Analysis of Residential Consumers’ Attitudes toward Electricity Tariff and Preferences for Time-of-Use Tariff in Korea

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ABSTRACT In recent years, a Time-of-Use (TOU) tariff for residential consumers has received much more attention with the increasing deployment of smart meters for residential consumers in Korea. The introduction of the TOU tariff for residential consumers is expected to allow residential consumers to have a choice of electricity rate plans in addition to load management. An analysis of residential consumers’ preferences for the TOU tariff is needed to identify TOU attributes’ levels. This paper analyzes Korean consumers’ attitudes toward current residential electricity tariff and preferences for TOU tariff using demographic characteristics collected by a face-to-face survey. Consumers’ preferences on key attributes of TOU tariff are analyzed using the conjoint analysis, and attitudes toward current residential electricity tariff are estimated by the multiple indicators multiple causes (MIMIC) model. The analysis results of this study show that based on their attitude toward electricity tariff, consumers’ attitudes can be divided into three latent variables, and preferences for TOU tariff are discrete by group rather than continuous by individual consumer.

INDEX TERMS time-of-use tariff, consumer attitude, consumer preference, structural equation model, conjoint, mixed-logit model, latent class conditional logit analysis

I. INTRODUCTION

In 2019, the government of South Korea presented its third energy master plan to shift to a low-carbon energy system with focus on renewable energy on the supply side and energy efficiency on the demand side [1]. From the perspective of the demand side, demand response and dynamic pricing will play a key role in moving toward a low-carbon energy system [2-3].

The time-based tariff structures can be configured with static or dynamic form. Time-of-Use (TOU) tariff generally applies to electricity usage over static time windows of several hours, where the price for each time window is typically divided into two or three per day. Critical peak pricing (CPP), which is combination of static and dynamic, applies a high price for on-peak during a specific period defined as a critical event. Real time pricing is charged for electricity usage based on hourly metering, and charged price is linked to the wholesale electricity market price [4].

Furthermore, a time-based electricity tariff for residential consumers has received increasing attention in recent years in Korea as the Korea Electric Power Corporation (KEPCO) installs more smart meters for residential consumers. Korea is at the initial stage of implementing a Time-of-Use (TOU) tariff for residential consumers. The introduction of the TOU tariff for residential consumers is expected to allow residential consumers to have a choice of electricity rate plans in addition to load management. The Korean government and KEPCO plan to begin with the residential TOU tariff in Jeju Island in the fourth quarter of the year 2021. Therefore, analyzing Korean residential consumers’ preferences for the TOU tariff is needed to identify TOU attributes’ levels.

A conjoint analysis is one of commonly adopted methods to investigate customer preferences prior to introducing new services or products. Conjoint analysis was frequently used in other fields such as electric vehicles (EVs) [5],[6].
Previous studies on consumers’ preferences for electricity tariff has been carried out. Nicolson et al. [7] found that 39% of British consumers are willing to switch to a TOU tariff. However, this study for British consumers only investigated if respondents would switch their current electricity tariff to a TOU tariff but it did not analyze the various attributes respondents preferred when selecting their TOU tariff. More recently, the heterogeneity of preferences for electricity service was analyzed in Britain [8]. This study for heterogeneity of preferences only shows the kind of compensation required for consumers willing to accept dynamic tariffs and did not examine the preference of the attributes that make up the TOU tariff. In Switzerland, Kaufmarn et al. [9] conducted conjoint analysis for attributes composed of a critical peak price (CPP) tariff. They found that customers prefer smart metering service if the electricity tariff changes to CPP and different customer segments exist. However, the conjoint analysis for attributes of CPP used a small sample of customers and a bottom-up cluster method using part-worth sensitivity values, which does not fit consumers’ preferences for CPP appropriately. Also, reference [9] mainly focuses on the attributes of smart metering. The consumers’ preferences for CPP attributes based on their demographic characteristics were not analyzed in Switzerland study. Consumers’ preferences were analyzed by combining the various tariffs and the amount of carbon dioxide emission reduction through conjoint analysis [10]. In their study, results indicated that households tend to accept heating limits rather than electricity usage, and monetary compensation can be replaced with carbon dioxide emission reduction level when customers accept a dynamic tariff.

There are eight principles impacting tariff design [11]. The primary focus of this study is on a public acceptance, i.e., consumers’ preferences. Furthermore, little is known about consumers’ preferences for TOU tariff options and attributes based on demographic characteristics of the customer. Therefore, it is also important to consider a combination of attributes, which comprise of TOU tariff by demographic characteristics when analyzing the preferences for TOU tariffs. The reason is that no matter how economical and technical a tariff design is, it is of no use unless the consumers choose the tariff.

