Optimal Scheduling of Distribution System with Edge Computing and Data-driven Modeling of Demand Response

Jianpei Han, Nian Liu, and Jiaqi Shi

***Abstract*—High penetration of renewable energies enlarge the peak-valley difference of the net load of the distribution system, which puts forward higher requirements for the operation scheduling of the distribution system. From the perspective of leveraging demand-side adjustment capabilities, an optimal scheduling method of the distribution system with edge computing and data-driven modeling of price-based demand response (PBDR) is proposed. By introducing the edge computing paradigm, a collaborative interaction framework between the control center and the edge nodes is designed for the optimization of the distribution system. At the edge nodes, a classified XGBoost-based PBDR modeling method is proposed for large-scale differentiated users. At the control center, a two-stage optimization method integrating pre-scheduling and re-scheduling is proposed based on demand response results from all edge nodes. Through the information interaction between the control center and edge nodes, the optimized scheduling of the distribution system with large-scale users is realized. Finally, a case study is implemented on the modified IEEE 33-node system, which verifies that the proposed classified modeling method has lower errors, and it is beneficial to improve the economics of the system operation. Moreover, the simulation results show that the application of edge computing can significantly reduce the calculation time of the optimal scheduling problem with PBDR modeling of large-scale users.**

***Index Terms*—Demand response, distribution system, edge computing, optimal scheduling, XGBoost.**

I. Introduction

VIGOROUSLY developing wind, solar, and other renewable energies is an effective way to deal with current energy and environmental problems [1]. The United States and China have proposed power system planning blueprints by 2050, in which renewable energy accounts for 80% and 60%, respectively [2]. Thus, high penetration of renewable energies will be an inevitable trend for the development of the future power system. With the increasing penetration of renewable energies, however, the net load of the distribution system will fluctuate dramatically, e.g., the high penetration of photovoltaic (PV) generation in the California of the United States causes its net load to show a "duck curve" [3]. Moreover, the peak-to-valley difference of the net load continues to increase with the growth of the PV penetration ratio, which puts forward higher requirements on the flexible adjustment and rapidly ramping ability of the distribution system. Therefore, how to enhance the flexible adjustment capability of the distribution system is a practical problem with high penetration of renewable energies. In addition to improving the flexibility adjustment potential of the distribution system from the power generation perspective [4], demand response (DR) is an effective means of invoking the adjustment capability of the demand side, which can be employed to improve the flexibility of the distribution system [5], [6]. However, there exist many challenges while implementing DR in distribution systems, e.g., numerous participants and large differences in DR behaviors. Thus, how to build DR models for large-scale differentiated users and guide users to participate in the optimal scheduling of the distribution system is a key scientific problem with high penetration of renewable energies.

In DR modeling, numerous researches have been carried out in the past few decades. According to the difference in response mechanism, DR can be generally divided into two types: the incentive-based and the price-based ones [7]. For the incentive-based DR, the typical application is direct load control, in which the distribution system operator can contract with the curtailable loads to perform load control procedure by paying a predefined fee [8]. Note that the incentive-based DR is usually compulsory and unfriendly to users. For the price-based demand response (PBDR), which is the research topic of this paper, the reasonable and effective modeling is the key to ensure its efficient implementation. Existing researches on PBDR modeling are mainly model-driven, which can be summarized into three key categories that are based on the price elasticity matrix [9]-[11], the detailed consumption behavior [12]-[14], and the utility function [15]-[18], respectively. For the first category, a linear model for the user's response to the changes in electricity prices is established in [9]. Based on the price elasticity matrix, a two-stage optimal scheduling method with DR is proposed in

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[10], and a game theory based energy management method for smart grids is presented in [11]. For the second category, the charging/discharging behavior model of plug-in electric vehicles is investigated in [12], and the detailed DR models of lighting, domestic water heating, and thermostatically controlled appliance are illustrated in [13]. As a typical industrial user, a cement plant industrial model is demonstrated in [14]. For the third category, the logarithmic utility functions are established for users to arrange their electricity consumption plans in [15], [16], the exponential dissatisfaction cost function is constructed in [17] for each device, and the quadratic utility function and the social welfare maximization problem are formulated in [18].

The above model-driven methods have good interpretability, but the key parameters such as the price elasticity coefficient and user utility coefficient in the model are often subjective and lack verification. Moreover, the implementation of these methods is difficult when the scale of the electricity users participating in DR programs is large. Thus, the data-driven method is an alternative for overcoming the above deficiencies. The existing data-driven methods with DR are mainly applied to load forecasting based on the deep learning technology, e. g., short-term load forecasting methods based on the long short-term memory (LSTM) approach are proposed in [19] - [22], a recurrent neural network-based household load forecasting method is formulated in [23], the deep belief network for the short-term load forecasting is built in [24], but few are concentrated on the PBDR modeling. Note that different from the load forecasting which commonly takes the historical load data as input, the PBDR modeling generally uses price signal as input to interpret the relationship between price incentive and response behaviors. Thus, it is a promising trend to apply deep learning methods to the PBDR modeling. As one kind of deep learning methods, XGBoost can avoid overfitting problems effectively that traditional machine learning methods suffer from, and it has been applied to load prediction of distribution system [25], stability assessment [26], electricity theft detection [27], and other fields, which provides a new idea for data-driven PBDR modeling.

For the operation of the distribution system, exact PBDR modeling is essential to improve the economics of system operation. However, there are the following difficulties in applying XGBoost to PBDR modeling of distribution system scheduling: ① the data-driven method of PBDR modeling confronts with the problem of soaring calculation time when large-scale users participate in DR programs; ② implementing the differentiated PBDR modeling for various users is a hard task, because there exist large differences in PBDR behaviors of various electricity users; ③ based on data-driven PBDR modeling, it is the key point to conduct optimal scheduling of the distribution system with PBDR.

