.
[27] Y. Yoshida, K. Tanaka, and S. Managi, "Which dynamic pricing rule is most preferred by consumers?—Application of choice experiment," *J. Econ. Struct.*, vol. 6, no. 1, pp. 1–11, Mar. 2017.
[28] W. Jung, B. J. Chung, and D. S. Kim, "Analysis of the single and general contracts in electricity supply for high-voltage apartments," *J. Inst. Electron. Inf. Eng.*, vol. 57, no. 10, pp. 87–95, Oct. 2020.
[29] D. S. Kim, W. Jung, and B. J. Chung, "Analysis of the electricity supply contracts for medium-voltage apartments in the republic of Korea," *Energies*, vol. 14, no. 2, p. 293, Jan. 2021.
[30] M. J. Kim, "A study of restructured residential electricity pricing toward the competitive power market," *Trans. Korean Inst. Electr. Engineers*, vol. 63, no. 7, pp. 889–895, Jul. 2014.

[31] J. Jung, D. S. Kim, B. J. Chung, and Y. M. Chung, "Analysis on the residential progressive and time-of-use rates based on AMI data," *J. Inst. Electron. Inf. Engineers*, vol. 58, no. 9, pp. 66–77, Sep. 2021.
[32] I. Koo, S. Lee, J. Sohn, and D. Rhie, "Analysis of domestic and foreign electricity rates based on electricity usage patterns of AMI applied apartments 2020," *J. Korea Academia-Ind. Cooperation Soc.*, vol. 21, no. 12, pp. 52–59, 2020.
[33] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, pp. 273–279, Sep. 1995.
[34] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning*. New York, NY, USA: Springer, 2001.
[35] Y. M. Chung, S. Kang, E. Hong, D. S. Kim, and B. J. Chung, "On selecting electricity rates for housing based on support vector machine," in *Proc. Int. Conf. Electron., Inf., Commun. (ICEIC)*, Feb. 2022, pp. 624–626.
[36] D. S. Kim, T. Kim, and S. U. Lee, "On testing trained vector quantizer codebooks," *IEEE Trans. Image Process.*, vol. 6, no. 3, pp. 398–406, Mar. 1997.
[37] D. S. Kim, "Training ratio and comparison of trained vector quantizers," *IEEE Trans. Signal Process.*, vol. 51, no. 6, pp. 1632–1641, Jun. 2003.
[38] D. S. Kim and M. R. Bell, "Upper bounds on empirically optimal quantizers," *IEEE Trans. Inf. Theory*, vol. 49, no. 4, pp. 1037–1046, Apr. 2003.

YOUNG MO CHUNG (Member, IEEE) received the B.S., M.S., and Ph.D. degrees from Seoul National University, Seoul, South Korea, in 1986, 1988, and 1993, respectively, all in electrical engineering. He was with the Engineering Research Center for Control and Instrumentation, Seoul National University, engaged in the development of digital wireless systems, from 1994 to 1995. In 1995, he joined the Department of Electronics and Information Engineering, Hansung University, Seoul, where he is currently a Professor. From August 1998 to July 1999, he was a Postdoctoral Fellow at the Wireless Systems Laboratory, Georgia Institute of Technology, Atlanta, GA, USA. From July 2005 to August 2006, he was a Visiting Professor at the School of Electrical Engineering and Computer Science, Oregon State University, Corvallis, OR, USA. His research interests include wireless communications, power line communications, and smart grid.

SONGHEE KANG received the B.S. degree jointly from the Department of Mathematics and the Department of Computer Engineering, Hankuk University of Foreign Studies, South Korea, in 2018, and the M.S. degree from the Department of Computer Engineering, Hankuk University of Foreign Studies, in 2020. She is currently with StradVision Inc., Seoul, South Korea, as a Researcher. Her research interests include the digital image processing, machine learning, deep learning, and statistical analysis.

JAEYONG JUNG is currently a Student with the Department of Computer Science Engineering, Jeonbuk National University, South Korea. His research interests include the big data processing, data statistical analysis, machine learning, and smart metering.

BEOM JIN CHUNG received the B.S. and M.S. degrees from Seoul National University, Seoul, South Korea, in 1986 and 1988, respectively, and the Ph.D. degree from the Hankuk University of Foreign Studies, South Korea, in 2014. He was with the Smart Green Home Research Center, Gachon University, engaged in the research of the smart grid, from 2008 to 2018. In 2019, he joined the Research Center of Electrical and Information Technology, Seoul National University of Science and Technology, where he is currently a Research Professor. His research interests include the smart grid, smart metering, AMI communication networks, and electric vehicle charging systems.

DONG SIK KIM (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees from Seoul National University, Seoul, South Korea, in 1986, 1988, and 1994, respectively, all in electrical engineering. Since 1986, he has been the Research Director with Automan Company Ltd., South Korea, where he has conducted RF circuit design projects. From 1998 to 1999, he was a Visiting Assistant Professor with the School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN, USA. He is currently a Professor with the Hankuk University of Foreign Studies, South Korea. His research interests include the theory of quantization, biomedical image processing, medical physics, sensor networks, and smart grid. He was a co-recipient of the 2003 International Workshop on Digital Watermarking Best Paper Prize.