This study conducted an extensive analysis of Korean residential consumers. First, this study attempts to analyze consumers’ preference heterogeneity for attributes, which is an important factor in selecting the TOU tariff. Peak-times, month, on-to-off peak ratio, and whether to include weekends are the factors that vary in accordance with the energy policy directions and the governments. Analysis of the consumer preferences on these attributes would be useful information in designing the effective future TOU tariff. In addition, the consumer preferences on the on-to-off peak ratio by peak hours and whether to include weekends would be important information in establishing strategies for utility companies. For example, if customers prefer a tariff with shorter peak hours but a higher on-to-off peak rate ratio, utilities better design the rate structure within the subscription level targeted by the utility based on consumers’ preference of each attribute for consumer acceptability of the TOU tariff. Therefore, the top-down model, which is latent class conditional logit model, is used to analyze which attribute is more important, according to each customer group’s propensity. The empirical results of analyzing consumers’ preference for TOU tariff are beneficial in increasing the acceptance of a TOU tariff.

Furthermore, in previous studies on EVs the relationship between consumers’ demographic characteristic and their opinion about electric vehicles were investigated using a structural equation model (SEM) [12][13]. Little known about consumers’ attitudes toward electricity tariff based on demographic characteristic. This study utilizes the multiple indicators multiple causes (MIMIC) model, which is a type of structural equation, for analyzing residential consumers’ attitudes for current electricity tariff [14]. Hence, this study also derives the relationship between residential consumers’ socio-demographic characteristics and their attitude toward the present electricity tariff. These results about residential consumers’ attitudes would be helpful for government and utility to plan energy policy.

These analyses for consumers’ preference and attitudes toward tariff are conducted by using STATA.

The remainder of the paper is organized as follows. Section II introduces the method for analyzing attitudes toward electricity tariff using the MIMIC model and consumers’ preferences for TOU using conjoint analysis. Section III presents the demographic data and survey, the results of attitudes toward electricity tariff, and the analysis of preferences for TOU using conjoint analysis. Finally, Section IV concludes the study.

II. ANALYSIS OF CONSUMERS’ ATTITUDES AND PREFERENCES FOR ELECTRICITY TARIFF

A. Structural Equation Model for Consumers’ Attitudes toward Electricity Tariff

In this section, the MIMIC model is applied to analyze Korean consumers’ attitudes toward electricity tariff. It is assumed in the MIMIC model that a relationship exists between latent variables and demographic variables. There is also a relationship between latent variables and indicator variables. In the first stage, a structural equation is used to estimate the relationship between latent variables and consumers’ demographic characteristics. In the second stage, a measurement equation is used to analyze the relationship between latent variables and indicator variables. The two equations, which are adopted from [14], are given by:

\[ X_{LC} = \beta_D X_{DLC} + \varepsilon_i \] 
\[ X_{LC} = \beta_L X_{L,LC} + \varepsilon_m \]
where, $X_{D,C}$ is a demographic information vectors of consumer $C$, which is collected by survey. $X_{I,C}$ is a latent variables, which was not observed and indicated consumers’ attitudes toward Korea’s electricity tariff. $\varepsilon_s$ is a normal distribution error of a structural equation. $X_{I,C}$ is an vector of indicator collected by a consumers’ attitude part in a survey. $\varepsilon_s$ is a normal distribution error of a measurement equation. For a measurement equation, if the questions of consumers’ attitude are asked by a discrete ordered case which is Likert scale with the scale of M, ordered probit model could better explain a discrete indicator than linear regression. An example would be “Do you believe that current electricity bill is too expensive?”: (1) agree, (2) neutral, (3) disagree. A discrete indicator $X_{I,C}$ is represented as follows [15]:

$$
X_{I,C} = \begin{cases} 
 j_1 & \text{if } z < \tau_1 \\
 j_2 & \text{if } \tau_1 \leq z < \tau_2 \\
 \vdots & \\
 j_{M-1} & \text{if } \tau_{M-2} \leq z < \tau_{M-1} \\
 j_M & \text{if } \tau_{M-1} \leq z 
\end{cases} 
$$

(3)

where, $j_1, \ldots, j_M$ are discrete values. $\tau_1, \ldots, \tau_M$ are parameters which is estimated by measurement equation, and $z$ is a discrete indicator value which is defined as (2). Then, the probability of a discrete indicator can be presented as follows:

$$
Pr(X_{I,C} = j_k) = Pr(\tau_{k-1} \leq z < \tau_k) = F(\tau_{k-1}) - F(\tau_k) 
$$

(4)

where $F$ is the cumulative distribution function (CDF) of the error term $\varepsilon_m$. If $\varepsilon_m$ assumed a normal distribution, equation (4) is called ordered probit.

**B. CONJOINT ANALYSIS FOR CONSUMERS’ TOU ATTRIBUTE PREFERENCES**

Currently, there are multiple methods for analyzing consumers’ preferences for goods or services. A conjoint analysis is a popular multivariate technique that examines respondents’ preferences for virtual goods or services, which are composed of the selected number of attributes. This method surveys respondents’ preferences for a virtual product that is created using levels constituting each attribute and analyzes how customers consider the importance of each attribute [16], [17].