To this end, the XGBoost method is adopted for PBDR modeling of large-scale users, and an optimal scheduling method of the distribution system with edge computing and data-driven modeling of PBDR is proposed in this paper. The main contributions of this paper are threefold.

1) An interactive optimization framework between the control center and edge nodes is constructed. In this framework, the edge computing paradigm is introduced to ease the computational burden of PBDR modeling for large-scale users in traditional centralized computing paradigm.

2) A classified XGBoost-based PBDR modeling method is proposed. In the proposed modeling method, the feature evaluation models for PBDR behaviors of users are employed to generate original training data, which can overcome the deficiency of XGBoost when the training data are insufficient.

3) A two-stage optimization method of the distribution system combining pre-scheduling and re-scheduling is proposed. In this two-stage optimization method, the information interaction between the control center and edge nodes is considered, which realizes the optimal scheduling of the distribution system in a distributed manner with PBDR modeling of large-scale users.

The rest of this paper is organized as follows. Section II introduces the proposed optimization framework based on edge computing paradigm. The classified XGBoost-based PBDR modeling and two-stage optimal scheduling are presented in Sections III and IV, respectively. Solution algorithms are carried out in Section V. Section VI analyzes numerical results, followed by concluding remarks in Section VII.

II. Optimization Framework

A. Edge Computing Paradigm

In view of the large-scale users participating in the PBDR program, the realization of data-driven PBDR modeling for large-scale differentiated users will place higher requirements on the calculation capability and calculation time in the traditional centralized computing paradigm. Different from other measures such as improving the calculation performance of the control center, this paper introduces the edge computing paradigm based on traditional centralized computing, in which part of the computing tasks of the control center can be offloaded to edge nodes, and the calculation pressure of the centralized control center could be relieved through local computing of calculation tasks [28], [29].

The computing architecture with the centralized computing paradigm and edge computing paradigm is shown in Fig. 1, which is an integration of cyber space and physical space. In the cyber space, the control center in edge computing paradigm only needs to interact with all edge nodes rather than establishing communication connections with each load node directly, which alleviates the communication and calculation burden brought by the centralized computing paradigm that all the calculation tasks are processed in the control center. In the physical space, various users are directly connected to the distribution network, and the entire process of electric energy production, distribution, and consumption is realized through the coordination between the distribution system and electricity users.

B. Interactive Optimization Framework

Based on the edge computing paradigm above, an interactive optimization framework between the control center and edge nodes is shown in Fig. 2.

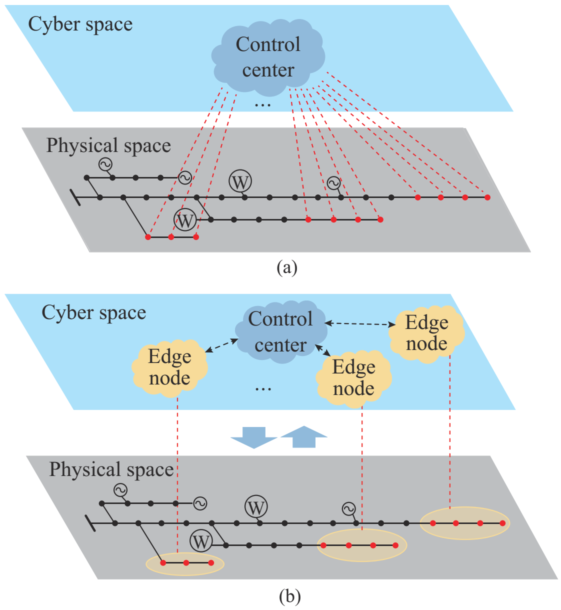

Fig. 1. Comparison of two different calculation frameworks. (a) Centralized computing paradigm. (b) Edge computing paradigm.

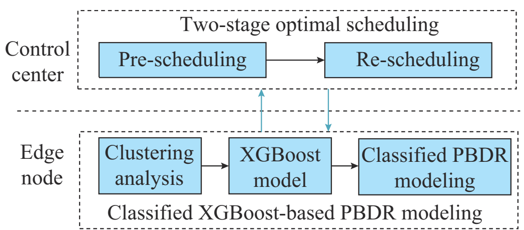

Fig. 2. Interactive optimization framework between control center and edge nodes.

The proposed optimal scheduling method contains two parts of calculation tasks: one is the response behavior modeling of large-scale demand-side resources; the other is the optimal scheduling of the distribution system. In the edge computing paradigm, parts of the calculation tasks are offloaded to edge nodes, specifically, the calculation tasks of demand-side resource modeling are executed at edge nodes while the control center only performs optimal scheduling of the distribution system. The detailed implementation is an interactive process: at each edge node, the classified XGBoost-based PBDR modeling for large-scale users is performed, which contains clustering analysis, XGBoost model construction, and classified PBDR modeling. Then, a two-stage optimization method of the distribution system is implemented in the control center, which integrates the process of pre-scheduling and re-scheduling. The control center and edge nodes can exchange information interactively through advanced communication technology, which achieves the optimal scheduling of the distribution system with PBDR. Note that the communication among edge nodes is not considered. This assumption is reasonable in this paper, where the optimum can be obtained in a distributed manner through the information interaction between the control center and edge nodes.

III. Classified XGBoost-Based PBDR Modeling

In response to the requirement of data-driven PBDR modeling for large-scale differentiated users, a classified XGBoost-based PBDR modeling method is proposed, and the calculation task of this section, i.e., the process of classified XGBoost-based PBDR modeling, is performed at each edge node as Section II illustrated.

