

Received September 23, 2021, accepted October 9, 2021, date of publication October 14, 2021, date of current version October 21, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3120099

Novel Single Group-Based Indirect Customer Baseline Load Calculation Method for Residential Demand Response

HYUNYONG LEE¹, HYUNSEOK JANG², SEUNG-HUN OH¹, NAC-WOO KIM¹,
SEONGCHEOL KIM², AND BYUNG-TAK LEE¹

¹Honam Research Center (HRC), Electronics and Telecommunications Research Institute (ETRI), Buk-gu, Gwangju 61012, Republic of Korea

²Paran Energy Company Ltd., Bundang-gu, Seongnam-si, Gyeonggi-do 13625, Republic of Korea

Corresponding author: Hyunyong Lee (hyunyonglee@etri.re.kr)

This work was supported in part by the Korea Institute of Energy Technology Evaluation and Planning (KETEP), and in part by the Ministry of Trade, Industry and Energy (MOTIE) of the Republic of Korea under Grant 20181210301570.

ABSTRACT Demand response (DR) is a voluntary program that encourages related stakeholders, in this case electricity consumers, to cut down on usage during periods of high electricity load. One key to fully exploiting DR is to encourage residential customers to join the DR program. Unlike in the DR programs for commercial and industrial customers, for the successful operation of the residential DR program, several issues have to be addressed, one of which is to provide a group-level incentive to participating customers. In particular, the issue comes up when the incentive calculated for a group is not equal to the aggregated incentives for each customer (i.e., non-equal incentive problem). The non-equal incentive problem deteriorates the successful operation of residential DR by decreasing the motivation of DR operators and customers. We first prove the non-equal incentive problem through mathematical and experimental methods. We then propose the novel single group-based indirect incentive calculation method. The basic idea of our approach is to indirectly calculate the incentive for each customer not using the customer's data but using the data of other customers of the same DR group. Through experiments involving the electricity usage data of 42,193 households and the real DR events in Korea, we show that our method solves the non-equal incentive problem in most cases. Furthermore, our method improves the accuracy of the baseline estimation (used for calculating the contribution).

INDEX TERMS Demand response, residential, customer baseline load, aggregator, incentive-based DR program.

I. INTRODUCTION

Demand response (DR) can handle the occasional high electricity load in an inexpensive manner [1], [2]. The DR attempts to shift the electricity load of the end customer when electricity demand surges through incentive- or pricing-based policies [3], [4]. The DR can provide economic benefits to related stakeholders: independent system operators (ISOs), DR operators, and end customers. An ISO who coordinates, controls, and monitors the operation of the electrical power system can reduce the cost of the investment by lowering the peak electricity load and enhancing the reliability of the power system [5], [6]. The DR operators, located between

ISOs and the end customers, ensure that the DR operates well, adding to the benefits of the DR program. The end customers can obtain incentives or reduce their electricity consumption costs by reducing their electricity usage.

One promising way to increase DR capacity (i.e., the amount of electricity that can be reduced when requested) is to include residential customers because they are responsible for a considerable proportion of electricity usage and have the most uncovered DR potential [7], [8].¹ The DR program intended for residential customers is the *residential* DR program. Unlike the other DR programs for commercial

The associate editor coordinating the review of this manuscript and approving it for publication was Peter Palensky¹.

¹ Throughout this paper, we are interested in the incentive-based DR program. In the remainder of this paper, we use the term DR to indicate an incentive-based DR.

and industrial customers, the residential DR has unique features and corresponding issues to be solved. Considering that electricity consumption of residential customers is highly random in nature, traditional deterministic customer baseline load (CBL) calculation methods are not effective for residential DR [9]. Therefore, to provide stable incentive to residential customers, CBL calculation methods suitable for residential customers are required. Considering that the electricity consumption level of residential customers is quite low [37], aggregation of residential customers is inevitable. Regarding this aspect, we may have two issues. First, an operation strategy for aggregating residential customers is required to maximize the profit of DR operators. Second, given a group-level incentive, a way to distribute the incentives to residential customers is required.

Most of the existing work focuses on CBL calculation methods for residential customers and operation strategies for DR operators. The CBL calculation methods include direct CBL calculation such as averaging methods [9], regression [13], [14], deep learning [15]–[21], and probabilistic methods [7], [22]–[25] and indirect CBL calculation methods such as control group methods [24], [26]–[35]. The operation strategies for DR operators include optimal bidding strategy [38]–[47] and modeling of residential customers [8], [23], [48]–[53]. However, to the best of our knowledge, none of the existing work considers the incentive distribution in the context of residential DR.

To this end, for a successful residential DR, we focus on the incentive distribution problem. We first prove the problem, called *non-equal incentive problem*, mathematically and empirically. Then, we propose a single group-based indirect CBL calculation method. Our idea is to *indirectly* calculate the contribution of each customer by utilizing data on the other members of the same DR group, unlike the common approach that calculates a customer's contribution using the data of that customer only or requires additional non-DR groups. The rationale behind this approach is to overcome the problem caused by the nonlinearity of the function used for calculating the contribution (i.e., the main reason for the non-equal incentive problem) through a single group-based indirect calculation.

To examine our method, we conduct experiments using electricity usage data on 42,193 households with six averaging CBL calculation methods that are widely used in the real world. First, we demonstrate that our method effectively solves the problem caused by the nonlinearity of the function. Then, we show that our method greatly reduces the gap between the incentive for a DR group calculated by ISO and the aggregated incentive of each customer calculated by a DR operator, implying that the proposed method effectively solves the non-equal incentive problem. Furthermore, our method improves the accuracy of the baseline estimation used for calculating the contribution. Using the real DR events data with six averaging CBL calculation methods, we demonstrate that our method outperforms the existing method in solving the non-equal incentive problem.

We also briefly discuss interesting aspects of the residential DR program.

The contributions of this study are as follows.

- 1) We define the non-equal incentive problem as an essential issue for successful residential DR. We prove the problem mathematically and empirically.
- 2) To the best of our knowledge, we are the first to propose a method for the non-equal incentive problem. We prove the usefulness of our method in solving the non-equal incentive problem and calculating group-level CBL accurately through extensive experiments using real-world data including residential DR events.
- 3) Our method has high applicability. It utilizes only data of the same DR group without requiring separate control groups. Furthermore, it can be easily applied to the averaging methods, which are widely used in the real-world.

The rest of this paper is organized as follows. In Section II, we describe the background for our research. In Section III, we describe related work. In Section IV, we describe our method along with the non-equal incentive problem. In Section V, we examine the feasibility of our method using real data. Finally, in Section VI, we provide some concluding remarks regarding this research.

II. BACKGROUND

A. INTRODUCTION TO DR

A DR program includes three stakeholders: ISOs, DR operators, and customers. A typical DR procedure consists of four steps. First, electricity customers including commercial, industrial, and other types of customers join the DR program (managed by an ISO) through DR operators, to reduce electricity usage when requested. Second, ISO issues a DR event when electricity demand surges to have the peak demand reduced. DR operators relay the DR event from ISO to their customers. Third, customers try to reduce their electricity consumption (e.g., by decreasing the electricity consumption level of the devices and by delaying their use). Finally, ISO provides incentives to customers as much as they reduced through the corresponding DR operators.

B. CUSTOMER BASELINE LOAD

In calculating incentives for customers as a reward for their participation in DR events, we need to know how much they saved by reducing electricity usage. CBL is used for this purpose. CBL denotes the expected electricity usage of the customer in the absence of a DR event. Therefore, the incentive for a customer is calculated based on the amount of reduction (i.e., the difference between the CBL and actual electricity usage). Fig. 1 illustrates an example case. In Fig. 1, the *DR window* indicates the duration of the DR event, and the red dotted line indicates the CBL. In addition, the green area indicates the amount of reduction used to calculate the incentives.

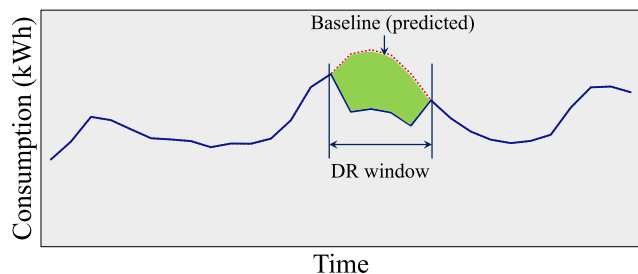


FIGURE 1. Calculation of incentive using CBL.

C. RESIDENTIAL DR IN KOREA

The residential DR began in December 2019, as a trial to increase the nationwide DR capacity of Korea. Customers of residential DR include electricity customers with contract power less than 70 kW (regardless of the type of contract), residential customers, and individual houses of collective buildings. The minimum required DR capacity (i.e., the sum of the DR capacity of individual customers managed by a DR operator) is 1 MW, and the duration of a DR event is 1 h. Pre-guidance for a DR event is issued 30 min before the DR event. The residential DR event occurs when a particulate matter warning is issued. One major goal of residential DR in Korea is to reduce the degree of particulate matter by reducing the operation of coal power plants. An incentive for residential DR is purely performance based. The incentive is calculated for a group of customers (i.e., a group of individual customers managed by a DR operator). Therefore, DR operators need to distribute the incentive among their customers. There is no penalty for an unfulfilled reduction request.