To accurately investigate customer preferences in conjoint analysis, the following descriptions are important. First, attributes must be independent of each other and it is desirable that attributes do not exceed eight [17]. Each attribute could be split into several levels. Second, in conjoint analysis, the main effects of an orthogonal design method guarantee orthogonality between individual attributes that are used to separate the impact of individual attributes on selection behavior. The orthogonal design method overcomes the widely recognized drawback that a high correlation between attributes is a problem in conjoint analysis [18]. Finally, consumers’ preferences data are analyzed using discrete choice models or methods.

The conditional logit model, introduced by McFadden et al. [19], is relatively easy to estimate and interpret results but has limitations in that it does not sufficiently account for the heterogeneity of preferences among individual consumers. In this study, a mixed-logit model and a latent class conditional logit model are introduced to solve the limitation of not accounting for preference heterogeneity [20],[21]. As preferences toward electricity vary according to each consumer’s environment, the preferences, i.e., utilities for factors that make up the electricity bill are also different. Preference heterogeneity is divided into systematic preference heterogeneity related to the observation of respondents and heterogeneity associated with unobserved characteristics. By estimating the distribution of coefficients showing the influence of factors that affect consumers’ preferences for the attributes of TOU tariff, the mixed-logit model can explain the heterogeneity showing individual consumers’ preferences for different factors. Consumers’ preference consists of a deterministic part observed through the proposed questionnaire and a stochastic part related to uncertainty.

The equations of the mixed-logit method are presented in (5), (6), and (7) as like [5], [20]. If respondent $n$ faces a choice set comprising $J$ alternatives, then the utility of respondent $n$ for alternative $j$ in the choice set is presented as:

$$
U_{nj} = \beta_n^j x_{nj} + \epsilon_{nj} 
$$

(5)

where, $x_{nj}$ is a vector of attributes, which respondent $n$ faces alternative $j$ in choice situation $t$ and $\beta_n$ is a vector of coefficients of each attribute. $\epsilon_{nj}$ is assumed as the random variables that are independent and have the identical distribution of extreme type I. The vector of coefficients, $\beta_n$, is assumed to be continuous random variable that have probability density function whose parameter $\theta$ follow a normal or lognormal distribution, i.e., $f(\beta|\theta)$. For a given $\beta_n$, the probability $P_{nj}(\beta)$ of respondent $n$ choosing alternative $j$ in choice situation is modeled as follows:

$$
P_{nj} = \int \left( \frac{e^{\beta_n x_{nj}}}{\sum_{j=1}^{J} e^{\beta_n x_{nj}}} \right) f(\beta|\theta) d\beta 
$$

(6)

A model representing the form of (6) is called a mixed-logit model. This model could approximate any random utility model depending on $f(\beta|\theta)$. As it is not possible to express $P_{nj}$ in a closed form, $\theta$ must be estimated by simulation for estimating the parameter. An approximation...
of \( P_{nj} \) is obtained by deriving \( \beta \) values as many as \( R \) from \( f(\beta|\theta) \).

\[
P_{nj} = \frac{1}{R} \sum_{r=1}^{R} \frac{e^{\beta_{r}^{'x_{nj}}}}{\sum_{j=1}^{J} e^{\beta_{r}^{'x_{nj}}}} \tag{7}
\]

By contrast, if each respondent is included in an unobserved class, it is assumed that the preferences within the class are homogeneous; however, there are heterogeneous preferences between classes in a latent class conditional logit model [21]. As documented in [20], if the parameter \( \beta_n \) of (6) is a discrete random variable with \( b_n \) values \((s = 1, \ldots, S)\), and each probability is \( p_s \) \((s = 1, \ldots, S)\), \( P_{nj} \) is the probability of a latent class conditional logit model as follows:

\[
P_{nj, latent} = \sum_{s=1}^{S} p_s \frac{e^{b_x x_{nj}}}{\sum_{j=1}^{J} e^{b_x x_{nj}}} \tag{8}
\]

where \( p_s \) is the probability that the respondent \( n \) will belong to the class \( s \).

\[
e^{b_x x_{nj}} / \sum_{k=1}^{J} e^{b_x x_{nk}} \]

is conditional probability of choosing an alternative \( j \) when a respondent \( n \) of class \( s \) in choice \( t \) set. A membership likelihood function, which classifies respondent \( n \) into class \( s \), can be modeled as

\[
M_{NS} = \lambda_s Z_n + 
\epsilon_{ns}
\tag{9}
\]

where \( Z_n \) is a vector of demographic characteristics and an attitude variable for the tariff of respondent \( n \). \( \epsilon_{ns} \) is assumed as random variables that are independent and have identical distribution of extreme type I. Then, \( p_s \), which is defined as conditional logit model, is given:

\[
p_s = \frac{e^{\lambda_s Z_n}}{\sum_{s=1}^{S} e^{\lambda_s Z_n}} \tag{10}
\]

In this study, CAIC (Consistent Akaike’s Information Criterion) and BIC (Bayesian information criterion) are used to determine the best model that accounts for preference heterogeneity among mixed-logit model and latent class conditional model as follows [22],[23]:

\[
CAIC = -2(ln L) + K(ln M + 1) \tag{11}
\]

\[
BIC = -2(ln L) + K ln M \tag{12}
\]

where, \( ln L \) is the maximized sample log likelihood, \( K \) is the total number of estimated parameters, and \( M \) is the number of decision makers.