A. Clustering Analysis

For any edge node $j \in \mathcal{J} \equiv \{j: j=1,2,\ldots,J\}$, the original training data set is denoted by $\boldsymbol{\Gamma}_j = \{\boldsymbol{p}^d, \Delta\boldsymbol{L}_i^{j,d}, i=1,2,\ldots,m_j, d=1,2,\ldots,D\}$, where J, m_j, and D are the number of edge nodes, the number of users at edge node j, and the number of samples in the training data set, respectively; and $\Delta\boldsymbol{L}_i^{j,d}$ is the response vector of user i at edge node j for sample d to the price incentive vector $\boldsymbol{p}^d$. The element of $\Delta\boldsymbol{L}_i^{j,d}$ can be calculated as:

$$\Delta L_{i,t}^{j,d} = L_{i,t}^{j,d} - L_{i,t}^{j,fix} \tag{1}$$

where $L_{i,t}^{j,d}$ and $L_{i,t}^{j,fix}$ are the optimized load and the fixed load of user i for sample d at time slot t, respectively. Note that for the case that training data set is insufficient, the generation method of original data is shown in Appendix A.

For the training data set $\boldsymbol{\Gamma}_j$, it contains PBDR data of various users. If the PBDR model is built for each user, there is a problem of excessive calculation, but if a unified PBDR model is built for all users, the differences among various users cannot be reflected. Thus, the K-means clustering method is employed in this section to cluster users based on their PBDR behavior characteristics. The basic idea of K-means clustering method is to classify the samples with high similarity into one cluster by measuring the similarity of different samples. In this paper, the clustering samples are the time-series PBDR data of different users, i.e., $\Delta\boldsymbol{L}_i^{j,d}$, and the Euclidean distance is used to measure the similarity of different samples. Detailed information about K-means clustering method can be found in [30] and [31].

B. XGBoost Model Construction

XGBoost is an optimization of the boosting algorithm, which is an ensemble algorithm based on trees and linear classifiers [25]. Without loss of generality, considering the given data set $\boldsymbol{\mathcal{H}} = \{(\boldsymbol{x}_h, y_h), h=1, 2, \ldots, H\}$, where H is the number of training samples; $\boldsymbol{x}_h$ is the input data of the XGBoost model; and y_h is the preference value of the XGBoost model. The XGBoost model can be expressed as:

$$\hat{y}_h = \sum_{n=1}^{N} f_n(\boldsymbol{x}_h) \quad f_n \in F \tag{2}$$

where $\hat{y}_h$ is the prediction value of the XGBoost model; F is the set of regression trees; f_n is the n^{th} regression tree in set F; and N is the number of regression trees in F.

The loss function of the XGBoost model contains two parts, i.e., the difference term and the regularization term, which can be calculated as:

$$Obj = \sum_{h=1}^{H} l(y_h, \hat{y}_h) + \sum_{n=1}^{N} \Omega(f_n) \tag{3}$$

$$\Omega(f_n)=\gamma R+\frac{1}{2}\lambda\sum_{r=1}^{R}\omega_r^2 \tag{4}$$

where $l(y_h,\hat{y}_h)$ is the difference value between the preference value y_h and prediction value $\hat{y}_h$, which can be measured by 1-norm, 2-norm, etc.; $\Omega(f_n)$ is the regularization term to control the complexity of the XGBoost model and prevent the model from overfitting; R is the leaf count; ω_r is the leaf score; and γ and λ are the given parameters. It can be observed from (4) that when γ and λ are equal to zero, the XGBoost model degenerates into the traditional boosting model.

The cumulative training method is adopted in the XGBoost model, i.e., in each iteration, a new function, i.e., a new tree, is added to the model based on the previous model. The specific iteration process is:

$$\begin{cases}\hat{y}_h^{(0)}=0\\ \hat{y}_h^{(1)}=f_1(\boldsymbol{x}_h)=\hat{y}_h^{(0)}+f_1(\boldsymbol{x}_h)\\ \vdots\\ \hat{y}_h^{(\tau)}=\displaystyle\sum_{n=1}^{\tau}f_n(\boldsymbol{x}_h)=\hat{y}_h^{(\tau-1)}+f_\tau(\boldsymbol{x}_h)\end{cases} \tag{5}$$

where $\hat{y}_h^{(\tau)}$ is the predicted value of the τ^{th} iteration, which retains the prediction result of the $(\tau-1)^{\text{th}}$ iteration $\hat{y}_h^{(\tau-1)}$ and adds a new function $f_\tau(\boldsymbol{x}_h)$ into the model.

As a result, (3) can be rewritten as:

$$Obj=\sum_{h=1}^{H}l(y_h,\hat{y}_h^{(\tau-1)}+f_\tau(\boldsymbol{x}_h))+\sum_{n=1}^{N}\Omega(f_n) \tag{6}$$

Then, by Taylors expansion and removing all constant terms, (6) is changed to the second-order form, which can obtain the unique optimum. Note that the optimal value of loss function indicates the maximum gain loss when selecting a tree structure, the smaller the value, the better the model. More detailed information about XGBoost can be found in [25] and [26].

C. Classified PBDR Modeling

Based on the XGBoost model above, a framework of classified PBDR modeling is shown in Fig. 3.

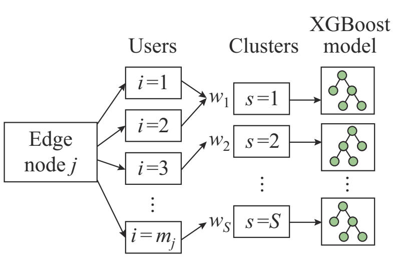

Fig. 3. Framework of classified PBDR modeling based on XGBoost model.

For edge node j, the K-means clustering method is employed to cluster m_j users into S clusters according to their PBDR behavior characteristics, and the s^{th} cluster contains w_s users, which meets $\sum w_s=m_j$. Then, the XGBoost model is constructed separately for each cluster s, which realizes the classified XGBoost-based PBDR modeling. Note that a unified XGBoost-based PBDR model can also be constructed for all m_j users at edge node j, but the unified model can not reflect the difference of various users participating in the PBDR program. Comparative analysis of the unified modeling and the classified modeling can be found in Section V.