D. REQUIREMENTS FOR SUCCESSFUL RESIDENTIAL DR

Residential DR holds the key to the potential growth of DR capacity and DR benefits because residential customers are responsible for a considerable proportion of the electricity usage and have the most uncovered DR potential [7], [8]. To facilitate residential DR, we need to encourage DR operators as well as residential customers. For residential customers, one simple and effective way is to provide incentives commensurate with their contribution. But, one notable challenge in realizing this is the electricity consumption of residential customers is highly random in nature. As a result, traditional deterministic CBL calculation methods are not effective for residential DR [9]. Thus, the first requirement for successful residential DR (**R1**) is to determine CBL calculation methods suitable for residential customers.

With residential DR, the DR operator takes on a critical role because the electricity consumption level of the residential customer is considerably low [37]. In other words, a DR operator provides DR services to ISOs and cost-beneficial consumption opportunities to customers through aggregation of customers. In this respect, the second requirement for successful residential DR (**R2**) is an operational strategy to maximize the profit of DR operators.

In adopting the aggregation-based approach, one inevitable issue is how to distribute incentives to customers because incentive is typically calculated for a group of residential customers. Thus, one problem that may arise is when the group-level incentive (i.e., incentive for a group of residential customers calculated by ISO) and the sum of incentives for individual residential customers (i.e., calculated by a DR operator) are different. Please refer to section IV.A for a detailed description of this issue. We call this the *non-equal incentive problem*. Therefore, the last requirement for successful residential DR (**R3**) is to determine a solution to the non-equal incentive problem.

III. LITERATURE REVIEW

We divide existing studies into three subgroups and briefly evaluate methods of each subgroup from the perspective of the three requirements described in Section II.D.

A. DIRECT CBL CALCULATION

Direct CBL calculation methods use the data of target residential customers.

1) PERFORMANCE STUDY

In [10], the authors analyze the DR baselines for residential customers. They also propose a simple baseline method called LowXofY. In [9], the authors conduct an error analysis of CBL methods for residential customers both theoretically and empirically. They demonstrate that the CBL methods for commercial and industrial DR programs do not perform efficiently for residential customers. A similar performance study is also conducted in [11], in the particular context of the South Korean and French DR programs. In [12], the authors empirically evaluate the performance of CBL estimation (including artificial neural network regression) for residential customers.

2) AVERAGING METHODS

Averaging methods assume that CBL can be estimated based on the average usage of recent days. HighXofY calculates CBL as the average electricity usage of the top X days of the recent Y non-DR days (e.g., days excluding holidays and weekends, and DR event days in Korea). Examples include High3of5 (SDG&E), High4of5 (PJM), and High5of10 (NewYork ISO). MidXofY calculates CBL as the average electricity usage of the middle X days of the recent Y non-DR days. LowXofY calculates CBL as the average electricity usage of the bottom X days of the recent Y non-DR days.

3) REGRESSION METHODS

The regression methods fit a linear/non-linear function to describe the relationship between electricity usage and explanatory variables (e.g., temperature) [13], [14]. For example, SDG&E applies regression to determine electricity usage during an event window based on the weather and the day of the week.

4) DEEP LEARNING METHODS

To handle highly irregular and volatile load profiles of residential customers, deep learning-based approaches are proposed. In [15], [16], the authors utilize long short-term memory (LSTM), which can effectively deal with time series data such as electricity usage data. In [17], the authors utilize the reconstruction capability of stacked Autoencoder. In [18], an ensemble model of multitask representation learning is proposed to quantify the load uncertainties of individual customers. In [19], the authors combine transfer learning and meta learning. Bayesian deep learning is also used to handle the uncertainty of residential customers [20], [21].

5) PROBABILISTIC METHODS

To handle the large uncertainty associated with residential customers and overcome the inability of deterministic approaches in capturing such uncertainty, probabilistic methods are studied. Gaussian process-based CBL calculation is discussed in [7], [22] as a rewarding mechanism. Quantile regression is used to generate the probabilistic CBL in [23], [24]. In [25], the authors introduce a convolutional neural network with squeeze-and-excitation modules for probabilistic residential load forecasting.

6) LIMITATIONS

These methods consider R1, but have the following limitation in satisfying R3. ISOs face challenges in applying the new CBL methods for several reasons (such as policy and conflicting incentives of stakeholders). Although a DR operator may be able to apply new CBL methods for personalized CBL calculation regardless of the CBL method of the ISO, even the near-optimal CBL method does not satisfy R3. Please see Section V.A.3) for the experimental results with real-world data covering this. Therefore, we need to satisfy R3 without changing the ISO's CBL method while still considering R1. This is the objective to be achieved through this study.

B. INDIRECT CBL CALCULATION

Indirect CBL calculation methods use the data of other residential customers related to the target residential customers.

1) CONTROL GROUP METHODS

Control group methods, as the name suggests, build a control group (i.e., a group of non-DR residential customers or a group of load patterns) to calculate the CBL of a test group (i.e., a group of target residential customers). Therefore, a main concern of these methods is how to generate the control group. In [26], the authors transform electricity load patterns using a self-organizing map (SOM). Then, they apply K-means clustering to find the load pattern that is similar to the potential load pattern of the DR event day. In [27], the authors apply K-means clustering with usage patterns and usage levels. In [28], the authors utilize density-based spatial clustering of applications with noise (DBSCAN) to extract load patterns, and then apply K-means clustering to

group customers displaying similar load patterns. In [29], the authors perform frequency response analysis using the discrete Fourier transform (DFT) to calculate the predictability index and further apply K-means clustering. In [30], using a sequential algorithm and constrained regression methods, the authors try to select a suitable control group by minimizing the distance between the load curves of the control and DR groups on historical non-DR event days. In [31], control group clusters are formed using K-means clustering based on load patterns and then, each DR participant is matched to the most similar cluster according to the similarity between its load curve segments and cluster centroids of the DR event day. In [24], the authors propose a deep embedded clustering technique to convert the daily load pattern pool into the clustered load patterns. Then, the optimal cluster with the most similar daily load pattern for the target residential customer is determined based on Euclidean distance. In [32], the authors utilize the bias information of control customers not participating in the DR program but displaying a bias distribution similar to the DR group on the historical days prior to the DR event day, to estimate the bias of the DR group on the DR event day. In [33], the authors propose the concept of a virtual control group. Using a mobile app for the DR program, DR customers who do not want to join a specific DR event are included as a virtual control group. In [34], the authors utilize temporal features from the history of the target customer and spatial features from the control group that was formed by K-means clustering and load patterns. In [35], the CBL estimation problem is converted into two sub-problems: the estimation of actual load power and the estimation of distributed photovoltaic system (DPVS) output power. First, the actual load power of DR customers is estimated based on the load power of the control group customers (using matching nighttime usage). Then, the DPVS output during the DR period is obtained based on the DPVS output estimation model. Finally, CBL is estimated based on the actual load power and DPVS output power.

2) LIMITATIONS

These methods consider R1. The control group method has limitations [36] in addition to the limitation described in Section III.A.6). One problem is that it works better with large sample sizes and the DR operators may lack a sufficient customer portfolio for the implementation. Another problem is that customers of the control group may not receive a DR incentive, and thus DR operators need to rotate the group periodically to provide equal incentive to customers [36]. In this study, we try to satisfy R3 without the specific requirements of the control group. In particular, we only use the data of the DR participants.

C. OPERATION STRATEGIES OF DR OPERATORS

DR operators are actors, common to all DR programs, but the DR operators for the residential DR program are critical because most residential customers have a low level of electricity consumption [37]. Therefore, in the residential DR

program, the operation strategies of the DR operators are important for maximizing their profit.

1) OPTIMAL BIDDING AND COORDINATION STRATEGY

To DR operators, an important issue is how to bid accurately in the electricity market and thereby maximize their profit. In [38], the objective of the authors is to maximize the profit of all stakeholders including DR operators. In [39], the authors propose a two-stage stochastic optimization model to minimize the net cost of the DR operator buying and selling energy in the electricity market. In [40], DR operators divide residential loads into several categories. Then, each load category is scheduled for distribution by grouping aggregates to maximize the benefits in the electricity market. In [41], using a mixed integer linear programming problem, the authors propose an optimal bidding strategy model for a DR operator to reduce the risk of financial loss caused by price volatility. In [42], the authors propose a self-scheduling framework for DR operators to consider the uncertainties posed by customers and electricity market prices. In [43], residential customers optimize their own household consumption including their comfort preferences. Then, a DR operator exploits this in implementing a coordination strategy for the aggregated loads while preserving the privacy of the users. In [44], considering the uncertainty in the electricity market, the authors formulate the problem using stochastic optimization and solve it using the sample average approximation method. In [45], the authors study an optimal bidding strategy considering the uncertainty of customer participation in DR events. In particular, they exploit the physical models of flexible loads to evaluate the ideal DR capacity. In [46], the authors propose the alternating direction method of multiplier (ADMM)-based approach to control and coordinate residential components of devices of various scales. In [47], the authors attempt to establish the customers' responsiveness function in relation to different incentives. Then, they let the DR operator utilize this for the decision-making process to formulate the optimal bidding strategy.