In this study, while investigating the attitude stage, Korean electricity consumers’ attitudes toward electricity tariff are analyzed. While investigating the TOU preference stage, conjoint analysis is performed to analyze attributes that are important to consumers in selecting a TOU tariff. The analysis process proposed in this study is shown in Fig 1.

III. EMPIRICAL RESULTS

A. DEMOGRAPHIC DATA AND SURVEY

For accurate screening, face-to-face data collection was performed. Prior to conducting the attitude and conjoint survey by the end of March 2021, respondents’ demographic characteristics were surveyed to identify heterogeneity among 1,103 electricity consumers, who currently live in Seoul and Gyeonggi-do. The summary of collected demographic data is presented in Table 1.

For the attitude survey, a set of questions were created to determine consumers’ attitudes toward the electricity tariff. Eight questions were asked to understand if consumers agree with them, primarily reflecting their attitude toward the electricity tariff. Table 2 presents the questions to gauge consumers’ attitudes toward the electricity tariff.

![Analysis of Consumers' Attitude](image)

**FIGURE 1.** Analysis procedure for residential consumers’ attitudes toward electricity tariff and preferences for time-of-use (TOU) tariff.

| Variable          | Description | Counts |
|-------------------|-------------|--------|
| Family members    | single      | 150    |
|                   | two         | 337    |
|                   | three       | 278    |
|                   | ≥ four      | 338    |
| Family income     | ≤ 2.4 million | 160   |
| [KRW]             | 2.41-3.1 million | 220  |
|                   | 3.11-3.8 million | 139  |
|                   | 3.81-4.4 million | 174  |
|                   | 4.41-5.1 million | 234  |
|                   | ≥ 5.11 million | 176   |
| Gender            | male        | 564    |
|                   | female      | 539    |
| Education level   | ≤ high school graduation | 625 |
|                   | ≥ university graduation | 478 |
| Age               | ≤ 30        | 220    |
|                   | 40-49       | 363    |
|                   | 50-59       | 287    |
|                   | ≥ 60        | 233    |

**TABLE 1.** Summary of Demographic information
Table 2: Questions for attitude toward electricity tariff

| Question                                                                 | Description                                                                 |
|-------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Q1) Do you know your monthly electricity usage?                         |                                                                             |
| Q2) What do you think about the domestic electricity tariff level?       |                                                                             |
| Q3) What is your average electricity bill?                              |                                                                             |
| Q4) Do you know about the current electricity tariff progressive system? |                                                                             |
| Q5) Do you think the progressive tariff system should be reformed?      |                                                                             |
| Q6) Do you think there should be a variety of electricity tariff options?|                                                                             |
| Q7) Do you usually make efforts related to saving electricity?           |                                                                             |
| Q8) Do you consider the energy efficiency rating of home appliances?     |                                                                             |

For the conjoint survey, a set of attributes and levels were created for generating the alternative choice sets describing the various TOU tariff types. The levels of each attribute designed in this study are shown in Table III.

In [11], principles of a desirable rate structure were presented. Public acceptability of tariff is also identified as an important principle among the eight principles for a desirable rate structure. Therefore, unlike previous studies which have provided a monitoring device for increasing acceptance of TOU tariff, the increase in consumer acceptance of TOU tariff is analyzed by reflecting a combination of the design features of the TOU tariff plan, which are defined as the length of the peak period, the ratio of the peak to off-peak price, what months TOU is in applying, and whether to apply weekends.

In this study, the structure of TOU tariff, which is the combined tier, on-to-off peak rate ratio, month, peak-times, and whether to include weekends is set as the key attributes that influence consumers’ TOU preference. Table III presents the attributes and levels with descriptions. The choice sets, which are designed to affect the probability of respondents’ selection of TOU alternatives, are very important. This study uses the orthogonal main effects design that ensures orthogonality of each attribute for composing simplified alternative cards for the survey. Therefore, four alternative choice sets comprising four cards each were generated using the orthogonal main effects design to separate the impact of each attribute based on respondents’ answers. Alternative choice sets, which are used in the study, are included in the Appendix.

To validate consumer responses for the conjoint survey and the analysis models, the following four methods were performed. For validating the consumers’ information, First, a relatively large number of surveys were conducted. Many samples could help the analysis model of consumer preferences have robustness from outliers. Second, the survey was conducted in an on-site environment that could prevent the respondents’ insincere responses as much as possible compared to on-line. Lastly, information of consumer’s replying cards in the same pattern, which is a representative example of insincere responses, was removed. For validating the analysis model, the statistical validity of the model parameter estimation was analyzed using the p-value, which is a representative statistical power.