IV. Two-stage Optimal Scheduling

The calculation task of this section, i.e., the process of two-stage optimal scheduling, is carried out in the control center of the distribution system. Considering that there exist errors between the results of the proposed classified modeling method and the actual PBDR modeling results of users, the optimal scheduling process is divided into two stages: the pre-scheduling stage and the re-scheduling stage. The pre-scheduling stage refers to formulating pre-scheduling strategies for the distribution system based on the PBDR modeling results before the actual PBDR modeling results of users are observed. The re-scheduling means that when the PBDR modeling results of users are observed, a power adjustment scheme is formulated based on the actual PBDR modeling results and the pre-scheduling strategies.

A. Stage 1: Pre-scheduling of Distribution System

1) Objective Function

The pre-scheduling stage aims at minimizing the day-ahead scheduling cost of the distribution system c_{pre}, which includes the cost of generating electricity from distribution generation (DG) c_{fuel}, the cost of purchasing electricity from transmission network $c_{purchase}$, and the cost of carbon emissions c_{carbon}. Note that the cost of power generation of wind, solar, and other renewable energies is ignored (only PV generation is considered in this paper). Thus, the objective function of the pre-scheduling stage can be described as:

$$\min c_{pre}=c_{fuel}+c_{purchase}+c_{carbon} \tag{7}$$

$$c_{fuel}=\sum_{t=1}^{T}\sum_{k=1}^{K}(a_kP_{k,t}^2+b_kP_{k,t}+c_k) \tag{8}$$

$$c_{purchase}=\sum_{t=1}^{T}p_{grid,t}P_{grid,t}\Delta t \tag{9}$$

$$c_{carbon}=p_cV_{real} \tag{10}$$

$$V_{real}=\sum_{t=1}^{T}\left(\sum_{k=1}^{K}\alpha_{k,t}P_{k,t}\Delta t+\alpha_{grid,t}P_{grid,t}\Delta t\right) \tag{11}$$

where T is the number of optimization periods; K is the number of DGs; $P_{k,t}$ is the output of DG k at time slot t; a_k, b_k, and c_k are the cost coefficients of DG k; $p_{grid,t}$ is the electricity purchase price at time slot t; $P_{grid,t}$ is the power from transmission network at time slot t; Δt is the length of time slot t; p_c is the price of carbon emissions; V_{real} is the amount of carbon emissions; $\alpha_{k,t}$ is the carbon emission factor of DG k; and $\alpha_{grid,t}$ is the carbon emission factor of purchasing electricity from transmission network.

2) Constraints

To ensure the safety of distribution network operation, the following constraints must be met.

$$\sum_{k=1}^{K}P_{k,t}+P_{grid,t}=\sum_{j=1}^{J}\hat{L}_t^j \tag{12}$$

$$u_{k,t}P_{k,\min}\le P_{k,t}\le u_{k,t}P_{k,\max} \tag{13}$$

$$-R_k^d \Delta t \le P_{k,t} - P_{k,t-1} \le R_k^u \Delta t \tag{14}$$

$$P_{grid,\min} \le P_{grid,t} \le P_{grid,\max} \tag{15}$$

$$-P_{l,\max} \le P_{l,t} \le P_{l,\max} \tag{16}$$

where $\hat{L}_t^j$ is the load of edge node j at time slot t; $u_{k,t}$ is the commitment state of DG k at time slot t, which equals 1 when DG k is committed, and 0 otherwise; $P_{k,\max}$ and $P_{k,\min}$ are the upper and lower limits of DG k, respectively; R_k^u and R_k^d are the maximum ramp-up and ramp-down rates of DG k, respectively; $P_{grid,\max}$ and $P_{grid,\min}$ are the upper and lower limits of $P_{grid,t}$, respectively; $P_{l,t}$ is the power flow of line l at time slot t; and $P_{l,\max}$ is the capacity of line l.

Formula (12) is the power balance constraint. Formulas (13) and (14) are the power output constraint and ramping constraint of DG k at time slot t. Formula (15) is the electricity purchase constraint. Formula (16) is the line capacity constraint.

B. Stage 2: Re-scheduling of Distribution System

1) Objective Function

Based on the optimization results of stage 1 and the observed PBDR modeling results of users, stage 2 takes 1 hour as the scheduling cycle and minimizes the re-scheduling cost c_t^{re}, which includes the power regulation cost of DG c_k^{re} and the power regulation cost of power from the transmission network c_{grid}^{re}.

$$\min c_t^{re} = \sum_{k=1}^{K} c_k^{re} \Delta P_{k,t} + c_{grid}^{re} \Delta P_{grid,t} \tag{17}$$

where $\Delta P_{k,t}$ and $\Delta P_{grid,t}$ are the power regulations of DG k and the power from the transmission network at time slot t, respectively.

2) Constraints

The constraints in stage 2 must be met are given in (18)-(21), which include the power balance constraint, power output constraint, and ramping constraint.

$$\sum_{k=1}^{K} (P_{k,t}^* + \Delta P_{k,t}) + P_{grid,t}^* + \Delta P_{grid,t} = \sum_{j=1}^{J} \hat{L}_t^{j*} \tag{18}$$

$$u_{k,t} P_{k,\min} \le P_{k,t}^* + \Delta P_{k,t} \le u_{k,t} P_{k,\max} \tag{19}$$

$$-R_k^d \Delta t \le P_{k,t}^* + \Delta P_{k,t} - P_{k,t-1}^* - \Delta P_{k,t-1} \le R_k^u \Delta t \tag{20}$$

$$P_{grid,\min} \le P_{grid,t}^* + \Delta P_{grid,t} \le P_{grid,\max} \tag{21}$$

where $P_{k,t}^*$ and $P_{grid,t}^*$ are the optimization results of DG k and power from the transmission network at time slot t in stage 1, respectively; and $\hat{L}_t^{j*}$ is the observed value of the load at edge node j at time slot t.