2) MODELING OF RESIDENTIAL CUSTOMERS

For a better aggregation of residential customers, the DR operators need to understand the residential customers. In [48], the authors propose the constrained non-linear programming model to optimize residential consumption of electricity by reducing the load at peak times and increasing the load at off-peak times. In [49], the authors propose a meta-heuristic optimization-based two-stage residential load pattern clustering approach to handle unreasonable typical load pattern extraction. In [50], the authors propose a time-frequency feature combination based household characteristic identification approach using smart meter data. In [23], the authors quantify the full probability distribution function of flexibility in response to economic incentives considering the surrounding variables through the quantile regression method. In [8], the authors demonstrate that the identification and extraction of features including the weather conditions

and monetary reward may have a noticeable influence on the aggregated DR capacity. In [51], a hierarchical control strategy via DR operators is proposed. In particular, an optimal allocation model is built to determine the response status of each residential load per minute, ensuring end-user satisfaction and demand response requirements. In [52], [53], a multi-agent-based optimization strategy is proposed to solve the issue of requiring the load to be temporarily decreased.

3) LIMITATIONS

These methods focus on R2. Even for a DR group with maximum profit using these methods, DR operators still face an incentive distribution issue (R3). A DR operator may be able to distribute the given group-level incentive proportionally based on the contribution of the residential customers (while ignoring actual contributions). However, this method does not allow the individual customers to be informed about their specific CBL before DR events, which can be a bottleneck in expanding residential DR participation. Therefore, to encourage the residential customers to participate in the residential DR program, we need to reflect the actual contribution of the customer in the group-level incentive distribution. This is the objective to be achieved by our method. Our method can be easily combined with the existing methods for DR operators because it does not impose special conditions on the aggregation of residential customers.

IV. SINGLE GROUP-BASED INDIRECT CBL CALCULATION

In this section, we first describe the non-equal incentive problem and then introduce our solution.

A. NON-EQUAL INCENTIVE PROBLEM

1) NOTATIONS

Hereafter, we use $CBL()$ to indicate High / Mid / LowXofY, which are widely used in the real world. We use the subscript t for the target day of the CBL calculation and the subscript $t - k$ ($1 \leq k \leq Y$) to indicate Y recent non-DR days. For brevity, we ignore the notation indicating the target hour of the CBL calculation. We use USE_t^i to indicate the electricity usage on day t of the i th customer of a DR group. Here, $USE_{t-Y:t-1}^i$ indicates the electricity usage of Y recent non-DR days of the i th customer of the DR group.

2) DESCRIPTIONS

An incentive for a DR group is calculated by an ISO as follows. The CBL of a DR group is

$$CBL_t^{ISO} = CBL\left(\sum_i USE_{t-Y:t-1}^i\right). \quad (1)$$

The actual electricity usage of a DR group on day t is $\sum_i USE_t^i$. Then, the actual DR capacity of a group (used to calculate an incentive) is

$$DR_Cap_t^{ISO} = CBL_t^{ISO} - \sum_i USE_t^i. \quad (2)$$

Incentives for individual customers of a DR group are calculated by a DR operator as follows. The CBL for the i th customer of a DR group is

$$CBL_t^{i,OP} = CBL(USE_{t-Y:t-1}^i). \quad (3)$$

Given the actual electricity usage of the i th customer of the DR group, which is indicated by USE_t^i , the actual DR capacity of the i th customer in the DR group is

$$DR_Cap_t^{i,OP} = CBL_t^{i,OP} - USE_t^i. \quad (4)$$

Therefore, the actual DR capacity of a DR group calculated by a DR operator is

$$\begin{aligned} DR_Cap_t^{OP} &= \sum_i (CBL_t^{i,OP} - USE_t^i) \\ &= \sum_i CBL_t^{i,OP} - \sum_i USE_t^i. \end{aligned} \quad (5)$$

In distributing the incentive calculated by the ISO to customers, a DR operator faces a practical issue when $DR_Cap_t^{ISO}$ and $DR_Cap_t^{OP}$ are not equal. In other words, the amount of the incentive provided by the ISO to a group of customers is not equal to the sum of the incentives of individual customers calculated by a DR operator.

Let us examine the problem in detail through the following:

$$\begin{aligned} DR_Cap_t^{ISO} &\neq DR_Cap_t^{OP} \\ \Rightarrow CBL_t^{ISO} - \sum_i USE_t^i &\neq \sum_i CBL_t^{i,OP} - \sum_i USE_t^i \\ \Rightarrow CBL_t^{ISO} &\neq \sum_i CBL_t^{i,OP} \\ \Rightarrow CBL(\sum_i USE_{t-Y:t-1}^i) &\neq \sum_i CBL(USE_{t-Y:t-1}^i) \end{aligned} \quad (6)$$

Equation (6) shows why $DR_Cap_t^{ISO}$ and $DR_Cap_t^{OP}$ are not equal. $CBL()$ is a nonlinear function, and thus, equality between $CBL(\sum)$ and $\sum CBL()$ is not guaranteed.

Let us describe Equation (6) differently. The CBL of the i th customer of a DR group can be expressed as

$$CBL(USE_{t-Y:t-1}^i) = \frac{\sum_{c \in D_a^i} USE_c^i}{X}, \quad (7)$$

where D_a^i is the selected X days of Y recent non-DR days for the i th customer in the DR group. Then, the CBL of a DR group (calculated by a DR operator) can be expressed as follows:

$$\begin{aligned} \sum_i CBL(USE_{t-Y:t-1}^i) &= \frac{\sum_i \sum_{c \in D_a^i} USE_c^i}{X} \\ &= \frac{\sum_{c \in D_a} \sum_i USE_c^i}{X}. \end{aligned} \quad (8)$$

The CBL of a DR group calculated by ISO can be expressed as

$$\begin{aligned} CBL_t^{ISO} &= CBL(\sum_i USE_{t-Y:t-1}^i) \\ &= \frac{\sum_{c \in D_b} \sum_i USE_c^i}{X}, \end{aligned} \quad (9)$$

where D_b is the selected X days of the Y recent non-DR days for the DR group. Equations (8) and (9) differ when D_a^i of Equation (8) and D_b of Equation (9) are different. In other words, the X days selected for $\sum_i USE_{t-Y:t-1}^i$ and X days selected for $USE_{t-Y:t-1}^i$ may be different.

For the successful operation of the residential DR program, incentives need to be assured for both DR operators and customers, failing which, nobody would join the residential DR program. In this respect, we may have two problematic cases: overestimation and underestimation of CBL [35]. Overestimation (i.e., $DR_Cap_t^{ISO} < DR_Cap_t^{OP}$) may attract more residential customers to the residential DR programs, but the interest of the DR operator to run the residential DR programs will diminish. Meanwhile, underestimation (i.e., $DR_Cap_t^{ISO} > DR_Cap_t^{OP}$) will decrease the motivation of the customer to participate in the residential DR program because the effort of the customer to reduce the electricity load is not appreciated. Therefore, for a successful operation of the residential DR program, $DR_Cap_t^{ISO}$ and $DR_Cap_t^{OP}$ need to be equal or similar, to provide stable incentives to both DR operators and customers.

Our goal is to propose a method to guarantee the similarity of $DR_Cap_t^{ISO}$ and $DR_Cap_t^{OP}$ without changing the ISO's CBL method (i.e., $DR_Cap_t^{ISO}$ is fixed). So, our concern is to find a method to calculate $DR_Cap_t^{OP}$.

B. PROPOSED METHOD

Our idea is to calculate CBL_t^i (i.e., CBL for the i th customer of a DR group) indirectly using the data of the other DR customers in the same DR group as follows.

$$\begin{aligned} CBL_t^{i,Pro} &= CBL(\sum_k USE_{t-Y:t-1}^k) \\ &\quad - CBL(\sum_{k(\neq i)} USE_{t-Y:t-1}^k) \\ &= CBL_t^{ISO} - CBL_t^{ISO, \sim i}. \end{aligned} \quad (10)$$

Thus, CBL_t for a DR group using our method is written as

$$CBL_t^{Pro} = \sum_i (CBL_t^{ISO} - CBL_t^{ISO, \sim i}). \quad (11)$$

To examine our method in detail, let us rewrite $CBL_t^{ISO, \sim i}$ in Equation (11) as follows:

$$CBL_t^{ISO, \sim i} = \frac{\sum_{c \in D_c^i} \sum_{k(\neq i)} USE_c^k}{X}, \quad (12)$$

where D_c^i is the selected X days from among the Y recent non-DR days, for the DR group, excluding the i th customer. Then, CBL_t^i , using our method can be expressed as follows.

$$\begin{aligned} CBL_t^{i,Pro} &= CBL_t^{ISO} - CBL_t^{ISO, \sim i} \\ &= \frac{\sum_{c \in D_b} \sum_i USE_c^i}{X} - \frac{\sum_{c \in D_c^i} \sum_{k(\neq i)} USE_c^k}{X} \end{aligned}$$

$$\begin{aligned}
&\approx \frac{\sum_{c \in D_b} (\sum_i USE_c^i - \sum_{k(\neq i)} USE_c^k)}{X} \\
&= \frac{\sum_{c \in D_b} USE_c^i}{X}. \quad (13)
\end{aligned}$$

In Equation (13), the transformation from $\frac{\sum_{c \in D_b} \sum_i USE_c^i}{X} - \frac{\sum_{c \in D_c^i} \sum_{k(\neq i)} USE_c^k}{X}$ to $\frac{\sum_{c \in D_b} (\sum_i USE_c^i - \sum_{k(\neq i)} USE_c^k)}{X}$ is allowed only when D_b and D_c^i are the same or similar. Fortunately, customers of the residential DR program have low electricity usage and thus the portion of electricity usage for the i th customer is marginal compared to the aggregated electricity usage of a DR group. As a result, D_b and D_c^i are the same or similar in most cases. This will be demonstrated in Section V.A.3).