Table 4: Factor analysis with consumers’ attitudes

| Question number | Factor 1 | Factor 2 | Factor 3 |
|-----------------|----------|----------|----------|
| Q1              | 0.19     | 0.22     | 0.46     |
| Q2              | 0.06     | 0.79     | -0.03    |
| Q3              | 0.14     | 0.48     | -0.26    |
| Q4              | 0.14     | 0.08     | 0.17     |
| Q5              | 0.44     | 0.02     | 0.06     |
| Q6              | 0.92     | -0.04    | -0.02    |
| Q7              | 0.16     | -0.08    | 0.19     |
| Q8              | 0.11     | 0.15     | 0.37     |

B. RESULTS OF INVESTING CONSUMERS’ ATTITUDES TOWARD THE ELECTRICITY TARIFF

First, factor analysis is performed to find latent variables that reflected consumers’ attitudes toward electricity tariff by using the maximum likelihood method with varimax rotation [13]. As a result of factor analysis, three is the optimal value for number of factors. Thus, questions related to consumers’ attitudes toward electricity tariff were aggregated, as shown in Table 4.

For each question, the attribute is included in the factor with the largest factor loading. By grouping factors with the largest factor loading, each factor’s characteristics can be observed, and a name is assigned to indicate the characteristics of each factor to make a latent variable. As questions 5 and 6 referred to the need for reforming the current electricity tariff and the need for various electricity tariffs, F1 was designated as a latent variable indicating consumers’ attitude toward the “Need for various types of electricity tariffs.” As questions 2 and 3 asked consumers about the current electricity bill, F2 was designated as a latent variable indicating the feeling that the “The current electricity tariff is too expensive.” As questions 1 and 10 have the common features of saving the electricity tariff, F3 was identified as consumers’ attitude toward “Saving on electricity tariff.” Based on the factor analysis, three latent variables are obtained from surveying consumers’ attitude toward electricity tariff. MIMIC result is presented in Fig 2.

Second, as shown in Fig 2, the structural equation was estimated using latent variables and consumers’ demographic information, as presented in Table 5. Table 5 shows that each latent variable is structured based on consumers’ demographic characteristics. The effect on the latent variable can be interpreted according to the significant coefficient of each demographic characteristic. To the question “Need for various types electricity tariffs,” female consumers respond more positively to the need for having different types of electricity tariffs than male. For the question “The current electricity tariff is too expensive,” male with many family members, high family income and education level think that the current electricity tariff is expensive. The number of family members per household has the greatest influence on the “The current electricity tariff is too expensive,” and it may show that the more number of members in a family, the higher the electricity...
consumption and more excessive the electricity bills. Residential electricity consumers with higher education level responded positively to the item “Saving on electricity tariff.”

Finally, the relationship between the latent variables and attitude indicators was estimated in the measurement equation, as shown in Table 6. Measurement equations using the MIMIC model can reduce the dimensionality of the effect indicators. For the item “Need for various types of electricity tariffs,” as question 6 is not statistically significant, latent class variables that require various tariffs can be defined through question 5. As question 3 is statistically significant with “Current electricity tariff is too expensive,” consumers who believe the current electricity bill is very expensive are paying a lot. As question 10 is statistically significant with “Saving on electricity tariff,” it is presumed that consumers’ attitudes toward saving on electricity is conspicuous if they are aware of the monthly electricity usage, and the energy efficiency rating of household appliances is perceptible.

Summing up the analysis results of consumers’ attitudes, Korean residential consumers’ attitudes toward electricity tariff are divided into three latent variables: (i) Need for various types of electricity tariffs, (ii) Current electricity tariff is too expensive, and (iii) Saving on electricity tariff. The latent variables are explained through the demographic characteristics of consumers and indicators belonging to each group.

### TABLE 5. The estimated the structural equation for electricity tariff attitude

| Demographic variables | Coefficients of $\beta_0$ | Standard Deviation of $\beta_0$ |
|-----------------------|---------------------------|-------------------------------|
| Necessity for various electricity tariff | | |
| Family members | -0.028 | 0.05 |
| Family income | 0.05 | 0.035 |
| Education level | 0.09 | 0.11 |
| Age | 0.038 | 0.05 |
| Gender | 0.28** | 0.11 |
| Current electricity tariff is too expensive | | |
| Family members | 0.188*** | 0.036 |
| Family income | 0.026** | 0.013 |
| Education level | 0.088* | 0.042 |
| Age | 0.025 | 0.019 |
| Gender | -0.105*** | 0.033 |
| Saving on electricity tariff | | |
| Family members | -0.0007 | 0.015 |
| Family income | -0.0023 | 0.009 |
| Education level | 0.128*** | 0.042 |
| Age | -0.018 | 0.015 |
| Gender | -0.0026 | 0.030 |