C. Optimization Model Transformation

The proposed pre-scheduling problem of the distribution system, i.e., (7)-(16), is a mixed-integer nonlinear programming problem (MINLP), and the nonlinear part of this problem lies in the fuel cost term of (7). The general idea to solve the nonlinear problem mainly includes the metaheuristic algorithm and linearized approximation. For the metaheuristic algorithm, it is intuitive but time-consuming and is difficult to guarantee the global optimum. To reduce the solution complexity of this problem, the piecewise linear method is adopted in this paper, which replaces the nonlinear part with piecewise linear segments. Thus, the optimization problem can be solved by mixed-integer linear programming (MILP), which is fast, robust, and can guarantee global optimum within predefined tolerances [32]. The process of transformation can be expressed as:

$$c_{fuel} = \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{l=1}^{L} (a_k^l P_{k,t}^l + b_k^l u_{k,t}^l) \tag{22}$$

where L is the number of segments in the interval $[P_{k,\min}, P_{k,\max}]$; $P_{k,t}^l$ and $u_{k,t}^l$ are the power output and state variable of the l^{th} segment of DG k at time slot t, respectively; and a_k^l and b_k^l are the corresponding coefficients. More information about the piecewise linear method can be found in [32].

After the above transformation, the original MINLP can be transformed into an MILP problem, which can be solved easily by commercial solvers such as CPLEX.

V. Solution Algorithm

The solution process of the optimal scheduling of the distribution system with edge computing and data-driven modeling of PBDR mainly includes two parts: ① the two-stage optimal scheduling of the distribution system, which is executed in the control center; ② the classified XGBoost-based PBDR modeling, which is executed at each edge node.

The solution process of the two-stage optimal scheduling problem is shown in Algorithm 1.

Algorithm 1

1. Input data: day-ahead PV forecasting output and real-time price (RTP) signal
2. **For** each edge node $j \in \mathcal{J}$ **do**
   Send RTP signal to edge node $j \in \mathcal{J}$
   Execute Algorithm 2
   Receive the PBDR modeling results from all edge nodes
3. **End for**
4. Solve pre-scheduling problem
   $\begin{cases} \min c_{pre} \\ \text{s.t. } (9)\text{-}(16), (22) \end{cases}$
   Obtain pre-scheduling results $P_{k,t}^*$ and $P_{grid,t}^*$
5. **For** each time slot t, solve re-scheduling problem
   $\begin{cases} \min c_t^{re} \\ \text{s.t. } (18)\text{-}(21) \end{cases}$
   Obtain re-scheduling results $\Delta P_{k,t}$ and $\Delta P_{grid,t}$
6. **End for**

The process of the classified XGBoost-based PBDR modeling is shown in Algorithm 2. The interaction process of the control center and edge nodes is shown in Fig. 4.

VI. Case Study

A. Basic Data

The modified IEEE 33-node distribution system is used as a case study. Figure 5 presents the topology of the modified IEEE 33-node distribution system, in which a micro-turbine (MT) is connected to node 22, and PV panels are connected to nodes 18, 25, 26, and 33, respectively. PBDR data are derived from the actual operation data in Henan Province, China.

Algorithm 2

1. Input data: historical time of use (TOU) and corresponding PBDR data
2. Solve bi-level optimal problem denoted by (A1)-(A6) in Appendix A
3. Obtain original data set $\boldsymbol{\Gamma}_j=\{\boldsymbol{p}^d, \Delta \boldsymbol{L}_i^{j,d}, i=1,2,\ldots,m_j, d=1,2,\ldots,D\}$
4. Standardize the obtained original data
5. K-means method is adopted to cluster m_j users into S_j clusters
6. **For** each cluster $s \in S_j$ **do**
   Train XGBoost model
   End for
7. Obtain S_j XGBoost models
8. Receive RTP signal from the control center
9. **For** each cluster $s \in S_j$ **do**
   Predict PBDR based on the trained XGBoost model
   End for
10. Obtain PBDR modeling results
11. Send the PBDR modeling results to the control center

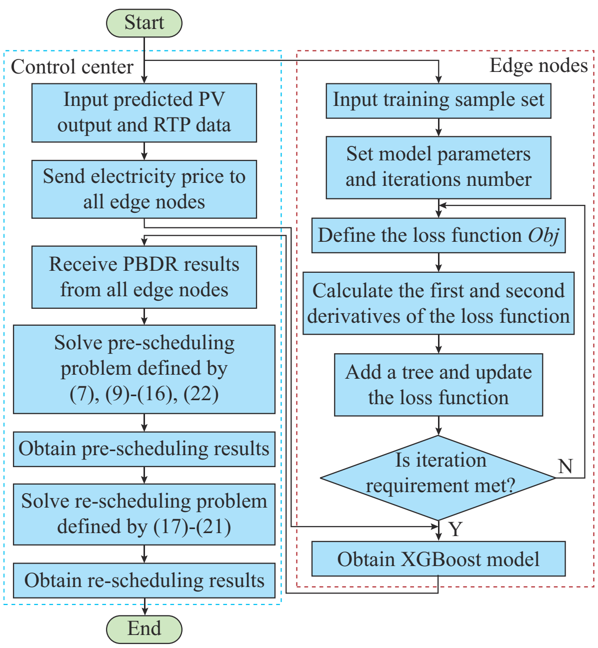

Fig. 4. Interaction process of control center and edge nodes.