The actual DR capacity of a DR group when applying our method is written as

$$\begin{aligned}
DR_Cap_t^{Pro} &= \sum_i (CBL_t^{i,Pro} - USE_t^i) \\
&= \sum_i CBL_t^{i,Pro} - \sum_i USE_t^i \\
&\approx \sum_i \frac{\sum_{c \in D_b} USE_c^i}{X} - \sum_i USE_t^i \\
&= \frac{\sum_i \sum_{c \in D_b} USE_c^i}{X} - \sum_i USE_t^i \\
&= \frac{\sum_{c \in D_b} \sum_i USE_c^i}{X} - \sum_i USE_t^i. \quad (14)
\end{aligned}$$

As a result, $DR_Cap_t^{Pro}$ becomes approximately equal to $DR_Cap_t^{ISO}$, which can be expressed as

$$\begin{aligned}
DR_Cap_t^{ISO} &= CBL_t^{ISO} - \sum_i USE_t^i \\
&= \frac{\sum_{c \in D_b} \sum_i USE_c^i}{X} - \sum_i USE_t^i. \quad (15)
\end{aligned}$$

V. EXPERIMENTS

A. FEASIBILITY STUDY

We first examine the feasibility of our method using data without any DR events.

1) CBL METHODS

We consider the averaging methods widely used in the real world. In particular, we consider Mid8of10, Mid4of6, High4of5, High5of10, Low4of5, and Low5of10. We ignore the regression methods because we do not have explanatory variables (e.g., temperature). We also ignore the control group methods because our method only utilizes data of the same DR group.

2) DATA

We use hourly electricity usage data of households in 40 apartment complexes geographically distributed

throughout Korea. The number of households of an apartment complex ranges from 13 to 4,210 (Fig. 2). The total number of households is 42,193. The data covers the time period from November 2016 to November 2019. We consider households in the same apartment complex as a DR group. We consider all available days (excluding weekends) as the target days of the CBL calculation and conduct experiments for the CBL calculation of various hours. We share the results of the CBL calculations for the period between 5 and 6 PM, as a representative case.

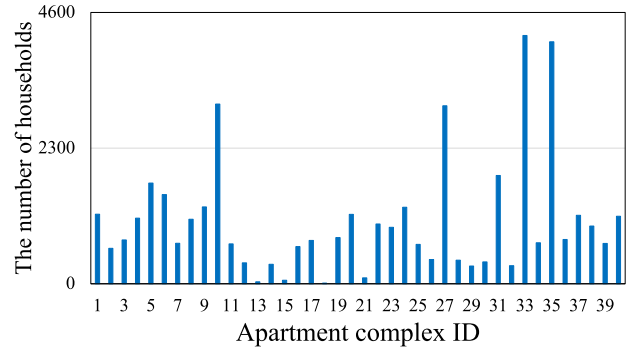


FIGURE 2. The number of households in apartment complexes.

3) RESULTS

a: SELECTION SIMILARITY

We first examine the fundamental aspect of our method. In Section IV.B, we argue that the transformation in Equation (13) is possible when D_b and D_c^i are the same or similar. To examine this, we define a particular metric, called *selection similarity* (SS), as follows:

$$SS = \frac{1}{N} \sum_i SUM(|m_b - m_c^i|), \quad (16)$$

where N is the number of households of a DR group, and m_b and m_c^i are Y -digit arrays showing the selection information of CBL_t^{ISO} and $CBL_t^{i,OP}$ or $CBL_t^{i,Pro}$ in choosing X days from Y non-DR days, respectively. In Equation (16), the subtraction is an element-wise operation. When Y digits for Y recent non-DR days are used, the digits corresponding to the selected X days are set to 0 and the other digits are set to 1. For example, if the last 8 days, among the 10 recent non-DR days are selected for CBL_t^{ISO} , m_b is [1,1,0,0,0,0,0,0,0,0]. Therefore, SS is close to zero when D_b and D_c^i are similar.

Fig. 3 displays SS as a function of the size of the DR groups for various CBL methods. The existing method (i.e., $CBL_t^{i,OP}$) displays high SS values. In the case of Mid8of10, Mid4of6, High4of5, High5of10, Low4of5, and Low5of10, the average SS across all DR groups are 2.97, 2.47, 1.43, 4.23, 1.36, and 4.24, respectively. This result shows that D_b (for CBL_t^{ISO}) and D_c^i (for $CBL_t^{i,OP}$) are significantly different, implying that the non-equal incentive problem is a natural result of the personalized direct CBL

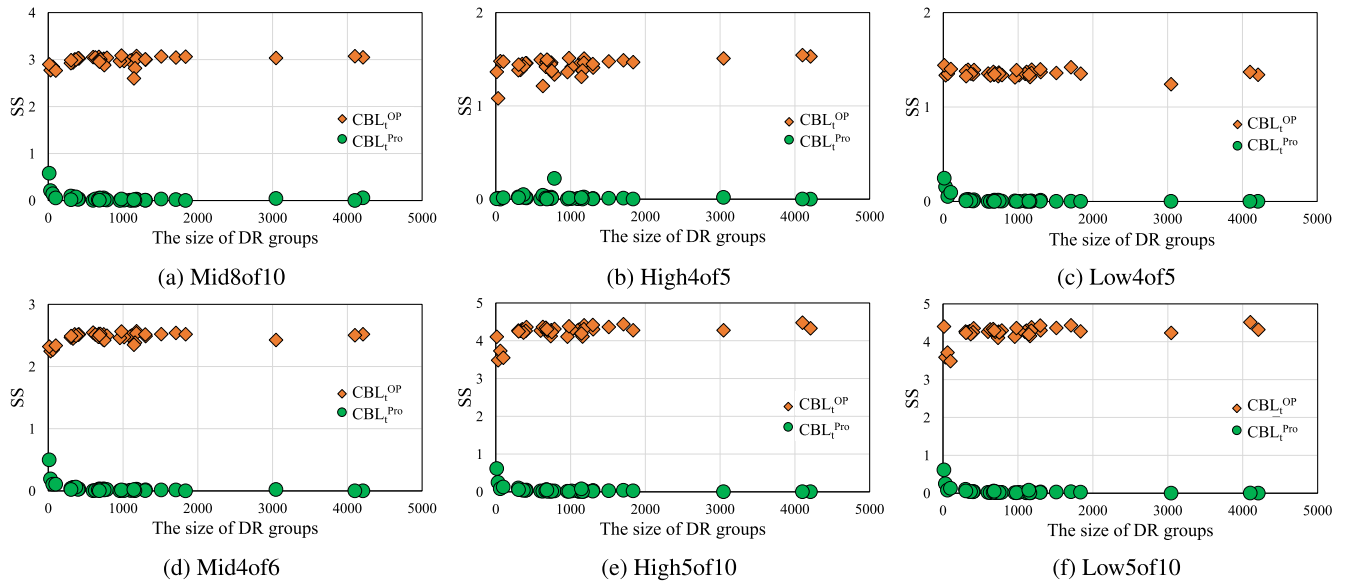


FIGURE 3. Selection similarity with regard to the size of DR groups.

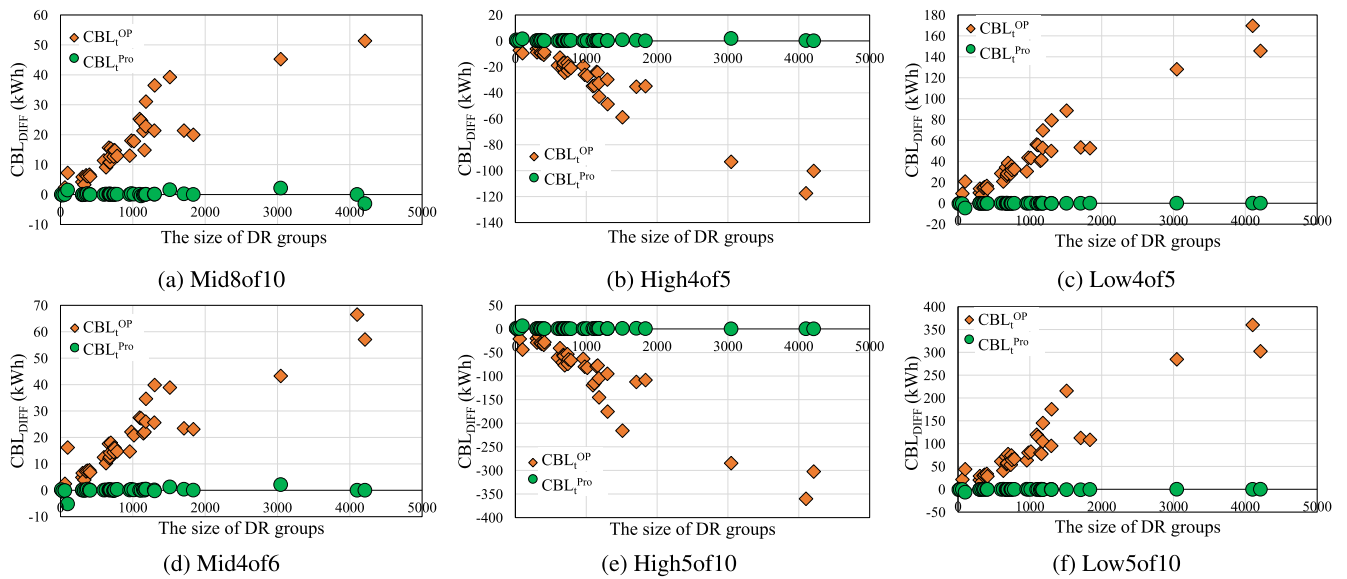


FIGURE 4. The group-level CBL differences to CBL_t^{ISO} .