***, **, * significance at 1%, 5%, and 10%, respectively.

### TABLE 6. The estimated the measurement equation for electricity tariff attitude

| Indicators | Coefficients of $\beta_1$ | Standard Deviation of $\beta_1$ |
|------------|---------------------------|-------------------------------|
| Necessity for various electricity tariff | | |
| Q5 (base) | 1 | |
| Q6 | 0.973 | 0.718 |
| Current electricity tariff is too expensive | | |
| Q2 (base) | 1 | |
| Q3 | 5.007** | 1.801 |
| Saving on electricity tariff | | |
| Q1 (base) | 1 | |
| Q10 | 15.073*** | 4.89 |

***, **, * significance at 1%, 5%, and 10%, respectively.

### FIGURE 2. The MIMIC result of consumers’ attitude for electricity tariff
As most previous studies adopted the log-normal and normal distribution for parametric mixed-logit estimation [24]. In a log-normal distribution, it is useful to estimate the expected parametric same sign for all respondents. At the same time, a normal distribution has no restrictions. For that reason, parameters are estimated using the normal distribution in this study. Results indicating the preference to use the mixed-logit model are shown in Table 7.

### Table 7. Customers’ preference for TOU tariff using mixed-logit model

| Variable | Mean of β | Variance of β |
|----------|-----------|---------------|
| Rate B   | 0.391*** (0.061) | 0.477** (0.186) |
| Rate C   | -0.631*** (0.139) | 1.172*** (0.70) |
| Rate D   | 0.209*** (0.055) | 0.524** (0.103) |
| Rate E   | 0.199** (0.093) | 0.204 (0.294) |
| Rate F   | -0.231*** (0.09) | -0.614*** (0.197) |
| Month    | 0.031 (0.031) | 0.253*** (0.061) |
| Whether of Weekends | 0.462** (0.064) | 0.40 (0.048) |
| Peak-times | -0.033 (0.028) | 0.084* (0.0476) |

**Note:** ***, **, * significance at 1%, 5%, and 10%.

The mean of Rate B coefficient is the highest positive value, whereas the mean of Rate C coefficient is the highest negative value in the rate design attribute, indicating that residential consumers prefer a lower on-to-off peak ratio. In addition, Rate D and Rate E, which are the 3-tier rate structure, with a lower on-to-off peak ratio have positive coefficients of means compared to Rate C and Rate F with a higher on-to-off peak ratio, indicating that consumers prefer a lower on-to-off peak ratio.

The mean of weekends coefficient is another significantly positive variable. This implies that consumers could control their electricity usage pattern following the TOU tariff over weekends. These results of the mixed-logit model were analyzed assuming that consumers’ preferences have continuous heterogeneity, suggesting that there are differences in preferences for TOU tariff among individual customers. Otherwise, the latent class conditional logit model assumes that respondents’ heterogeneity has a discrete distribution that can be endogenously or potentially partitioned. The criterion for classifying latent class for conditional logit model is influenced by an individual’s demographic characteristics. In this study, latent classes are divided using individual characteristics that affect the utility variable and (8). For determining the number of classes, both CAIC and BIC are used.

### Table 8. The criterion for optimizing class

| Class | Log-likelihood | Parameters | CAIC | BIC |
|-------|----------------|------------|------|-----|
| 2     | -5865.776      | 22         | 11907.68 | 11885.68 |
| 3     | -5799.996      | 36         | 11885.82 | 11852.2 |
| 4     | -5695.492      | 50         | 11741.27 | 11741.27 |
| 5     | -5667.684      | 64         | 11783.74 | 11783.74 |

Since both BIC and CAIC show small values in the 4 class, it is the optimal one, as shown in Table 8. Therefore, the latent class conditional logit model is conducted following the 4 class. Therefore, the latent class conditional logit model results using 4 classes is presented in Table 9.

### Table 9. Customers’ preference for TOU tariff using latent class conditional logit

| Variable | Class 1 | Class 2 | Class 3 | Class 4 |
|----------|---------|---------|---------|---------|
| Rate B   | 1.78*** | 2.61*** | -0.03   | 0.01    |
| Rate C   | 2.25*** | -7.84***| 1.37*** | -1.29***|
| Rate D   | 0.36    | -1.94** | 1.34**  | 0.16**  |
| Rate E   | 1.19*** | -1.09   | 2.19*** | -1.13***|
| Rate F   | -3.88** | -0.21   | 2.73*** | -0.66***|
| Month    | 0.839** | -3.53***| -0.63***| 0.20**  |
| Weekends | -0.52***| 5.09***  | -0.79** | 0.55**  |
| Peak-times| -0.62***| -1.04***| -0.33   | 0.06    |

**Note:** ***, **, * significance at 1%, 5%, and 10%.

The mixed-logit model and the latent class conditional logit model do not have the tendency to show that one model is more superior [25]. However, while explaining the heterogeneity in consumers’ preferences for the TOU tariff, both BIC and AIC have smaller values for the latent class conditional logit model, as shown in Tables 7 and 9. Therefore, the latent class conditional logit model is well fitted for this study.