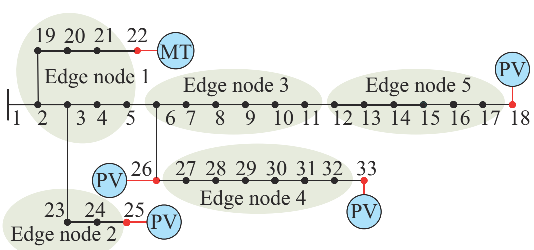

Fig. 5. Topology of modified IEEE 33-node distribution system.

To verify the effectiveness of the proposed optimal scheduling method of the distribution system with large-scale users, it is assumed that the distribution system is equipped with 1 control center and 5 edge nodes (i.e., $J=5$), which is utilized for data-driven PBDR modeling for 27 load nodes. Among them, edge node 1 models PBDR for load nodes 2-5 and 19-21 (i.e., $m_1=7$), edge node 2 models PBDR for load nodes 23 and 24 (i.e., $m_2=2$), edge node 3 models PBDR for load nodes 6-11 (i.e., $m_3=6$), edge node 4 models PBDR for load nodes 27-32 (i.e., $m_4=6$), and edge node 5 models PBDR for load nodes 12-17 (i.e., $m_5=6$).

The parameters of MT are given in [33], the carbon emission parameters and carbon emission price parameters can be found in [34], and the electricity price data are derived from [15], [35]. The electricity prices of the case study and the parameters of the modified IEEE 33-node distribution system are presented in Fig. 6 and Table I, respectively.

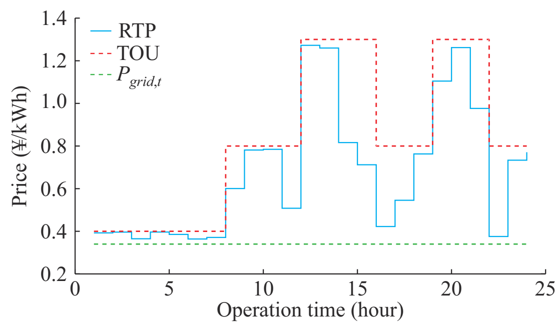

Fig. 6. Electricity prices of case study.

TABLE I
TECHNO-ECONOMIC PARAMETERS OF MODIFIED IEEE 33-NODE DISTRIBUTION SYSTEM

Techno-economic parameter	Value
a_k (¥/MWh^2)	0.183 [33]
b_k (¥/MWh)	14.64 [33]
α_k (¥/h)	48.8 [33]
$\alpha_{k,t}$ (kg/MWh)	724 [34]
$\alpha_{grid,t}$ (kg/MWh)	889 [34]
p_c (¥/kg)	0.023 [34]

All numerical tests are carried out on a laptop with an Intel(R) Core(TM) i7-4790 CPU at 3.60 GHz and 8 GB RAM, and the optimal problems are solved using MATLAB software R2018b by calling CPLEX solver 12.5.

B. Results of Classified XGBoost-based PBDR Modeling

Since the PBDR data from the actual operation data in Henan Province, China is based on TOU, there exists a problem that the training data are insufficient when modeling RTP-based PBDR. Therefore, the bi-level PBDR parameter evaluation approach (shown in Appendix A) is adopted to model the responsive behavior of users and generate the original training data based on TOU data. In this case study, the number of training samples is set to be 100, and the first 95 samples are used for training, whereas the last 5 samples are used for testing.

1) Validation of Classified XGBoost-based PBDR Modeling

Taking edge node 3 as an example, the unified XGBoost-based PBDR modeling method is used to analyze the effectiveness of the classified XGBoost-based PBDR modeling method proposed in this paper.

Taking load nodes 8 and 10 as examples, the PBDR data of continuous 72 hours in the testing set are used to test the performance of the above two modeling methods, and the results are shown in Fig. 7. It can be observed from Fig. 7 that, because of the large difference of PBDR characteristics between load nodes 8 and 10, the unified modeling method has large modeling errors, while the classified modeling method can achieve good modeling performance, which demonstrates the effectiveness of the classified modeling method.

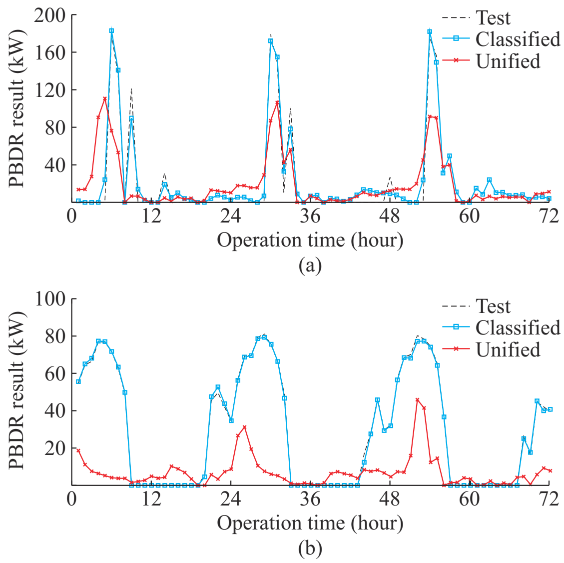

Fig. 7. Performance comparison of unified and classified XGBoost-based PBDR modeling. (a) PBDR modeling results of load node 8. (b) PBDR modeling results of load node 10.

2) *Comparison with Existing PBDR Modeling Methods*

To further analyze the effectiveness of the proposed PBDR modeling method, the following three methods are used for comparative analysis: ① the price elasticity (PE) method [10]; ② the utility function (UF) method [15]; ③ LSTM method [20].

The above PBDR modeling methods are used to model the PBDR of the load node 10, and the PBDR modeling results are shown in Fig. 8. Besides, the mean absolute error (MAE) and root mean squared error (RMSE) are employed to evaluate the performance of the above methods, and the comparative analysis is shown in Table II.