calculation using the averaging methods. In contrast, our method (i.e., $CBL_t^{i,Pro}$) displays low SS values, close to 0. In the case of Mid8of10, Mid4of6, High4of5, High5of10, Low4of5, and Low5of10, the average SS values across all DR groups are 0.05, 0.04, 0.02, 0.05, 0.02, and 0.05, respectively. This result demonstrates that the fundamental assumption in deriving Equation (13) is valid, implying that the non-equal incentive problem primarily caused by the selection difference can be solved by our method.

b: CLOSENESS TO ISO'S CBL

We examine the feasibility of our method in terms of difference between the group-level CBL (i.e., $\sum CBL()$) and ISO's CBL (i.e., $CBL(\sum)$). Furthermore, the CBL function used

by ISO is fixed as described in Section IV.A. To examine the feasibility of our method, we compare the differences of CBL_t^{OP} and CBL_t^{Pro} to CBL_t^{ISO} (Fig. 4). In Fig. 4, CBL_{DIFF} of the Y-axis is calculated as

$$CBL_{DIFF} = CBL_t^{ISO} - CBL_t^{OP} \text{ (or } CBL_t^{Pro}). \quad (17)$$

With CBL_t^{OP} , one common observation is that the difference increases as the size of DR groups increases. This is because errors in calculating $CBL_t^{i,OP}$ for customers in the same DR group are cumulated. In the case of Mid8of10, Mid4of6, Low4of5, and Low5of10, CBL_t^{OP} demonstrates positive values for CBL_{DIFF} . This implies that user participation is underestimated. Conversely, in the case of High4of5 and High5of10, CBL_t^{OP} shows negative values

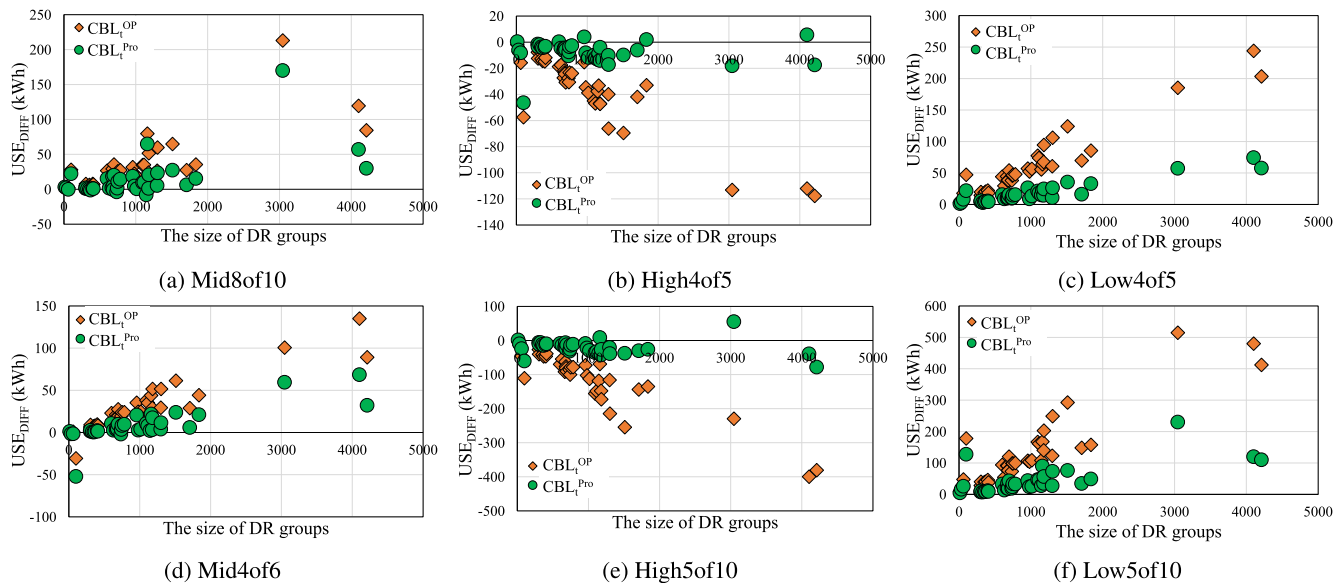


FIGURE 5. The group-level CBL differences to $\sum_i USE_t^i$.

for CBL_{DIFF} . This implies that user participation is overestimated. In the case of Mid8of10, Mid4of6, High4of5, High5of10, Low4of5, and Low5of10, the average CBL_{DIFF} across all DR groups are 17.33, 19.37, -27.46 , -88.75 , 42.53, and 88.75, respectively.

By contrast, with CBL_t^{Pro} , CBL_{DIFF} is close to 0 regardless of the CBL method. In the case of Mid8of10, Mid4of6, High4of5, High5of10, Low4of5, and Low5of10, the average CBL_{DIFF} s across all DR groups are 0.09, 0.04, 0.31, 0.66, -0.25 , and -0.66 , respectively. The above results demonstrate that our method performs well in calculating a group-level CBL close to CBL_t^{ISO} , and thus it adequately solves the non-equal incentive problem.

c: CLOSENESS TO ACTUAL GROUP-LEVEL USAGE

We examine the feasibility of our method in terms of difference between the group-level CBL and group-level usage. The accuracy of CBL should be considered, additionally, as it is important for both DR operators and customers. The incentive is calculated based on $DR_Cap_t = CBL_t - USE_t$. An inaccurate CBL calculation may lead to problems. If the calculated CBL_t is greater than the actual value, the DR operator must pay more money than prescribed. If the calculated CBL_t is less than the actual value, the user participation is underestimated. To examine this, we compare the differences of CBL_t^{OP} and CBL_t^{Pro} to $\sum_i USE_t^i$. In Fig. 5, USE_{DIFF} representing the Y-axis is calculated as

$$USE_{DIFF} = \sum_i USE_t^i - CBL_t^{OP}(CBL_t^{Pro}), \quad (18)$$

The data for the experiments described in this subsection do not include DR events, and thus $\sum_i USE_t^i$ indicates the actual electricity consumption without a reduction prompted by a DR event.

One common observation for both CBL_t^{OP} and CBL_t^{Pro} is that they tend to have positive values for USE_{DIFF} in the case of Mid8of10, Mid4of6, Low4of5, and Low5of10. This implies that the actual usage is underestimated, but the difference in CBL_t^{Pro} is much smaller than that of CBL_t^{OP} . In the case of Mid8of10, Mid4of6, Low4of5, and Low5of10, the average USE_{DIFF} s across all DR groups for CBL_t^{OP} (CBL_t^{Pro}) are 31.88 (14.64), 27.88 (8.54), 60.03 (17.26), and 131.55 (42.14), respectively. Furthermore, both CBL_t^{OP} and CBL_t^{Pro} tend to have negative values for USE_{DIFF} in the case of High4of5 and High5of10. In this case, the users' actual usage is overestimated. But, the difference in CBL_t^{Pro} is much smaller than that of CBL_t^{OP} . In the case of High4of5 and High5of10, the average USE_{DIFF} s across all DR groups for CBL_t^{OP} (CBL_t^{Pro}) are -35.18 (-7.41) and -109.75 (-20.34), respectively. These results demonstrate that our method displays much better performance than the existing method in estimating the actual group-level CBL.

d: EFFECTIVENESS OF OPTIMAL CBL METHOD

In Section III.A.6, we mentioned that even the optimal CBL calculation method may not solve the non-equal incentive problem if we do not change the ISO's CBL method. Here, we examine the effectiveness of the optimal CBL method in solving the non-equal incentive problem. The optimal CBL method calculates the actual usage of the customer accurately, without any error (i.e., CBL_t^{OP} is equal to $\sum_i USE_t^i$). ISO's CBL (i.e., CBL_t^{ISO}) is calculated by one of the averaging methods. Fig. 7 displays the group-level CBL differences to CBL_t^{ISO} . When the ISO adopts High4of5 or High5of10 as its CBL method, user participation is overestimated. When the ISO adopts Mid8of10, Mid4of6, Low4of5, or Low5of10 as its CBL method, user participation is underestimated. This