Consumers in class 1 have more numbers of family members and relatively low-income level. Class 1, referred to as big-family group, clearly shows a positive preference for the 2-tier rate structure compared to other groups, and prefers Rate C to Rate B. As a result, 2-tier rate structure and lower off-peak rates are preferred in the big-family group. In the case of other attributes, the big-family group clearly shows a negative preference for the coefficient of weekends and peak times but has a positive preference for the coefficient of month in comparison other groups. Therefore, the big-family group prefers a longer month period with short peak times only on weekdays. As customers, females are more likely to be included in class 2, which is referred to as the female consumer group. This group prefers Rate B and peak hours both on weekdays and weekends. Consumers included in the female consumer group clearly show a negative preference for longer peak times and months. Consumers in class 3, which is referred to as the strategy group, clearly prefer the 3-tier rate structure and higher on-peak rate. There is no significant demographic difference between the strategy group and the reference group, which is class 4. Moreover, the strategy group has a negative
preference for all the variables representing period such as *weekends* and *month*. This implies that the strategy group minimizes the inconvenience of behavioral changes and tries to obtain maximum benefits by reducing electricity consumption for a shorter period with a higher on-peak rate. Relatively, class 4, referred to as the main group, has more consumers than other groups. The main group prefers *Rate D*, which has a lower on-peak rate, a higher off-peak, and 3-tier rate structure, compared to other rate options. The main group also prefers the TOU tariff with all week and a longer month period.

The next phase of this research is to study the consumers’ preference for TOU tariff in combination with clustering of customers’ load profiles to design a customized electricity tariff for a targeted group.

**IV. CONCLUSION**

In this study, an analysis of Korean residential electricity consumers’ attitudes toward electricity tariff are divided into three latent variables. The latent variables are explained through the demographic characteristics of consumers and their answers for questions about attitudes toward electricity tariff belonging to each group.

Consumers’ preferences for TOU tariff were analyzed with *rate design*, *month*, *weekends*, and *peak-times*, which are key attributes in composing a TOU tariff. The results of the mixed-logit model describe the individual consumer’s preference for attributes of TOU tariff. However, there is a physical limit to designing tariff plans that are suitable for an individual consumer based on its personal preference. Hence, latent class conditional logit model is conducted additionally using consumers’ demographic characteristics. The results of the latent class conditional logit model are presented as four classes: big-family group, females, strategy group, and main group. These four groups show different preferences for the TOU tariff, which is according to the demographic characteristics of each group.

Considering the main group, which accounts for 50% of the participation among the four groups, to increase the consumer acceptance of TOU tariff for residential consumers, the proposed rate structure is combination of lower peak price, lower on-to-off peak rate ratio, longer month period, and only mid-peak or off-peak on weekends. In addition, although the peak-times coefficient is not statistically significant, it could be seen that consumers tend to want a longer peak period on the lower peak price. These results suggest that a tariff option such as rate discount is possible to increase the acceptability of the TOU tariff as like previous studies implying that supplying a monitoring device such as IHD could increase the acceptability of the TOU rate system. Furthermore, even if a lower price is applied in peak period, consumers tend to accept a longer peak period. Therefore, the consumer acceptance of TOU tariff can be achieved while maintaining the principle of efficient pricing.

Future research needs to be directed toward the development of method that combines residential consumers’ historical data responding to actual TOU tariff and demographic characteristic. Such the future study will be useful in designing a customized electricity tariff for a targeted specific socioeconomic group.

**APPENDIX**

Tables A-I to A-IV show the choice sets of alternative cards composed of attributes proposed in this study. The respondents choose the most attractive alternative card in each choice set.

**TABLE A-I. Choice set 1 of TOU tariff in the face-to-face survey**

| Rate Design | Type A | Type B | Type C | Type D |
|-------------|--------|--------|--------|--------|
| Month       | July-August | July-August | July-August | July-August |
| Weekends    | Yes     | No     | Yes    | No     |
| Peak-times  | 4 hours/day | 3 hours/day | 3 hours/day | 2 hours/day |

**TABLE A-II. Choice set 2 of TOU tariff in the face-to-face survey**

| Rate Design | Type A | Type B | Type C | Type D |
|-------------|--------|--------|--------|--------|
| Month       | July-August | June-August | June-August | August |
| Weekends    | Yes     | Yes    | Yes    | Yes    |
| Peak-times  | 2 hours/day | 2 hours/day | 3 hours/day | 4 hours/day |

**TABLE A-III. Choice set 3 of TOU tariff in the face-to-face survey**

| Rate Design | Type A | Type B | Type C | Type D |
|-------------|--------|--------|--------|--------|
| Month       | May-August | June-August | June-August | August |
| Weekends    | No      | No     | No     | No     |
| Peak-times  | 2 hours/day | 4 hours/day | 4 hours/day | 3 hours/day |

**TABLE A-IV. Choice set 4 of TOU tariff in the face-to-face survey**

| Rate Design | Type A | Type B | Type C | Type D |
|-------------|--------|--------|--------|--------|
| Month       | July-August | May-August | June-August | August |
| Weekends    | No      | No     | Yes    | No     |
| Peak-times  | 2 hours/day | 2 hours/day | 2 hours/day | 2 hours/day |