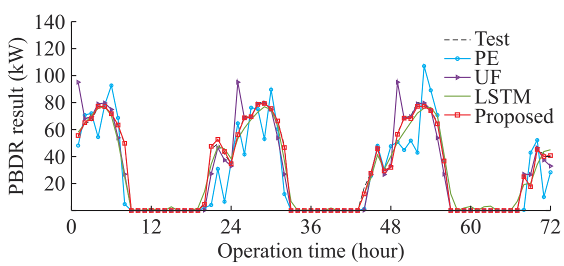

Fig. 8. Comparison of different PBDR modeling methods.

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT PBDR MODELING METHODS

Method	MAE (kW)	RMSE (kW)
PE	8.6316	14.9816
UF	4.9856	9.7193
LSTM	3.5980	5.5591
Proposed	1.5946	2.0727

From Fig. 8 and Table II, it can be concluded that the modeling error based on the proposed PBDR modeling method is lower than the PE, UF, and LSTM methods, which verifies the effectiveness of the proposed PBDR modeling method.

C. *Results of Two-stage Optimal Scheduling*

With the given RTP signal, the PE, UF, LSTM, and proposed methods are used to model the PBDR of various users, and the net load curve of the distribution system with different PBDR modeling methods (load minus PV output) is shown in Fig. 9. The pre-scheduling and re-scheduling results are shown in Fig. 10 and Fig. 11, respectively, and the comparison of scheduling costs with different PBDR modeling methods is shown in Table III.

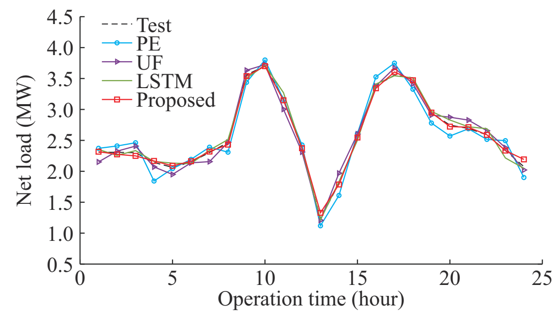

Fig. 9. Net load curves for different PBDR modeling methods.

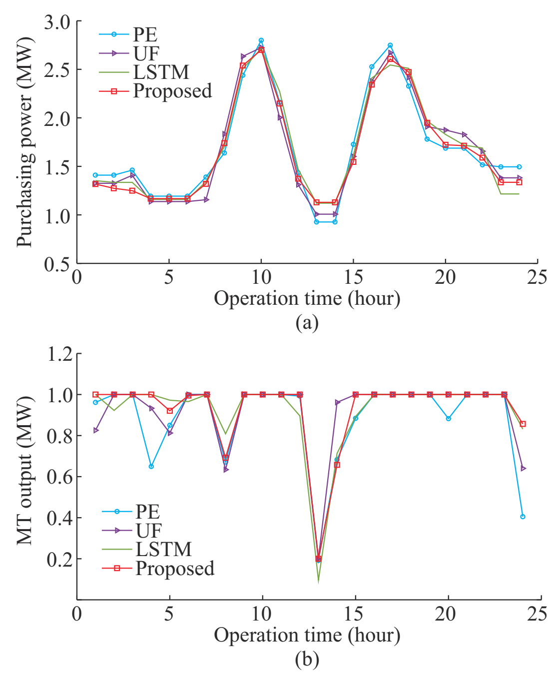

Fig. 10. Pre-scheduling results of distribution system with different PBDR modeling methods. (a) Pre-scheduling results of purchasing power. (b) Pre-scheduling results of MT output.

It can be observed from Figs. 9-11 that due to the difference of net load curves obtained by different PBDR modeling methods, the pre-scheduling and re-scheduling results of the distribution system with different PBDR modeling methods differ greatly. According to Table III, it is not difficult to observe that the proposed modeling method can reduce the pre-scheduling and re-scheduling costs of the distribution system effectively compared with the PE and LSTM methods, which decreases the total cost of the distribution system. Additionally, the pre-scheduling cost of the distribution system with the proposed modeling method increases compared with the UF method, but the re-scheduling cost is significantly reduced, which makes the total cost of the distribution system still lower than the UF method. Therefore, it is proven that the proposed modeling method is beneficial to improve the economics of the distribution system operation.

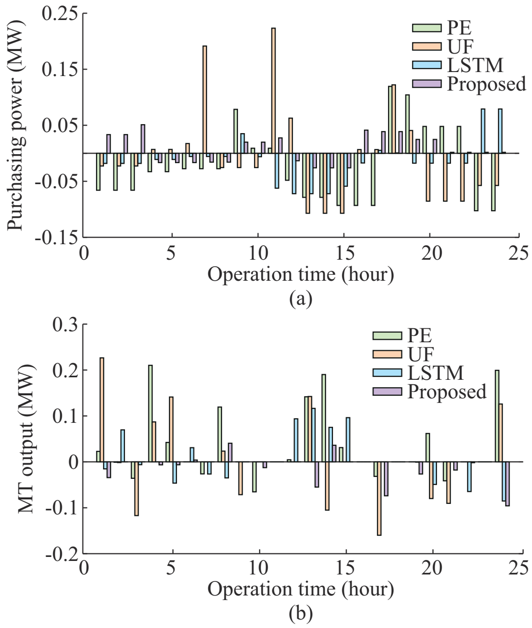

Fig. 11. Re-scheduling results of distribution system with different PBDR modeling methods. (a) Re-scheduling results of purchasing power. (b) Re-scheduling results of MT output.