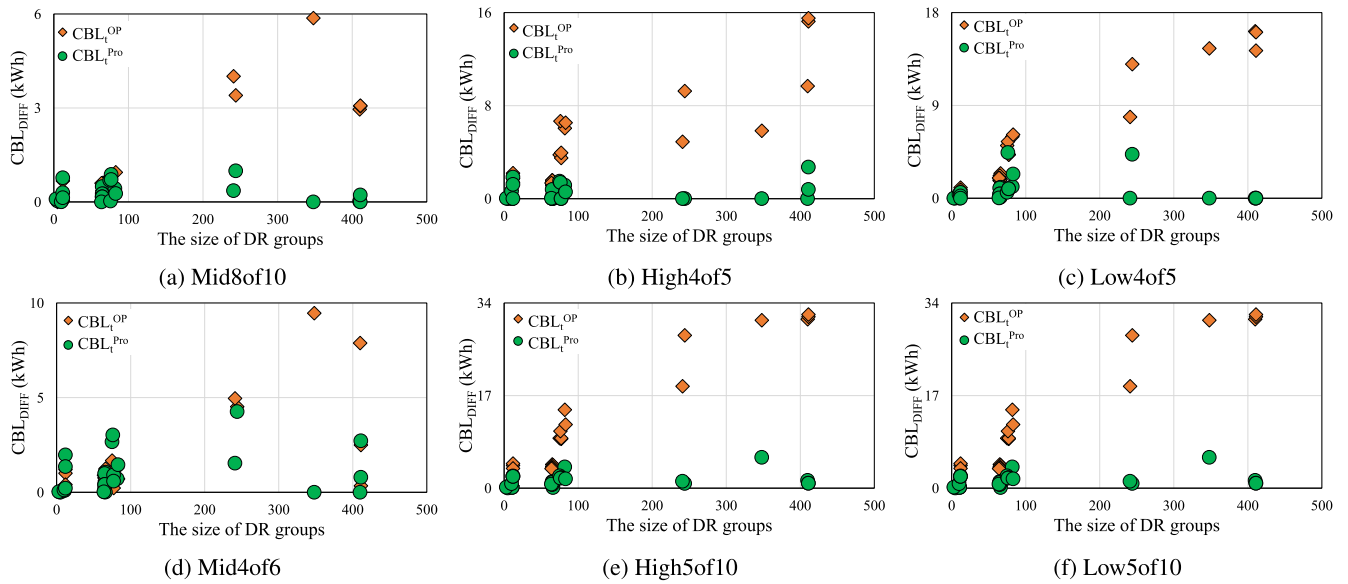


FIGURE 6. The group-level CBL differences to CBL_t^{ISO} (with DR events data).

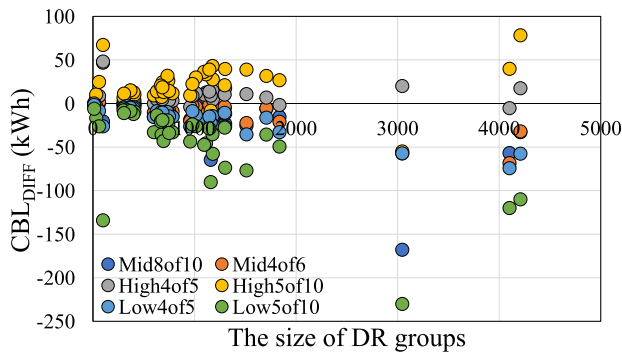


FIGURE 7. Group-level CBL differences versus CBL_t^{ISO} with the optimal CBL calculation method.

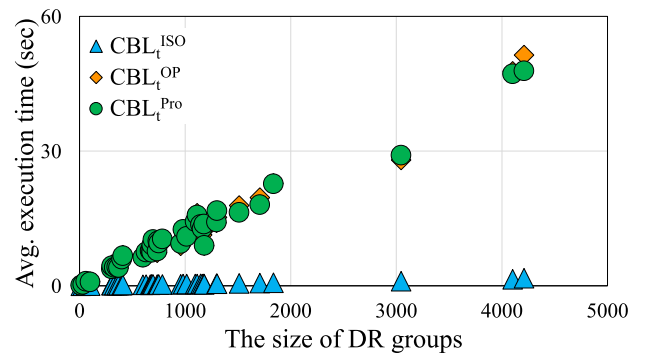


FIGURE 8. The execution time as a function of the size of DR groups.

demonstrates that the non-equal incentive problem cannot be solved by simply changing CBL methods for customers (even with the optimal CBL method) if the ISO’s CBL method is fixed. Given that ISO’s CBL method cannot be changed easily, a solution that does not require a change in the ISO’s CBL method is needed. As illustrated in Fig. 4, the proposed method solves the non-equal incentive problem to address this issue.

e: EXECUTION TIME

To derive the group-level CBL, CBL_t^{OP} and CBL_t^{Pro} , the CBL calculations should be personalized for all customers. To examine the scalability of this approach, we measure the average execution time. Fig. 8 displays the average execution time as a function of the size of the DR groups for the case of Mid8of10. The results are averaged across 10 runs. The other CBL averaging methods show similar results. CBL_t^{ISO} considers less than two seconds to handle a group

of 4,210 customers. On the contrary, the execution time of CBL_t^{OP} and CBL_t^{Pro} increases linearly as the size of the DR group increases. When handling a group of 4,210 customers, the time involved is approximately 50 s. But, CBL calculations do not need to be carried out in real-time. The group-level CBL can be calculated in advance before the DR event. Alternatively, after the DR event, the group-level CBL can be calculated when settling the incentive for user participation. Therefore, we believe that CBL_t^{OP} and CBL_t^{Pro} do not have a scalability issue in real-world applications.

B. APPLICATION TO DR EVENTS

We examine our method using real DR event data.

1) DATA

We use the data of real DR customers managed by Paran Energy, one of the largest DR operators in the residential DR program in South Korea. The residential DR customers include individual households of apartment complexes,

TABLE 1. Results with the real residential DR events (part 1).

Date	Usage (kWh)	Group size	CBL_t by Mid8of10			CBL_t by Mid4of6			CBL_t by High4of5		
			ISO	OP	Pro	ISO	OP	Pro	ISO	OP	Pro
Dec. 11, 2019, 9-10 AM	1.62	5	1.24 (N)	1.24	1.21	1.35 (N)	1.33	1.34	1.52 (N)	1.55	1.52
Dec. 23, 2019, 9-10 AM	4.94	11	3.37 (N)	3.28	3.49	3.35 (N)	3.2	3.51	3.35 (N)	3.45	3.35
Dec. 24, 2019, 9-10 AM	3.11	11	3.39 (Y)	3.33	3.43	3.35 (Y)	3.23	3.44	3.81 (Y)	3.89	3.81
Mar. 9, 2020, 9-10 AM	24.36	65	25.31 (Y)	25.03	25.48	27.14 (Y)	27.05	26.95	27.14 (Y)	28.73	26.95
Mar. 10, 2020, 10-11 AM	22.66	65	25.14 (Y)	24.78	25.31	24.32 (Y)	23.72	24.33	24.81 (Y)	26.02	24.81
Mar. 17, 2020, 9-10 AM	24.93	66	24.57 (N)	24.01	24.83	24.43 (N)	23.19	25.49	25.88 (Y)	27.11	25.88
Mar. 18, 2020, 6-7 PM	26.75	66	26.71 (N)	26.09	26.86	26.59 (N)	25.87	26.60	27.15 (Y)	28.56	27.06
Mar. 19, 2020, 9-10 AM	30.99	65	24.43 (N)	23.89	24.69	24.96 (N)	24.16	25.95	26.97 (N)	28.47	26.82
Mar. 24, 2020, 7-8 PM	24.96	65	24.83 (N)	24.35	24.67	25.78 (Y)	24.99	26.18	26.29 (Y)	27.41	26.29
Mar. 25, 2020, 7-8 PM	23.49	65	24.81 (Y)	24.32	24.65	25.72 (Y)	24.99	26.13	26.29 (Y)	27.87	25.51
Apr. 1, 2020, 9-10 AM	21.94	64	24.73 (Y)	24.13	24.73	22.93 (Y)	22.03	22.95	23.60 (Y)	24.95	23.56
May 26, 2020, 4-5 PM	5.91	3	6.29 (Y)	6.19	6.38	6.25 (Y)	6.30	6.22	6.41 (Y)	6.46	6.38
Jun. 22, 2020, 4-5 PM	13.13	10	28.71 (Y)	28.61	28.72	29.53 (Y)	29.46	29.40	29.53 (Y)	30.24	28.89
Jul. 21, 2020, 4-5 PM	58.10	82	70.34 (Y)	70.55	70.77	69.88 (Y)	68.59	69.17	73.90 (Y)	79.96	72.74
Aug. 04, 2020, 6-7 PM	43.39	75	61.71 (Y)	61.30	61.02	63.65 (Y)	61.98	60.98	67.99 (Y)	71.77	66.49
Oct. 27, 2020, 6-7 PM	48.39	77	83.39 (Y)	83.29	84.27	83.14 (Y)	82.47	84.05	85.64 (Y)	89.14	85.64
Oct. 28, 2020, 6-7 PM	52.79	77	80.38 (Y)	80.45	81.09	74.91 (Y)	74.68	75.49	85.64 (Y)	89.58	85.64
Nov. 12, 2020, 6-7 PM	46.39	76	90.64 (Y)	90.36	90.62	92.83 (Y)	93.99	95.86	95.02 (Y)	101.69	93.62
Nov. 13, 2020, 4-5 PM	62.63	83	96.51 (Y)	95.57	96.78	100.59 (Y)	101.29	102.04	100.59 (Y)	107.11	100.00
Nov. 16, 2020, 6-7 PM	106.88	244	155.33 (Y)	151.93	156.32	156.06 (Y)	151.54	160.31	160.10 (Y)	169.35	160.10
Nov. 17, 2020, 10-11 AM	78.51	241	86.53 (Y)	82.52	86.89	82.90 (Y)	77.93	84.43	82.90 (Y)	87.79	82.90
Nov. 26, 2020, 5-6 PM	138.06	348	130.27 (N)	124.40	130.27	134.43 (N)	124.98	134.43	138.58 (Y)	144.42	138.58
Dec. 7, 2020, 4-5 PM	21.39	12	35.48 (Y)	35.44	34.71	34.90 (Y)	36.10	32.93	37.03 (Y)	39.22	35.18
Dec. 10, 2020, 4-5 PM	28.01	12	37.36 (Y)	37.34	37.65	38.37 (Y)	39.37	38.58	41.25 (Y)	42.98	41.25
Dec. 11, 2020, 9-10 AM	15.81	12	32.64 (Y)	31.97	32.78	31.89 (Y)	32.3	30.54	33.08 (Y)	34.49	31.86
Dec. 22, 2020, 9-10 AM	149.11	410	187.62 (Y)	184.66	187.59	197.57 (Y)	189.69	197.57	198.13 (Y)	207.81	198.13
Dec. 23, 2020, 9-10 AM	141.79	411	182.98 (Y)	179.93	182.98	188.19 (Y)	185.69	185.47	190.67 (Y)	205.92	187.96
Dec. 24, 2020, 9-10 AM	135.41	411	178.53 (Y)	175.45	178.30	175.91 (Y)	175.57	175.12	175.91 (Y)	191.43	175.12
Count			Y: 21	9	19	Y: 22	12	16	Y: 25	0	28

offices, and stores. We examine the DR events that occurred from December 2019 (when the residential DR program began) to December 2020. Table 1 briefly summarizes the data. The number of residential DR events examined in this study is 28. Most residential DR events occurred during Spring and Winter when the particulate matter concentration is strong. Residential DR events occurred in the morning (i.e., 9-11 AM), late afternoon (i.e., 4-6 PM), and in the evening (i.e., 6-8 PM).