**REFERENCES**

[1] KEEI, “Third Energy Master Plan.” 2019, [Online]. Available: http://www.keei.re.kr/web/keei/en_news.nsf/XML/XML_PORTAL2/9CC1EC56D87E61FC492584A1002099CC/$file/Energy%20Master%20Plan_2019.pdf

[2] IEA, “Net Zero by 2050-a Roadmap for the Global Energy Sector.” 2021, [Online]. Available: https://iea.blob.core.windows.net/assets/4482cac7-eedd-4c03-b6a2-8e79792f1649/NetZeroby2050-ARoadmapfortheGlobalEnergySector.pdf

[3] S. Impram, S. V. Nese, and B Ora, “Challenges of renewable energy penetration on power system flexibility: A survey”, *Energy Strategy Reviews*, vol. 31, p. 100539, 2020.

[4] IRENA. "Time-of-use tariffs: Innovation landscape brief." (2019).

[5] W. Ko, T. K. Hahn, “Analysis of Consumer Preferences for Electric
Vehicles”, IEEE Transactions on Smart Grid, vol. 4, pp. 437-442, 2013

[6] H. Moon, S. Y. Park, C. Jeong, J. Lee, “Forecasting electricity demand of electric vehicles by analyzing consumers’ charging patterns”, Transportation Research Part D: Transport and Environment, vol. 62, pp 64-79, 2018.

[7] M. Nicolson, G. Huebner, and D. Shipworth, “Are consumers willing to switch to smart time of use electricity tariffs? The importance of loss-aversion and electric vehicle ownership”, Energy Research & Social Science, vol. 23, pp. 82-96, 2017.

[8] L. Richter, M. Pollitt, “Which smart electricity service contracts will consumers accept? The demand for compensation in a platform market”, Energy Economics, vol. 72, pp 436-450, 2018.

[9] S. Kaufmann, K. Künzel, and M. Looke, “Customer value of smart metering: Explorative evidence from a choice-based conjoint study in Switzerland”, Energy Policy, vol. 53, pp. 229-239, 2013.

[10] E. Ruokamo, M. K. Savolainen, T. Meriläinen, R. Svento, “Towards flexible energy demand – Preferences for dynamic contracts, services and emissions reductions”, Energy Economics, vol. 84, 2019.

[11] Bonbright, James C. Principles of public utility rates. Columbia University Press, 1961.

[12] GHASRI, Milad; ARDESHIRI, Ali; RASHIDI, Taha. Perception towards electric vehicles and the impact on consumers' preference. Transportation Research Part D: Transport and Environment, 2019, 77: 271-291.

[13] JUNGH, Jihyeok, et al. Factors affecting consumers’ preferences for electric vehicle: A Korean case. Research in Transportation Business & Management, 2021, 100666.

[14] BOLLEN, Kenneth A. Structural equations with latent variables. John Wiley & Sons, 1989. Green, Paul E., and Venkatachary Srinivasan. "Conjoint analysis in consumer research: issues and outlook." Journal of consumer research 5.2 (1978): 103-123.

[15] MUTHÉN, Bengt; KAPLAN, David. A comparison of some methodologies for the factor analysis of non-normal Likert variables. British Journal of Mathematical and Statistical Psychology, 1985, 38.2: 171-189.

[16] Bateman, Ian J., et al. "Economic valuation with stated preference techniques: a manual." Economic valuation with stated preference techniques: a manual. (2002).

[17] Phelps, Ruth H., and James Shanteau. "Livestock judges: How much information can an expert use?" Organizational Behavior and Human Performance 21.2 (1978): 209-219.

[18] Hanley, Nick, Robert E. Wright, and Vic Adamowicz. "Using choice experiments to value the environment." Environmental and resource economics 11.3 (1998): 413-428.

[19] McFadden, Daniel. "The measurement of urban travel demand." Journal of public economics 3.4 (1974): 303-328.

[20] Jang, M., Jeong, H. C., Kim, T., & Joo, S. K. (2021). Load Profile-Based Residential Customer Segmentation for Analyzing Customer Preferred Time-of-Use (TOU) Tariffs. Energies, 14(19), 6130.

[21] Boxall, Peter C., and Wiktor L. Adamowicz. "Understanding heterogeneous preferences in random utility models: a latent class approach." Environmental and resource economics 23.4 (2002): 421-446.

[22] Kuhla, Jouni. "AIC and BIC: Comparisons of assumptions and performance." Sociological methods & research 33.2 (2004): 188-229.

[23] ANDERSON, D. R.; BURNHAM, K. P.; WHITE, G. C. Comparison of AIC and CAIC for model selection and statistical inference from capture-recapture studies. Journal of Applied Statistics, 1998, 25.2: 263-282.

[24] Train, Kenneth E. Discrete choice methods with simulation. Cambridge university press, 2003.

[25] Greene, William H., and David A. Hensher. "A latent class model for discrete choice analysis: contrasts with mixed logit." Transportation Research Part B: Methodological 37.8 (2003): 681-698.

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