2) RESULTS

a: CLOSENESS TO ISO'S CBL

With CBL_t^{OP} , the difference (i.e., CBL_{DIFF}) increases as the size of the DR groups increases (Fig. 6). This is because errors in calculating $CBL_t^{i,OP}$ for customers in the same DR group are cumulated. In all CBL methods, CBL_t^{OP} displays positive values for CBL_{DIFF} , implying that user participation is underestimated. In the case of Mid8of10, Mid4of6, High4of5, High5of10, Low4of5, and Low5of10, the average CBL_{DIFF} s across all DR groups are 1.05, 1.58, 3.86, 10.06, 4.72, and 10.06, respectively. By contrast, with CBL_t^{Pro} , CBL_{DIFF} is much lower than that of CBL_t^{OP} and close to 0 in many cases. In the case of Mid8of10, Mid4of6, High4of5, High5of10, Low4of5, and Low5of10, the average CBL_{DIFF} s across all DR groups are 0.28, 0.92, 0.47, 1.36, 0.68, and 1.36, respectively. The above results confirm that our method adequately solves the non-equal incentive problem for residential DR events all around the real-world.

Table 1 and Table 2 display results in detail. The Y or N inside the parentheses in the ISO columns indicate whether

the DR event has been successful or not. Between CBL_t^{OP} and CBL_t^{Pro} , the better performing method is highlighted in bold. The last row of the tables display the number of successful DR events, the number of best-performing cases of CBL_t^{OP} and CBL_t^{Pro} . Among 28 DR events, our method outperforms the existing methods in 19, 16, 28, 28, 28, and 28 events with Mid8of10, Mid4of6, High4of5, High5of10, Low4of5, and Low5of10, respectively. Here, there are two main observations. First, our method is not as effective with MidXofY as with the other CBL methods. Second, with MidXofY, our method is not that effective when the size of the DR group is small. Please note that our method is effective when electricity usage by the i th customer is marginal compared to the aggregated electricity usage of a DR group, as described in Section IV.B. By contrast, given DR groups with a sufficient number of customers, our method exhibits noticeable improvements. As the number of customers of a DR group increases, our method demonstrates greater improvement (Fig. 6).

b: INTERESTING OBSERVATIONS

Examining the DR events in detail, we made some interesting observations (Fig. 9 to Fig. 11). First, not all customers were successful in reducing electricity usage. Comparing Fig. 9 to Fig. 11, positive values indicate a successful reduction of electricity usage. For all events, the successful and non-successful cases are mixed. This may be because some customers do not try to reduce electricity usage. There is no penalty for the residential DR program in Korea, and the incentive for participation may be extremely low for

TABLE 2. Results with the real residential DR events (part 2).

Date	Usage (kWh)	Group size	CBL_t by High5of10			CBL_t by Low4of5			CBL_t by Low5of10		
			ISO	OP	Pro	ISO	OP	Pro	ISO	OP	Pro
Dec. 11, 2019, 9-10 AM	1.62	5	1.48 (N)	1.65	1.45	1.30 (N)	1.23	1.30	1.07 (N)	0.90	1.10
Dec. 23, 2019, 9-10 AM	4.94	11	3.77 (N)	4.23	3.65	3.05 (N)	2.90	3.05	3.01 (N)	2.56	3.13
Dec. 24, 2019, 9-10 AM	3.11	11	3.93 (Y)	4.37	3.81	3.25 (Y)	3.04	3.34	3.01 (N)	2.57	3.13
Mar. 9, 2020, 9-10 AM	24.36	65	30.59 (Y)	34.95	29.39	24.19 (N)	22.47	24.35	23.48 (N)	19.13	24.69
Mar. 10, 2020, 10-11 AM	22.66	65	29.22 (Y)	32.88	28.51	21.87 (N)	20.07	21.94	21.40 (N)	17.74	22.11
Mar. 17, 2020, 9-10 AM	24.93	66	27.11 (Y)	30.92	26.51	23.70 (N)	21.29	24.75	22.27 (N)	18.46	22.88
Mar. 18, 2020, 6-7 PM	26.75	66	30.03 (Y)	34.24	29.92	24.74 (N)	22.94	24.85	23.94 (N)	19.74	24.05
Mar. 19, 2020, 9-10 AM	30.99	65	26.93 (N)	30.92	26.22	24.96 (N)	22.77	25.95	22.16 (N)	18.17	22.87
Mar. 24, 2020, 7-8 PM	24.96	65	26.07 (Y)	29.70	25.03	25.24 (Y)	23.53	25.65	23.69 (N)	20.07	24.74
Mar. 25, 2020, 7-8 PM	23.49	65	26.07 (Y)	29.80	25.43	25.72 (Y)	23.79	26.13	23.67 (Y)	19.94	24.31
Apr. 1, 2020, 9-10 AM	21.94	64	27.41 (Y)	30.99	26.67	22.93 (Y)	20.96	22.95	22.32 (Y)	18.74	23.06
May 26, 2020, 4-5 PM	5.91	3	6.52 (Y)	6.72	6.35	6.14 (Y)	6.14	6.14	6.07 (Y)	5.88	6.24
Jun. 22, 2020, 4-5 PM	13.13	10	33.06 (Y)	34.23	32.26	25.82 (Y)	25.27	26.20	23.47 (Y)	22.31	24.28
Jul. 21, 2020, 4-5 PM	58.10	82	77.98 (Y)	92.37	74.10	69.88 (Y)	63.90	71.01	63.67 (Y)	49.27	67.55
Aug. 04, 2020, 6-7 PM	43.39	75	67.55 (Y)	76.72	65.29	63.64 (Y)	58.53	64.21	56.53 (Y)	47.36	58.79
Oct. 27, 2020, 6-7 PM	48.39	77	89.74 (Y)	98.78	87.85	74.91 (Y)	70.68	75.82	74.00 (Y)	64.95	75.89
Oct. 28, 2020, 6-7 PM	52.79	77	89.74 (Y)	98.91	87.85	73.72 (Y)	69.50	74.63	68.23 (Y)	59.05	70.12
Nov. 12, 2020, 6-7 PM	46.39	76	96.63 (Y)	107.10	94.79	92.58 (Y)	87.09	97.01	84.43 (Y)	73.96	86.28
Nov. 13, 2020, 4-5 PM	62.63	83	101.54 (Y)	113.21	99.83	97.97 (Y)	91.79	100.31	90.56 (Y)	78.88	92.27
Nov. 16, 2020, 6-7 PM	106.88	244	163.86 (Y)	191.91	163.01	145.77 (Y)	132.77	150.03	139.95 (Y)	111.90	140.80
Nov. 17, 2020, 10-11 AM	78.51	241	93.59 (Y)	112.28	92.33	71.18 (N)	63.30	71.18	73.99 (N)	55.30	75.24
Nov. 26, 2020, 5-6 PM	138.06	348	138.02 (N)	168.85	132.36	122.20 (N)	107.67	122.20	117.51 (N)	86.68	123.17
Dec. 7, 2020, 4-5 PM	21.39	12	41.07 (Y)	45.25	38.84	33.92 (Y)	32.89	34.47	30.38 (Y)	26.21	32.61
Dec. 10, 2020, 4-5 PM	28.01	12	43.00 (Y)	47.52	40.85	34.54 (Y)	33.72	34.75	30.69 (Y)	26.17	32.84
Dec. 11, 2020, 9-10 AM	15.81	12	35.28 (Y)	38.90	33.13	30.98 (Y)	30.35	30.98	28.86 (Y)	25.24	31.01
Dec. 22, 2020, 9-10 AM	149.11	410	199.55 (Y)	230.55	198.12	187.98 (Y)	171.80	187.98	170.02 (Y)	139.02	171.44
Dec. 23, 2020, 9-10 AM	141.79	411	199.69 (Y)	231.17	198.80	176.09 (Y)	161.77	176.09	162.50 (Y)	131.02	163.39
Dec. 24, 2020, 9-10 AM	135.41	411	199.56 (Y)	231.44	198.67	161.69 (Y)	145.59	161.69	155.47 (Y)	123.59	156.36
Count			Y: 24	0	28	Y: 19	1	28	Y: 17	0	28

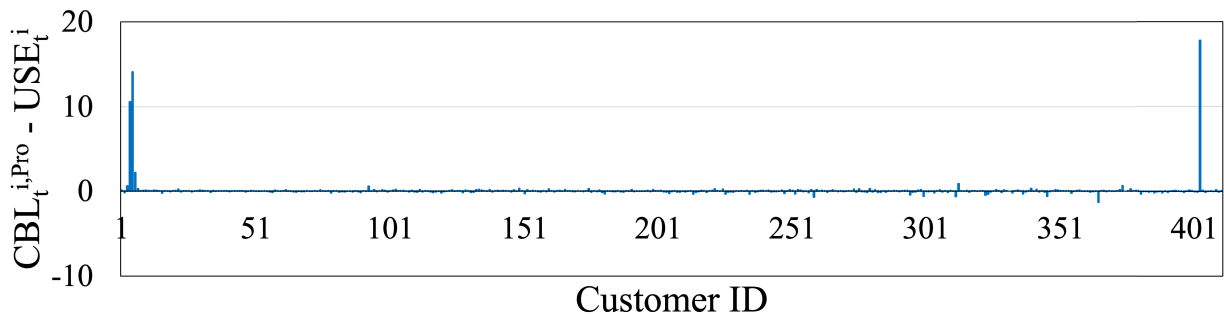


FIGURE 9. User-level contribution of the successful DR event happened in December 24, 2020.

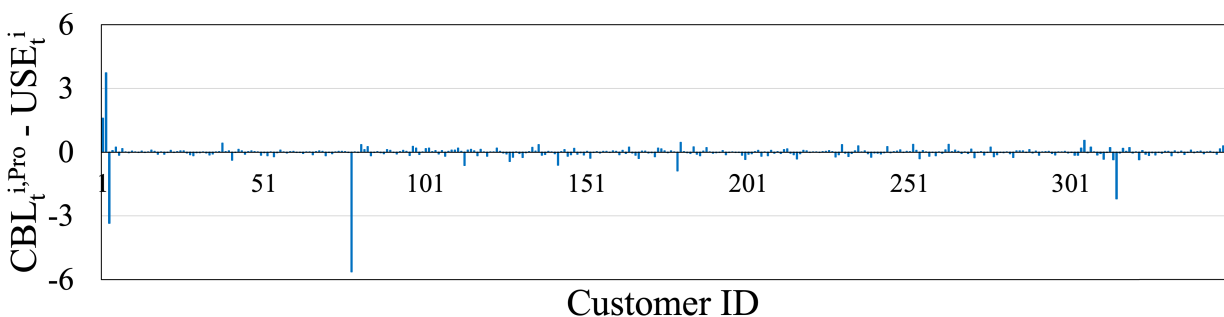


FIGURE 10. User-level contribution of the non-successful DR event happened in November 26, 2020.

them. The incentive is approximately 1.15 US dollars per 1 kWh. For example, for the DR event that occurred on December 24, 2019, the incentive for the customer was just

0.0288 US dollars. This incentive may be extremely low to encourage users to willingly inconvenience themselves to reduce their electricity usage. Non-successful cases may

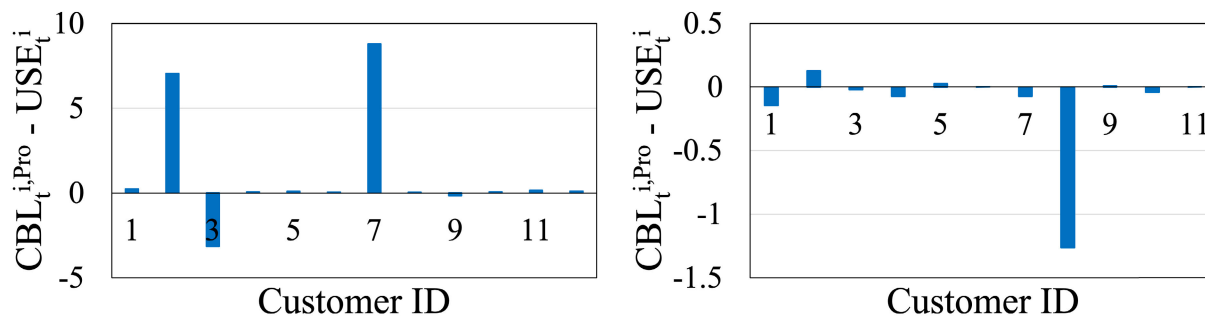


FIGURE 11. User-level contribution of DR events that occurred on December 7, 2020 (successful case, left) and December 23, 2019 (non-successful case, right).

have also occurred because the CBL for a residential customer was inaccurate. As described in Section III.A, typical deterministic CBL methods designed for commercial and industrial customers are unsuitable for residential customers who display highly dynamic load patterns.

Second, the success of a DR event could be heavily affected by a few customers in most cases. Fig. 9, Fig. 10, and Fig. 11 illustrate representative examples of successful and non-successful DR events. The DR event that occurred on December 24, 2020 (Fig. 9) was successful because of a few good contributors (i.e., customers 4th, 5th, 6th, and 403rd) who considerably reduced their electricity usage (i.e., by 44.6 kWh in total). The remaining customers contributed to a marginal reduction or increase in electricity usage. Another successful DR event (December 7, 2020) is displayed on the left-hand side of Fig. 11. In this case, two main contributors were 2nd and 7th customers, who reduced their electricity usage by 15.83 kWh, and one opposer, who increased his/her electricity usage by 3.15 kWh. By contrast, the DR events that occurred on November 26, 2020 (Fig. 10) and December 23, 2019 (the image on the right side of Fig. 11) were unsuccessful because of the few opposers. In the case displayed in Fig. 10, there are three opposers (i.e., the 3rd, 78th, and 315th customers), who increased their electricity usage by 11.15 kWh, and two contributors (i.e., the 1st and 2nd customers), who reduced their electricity usage by 5.32 kWh. Another opposer case is displayed on the right side image of Fig. 11; we see that the opposer has increased electricity usage by 1.26 kWh.

VI. CONCLUSION

DR programs have several attractive benefits. The residential customers are key to fully exploiting such programs. In this study, to realize the successful operation of the residential DR program, we attempted to solve the non-equal incentive problem, not addressed in the existing literature, through a single group-based indirect CBL calculation. The experimental results using real data demonstrate that our method solves the non-equal incentive problem and improves the accuracy of the CBL estimation. As a future study, we plan to extend our research to develop a method to adaptively apply indirect CBL calculation given a targeted DR group. It would

also be interesting to study methods to solve residential DR program-related issues including customer incentive and customer grouping.

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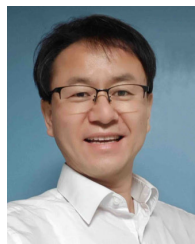
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HYUNYONG LEE received the B.S. degree in computer science from Chonnam National University, South Korea, in 2003, and the M.S. and Ph.D. degrees in computer science from Gwangju Institute of Science and Technology, South Korea, in 2005 and 2010, respectively. He is currently a Senior Researcher of the Electronics Telecommunications and Research Institute (ETRI), South Korea. His research interests include demand response, anomaly detection, deep learning, and uncertainty.



HYUNSEOK JANG is currently pursuing the H.B.Sc. degree in mathematics, physics, and astrophysics with the University of Toronto, Toronto, ON, Canada. He is also working on machine learning models for time-series forecasting, customer segmentation, and recommendation systems as a Researcher and a Product and Business Strategy Lead with Paran Energy Company Ltd., South Korea. His research interests include statistics, machine learning, and quantum-enhanced machine learning.



SEONGCHEOL KIM received the B.S. and M.S. degrees in electrical engineering from Dongguk University, South Korea, in 1994 and 1996, respectively, and the Ph.D. degree in electrical engineering from Konkuk University, South Korea, in 2008. In 2018, he founded Paran Energy Company Ltd., an energy AI consulting firm in South Korea. He is currently the CEO of Paran Energy Company Ltd. His research interests include demand response, smart grid technology, electricity pricing systems, and demand-side management systems.



SEUNG-HUN OH received the B.S. degree in electronic engineering and the M.S. and Ph.D. degrees in information and communication engineering from Soongsil University, South Korea, in 2000, 2002, and 2006, respectively. He is currently working as a Principal Researcher with the Electronics and Telecommunications Research Institute (ETRI), South Korea. His research interests include the IoT standards, block-chain, demand response, and human resource digital transformation.



NAC-WOO KIM received the B.S. degree in control and instrumentation engineering and the M.S. and Ph.D. degrees in image engineering from Chung-Ang University, South Korea, in 1997, 2002, and 2006, respectively. He is currently working as a Principal Researcher with the Electronics and Telecommunications Research Institute (ETRI), South Korea. His research interests include data engineering, machine learning, and anomaly detection.



BYUNG-TAK LEE received the B.S. degree in electronic engineering from Yonsei University, South Korea, in 1992, and the M.S. and Ph.D. degrees in electrical and electronic engineering from the Korea Advanced Institute of Science and Technology (KAIST), South Korea, in 1994 and 2000, respectively. From 2000 to 2004, he was a Principal Research and Development Engineer with LG Electronics Inc., South Korea. Since 2005, he has been a Research Engineer with the Electronics Telecommunications and Research Institute (ETRI), South Korea. His current research interests include deep learning, time series forecasting, anomaly detection, and renewable energies.

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