TABLE III
COMPARISON OF SCHEDULING COSTS FOR DIFFERENT PBDR MODELING METHODS

Method	Pre-scheduling cost (¥)	Re-scheduling cost (¥)	Total cost (¥)
PE	19432	5598	25030
UF	19340	5667	25007
LSTM	19378	5457	24835
Proposed	19353	5404	24757

D. Results of Calculation Time with Edge Computing

This paper assumes that the control center and the edge nodes are connected by the advanced metering infrastructure (AMI) system. Because the transmission delay of price and PBDR signals in the communication link is generally in millisecond time scale, which is far less than the calculation time of the optimal scheduling of the distribution system (usually in second or minute time scale), so this paper does not take the transmission delay between the control center and edge nodes into consideration. Therefore, the calculation time of the optimal scheduling problem with PBDR mainly includes two parts: the PBDR modeling time and the optimal scheduling calculation time.

For the aforementioned case study, where the number of users for PBDR modeling is 27 and the number of edge nodes is 5, the traditional centralized computing paradigm and the edge computing paradigm proposed in this paper are adopted, respectively, and the calculation time comparison for solving the optimal scheduling problem with PBDR is shown in Table IV. Note that the testing is carried out on a laptop with an Intel(R) Core(TM) i7-4790 CPU at 3.60 GHz and 8 GB RAM.

TABLE IV
COMPARISON OF CALCULATION TIME WITH CENTRALIZED COMPUTING AND EDGE COMPUTING PARADIGMS

Paradigm	Calculation time (s)		
	PBDR modeling	Optimal scheduling	Total
Centralized computing	19.116	78.856	97.972
Edge computing	4.956	78.943	83.899

It is not difficult to find that with the edge computing paradigm, the calculation time of PBDR modeling is significantly reduced because different edge nodes simultaneously implement PBDR modeling after receiving the price signal from the control center, thereby the total calculation time of optimal scheduling problem with PBDR is decreased.

To verify the effectiveness of the proposed modeling method for large-scale users further, we assume that users are evenly distributed at each edge node. The total calculation time changing with the number of users for PBDR modeling is shown in Fig. 12, which supposes the number of edge nodes is 5. Besides, the total calculation time changing with the number of edge nodes is shown in Fig. 13, which supposes the number of PBDR is 60, 80, 100, respectively.

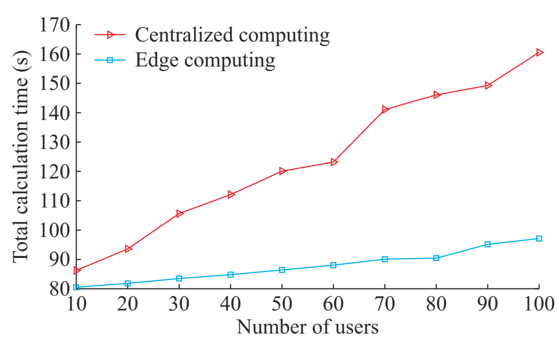

Fig. 12. Total calculation time changing with number of users.

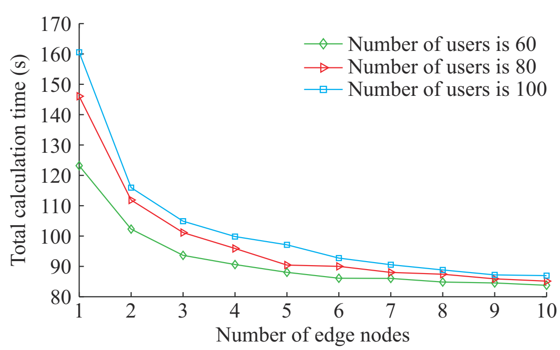

Fig. 13. Total calculation time changing with number of edge nodes considering given number of users.

It can be observed from Fig. 12 that for a certain number of edge nodes (5 in this case), the proposed edge computing paradigm can effectively reduce the total calculation time compared with the centralized computing paradigm. Moreover, this reduction effect is more obvious as the number of users increases, which verifies that the proposed edge computing paradigm has a significant effect on reducing the calculation time with PBDR modeling for large-scale users. Besides, the increase of the number of edge nodes can also significantly reduce the calculation time, as shown in Fig. 13, but for a given number of users, the reduction effect is less obvious as the number of edge nodes increases. Therefore, for PBDR modeling of a certain number of users, there exists a reasonable number of edge nodes.

For simplicity, we assume that each edge node is in charge of PBDR modeling of 15 users. Thus, the total calculation time of the optimal scheduling problem with different computing paradigms is shown in Fig. 14. It can be observed that with the traditional centralized computing paradigm, the total calculation time increases sharply with the growth of the number of users, while in the proposed edge computing paradigm, the number of users has no significant effect on the total calculation time, which demonstrates that the proposed optimal scheduling method with edge computing has good scalability and robustness. Note that the configuration of edge nodes needs to comprehensively consider various factors such as technology and economy, which is not further analyzed in this paper, and how to achieve a reasonable configuration of edge nodes will be the future research field.

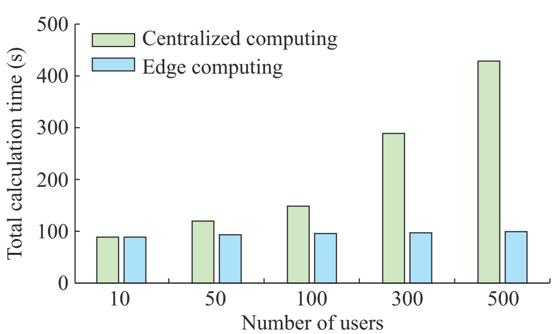

Fig. 14. Total calculation time of optimal scheduling problem with different computing paradigms.

VII. Conclusion

In this paper, an optimal scheduling method of the distribution system with edge computing and PBDR is proposed, which supports the participation of large-scale users. The modified IEEE 33-node system is used as a case study, and the following conclusions are obtained.

1) The application range of the proposed XGBoost-based PBDR modeling method is expanded. With the bi-level model for generating original training data, this method can overcome the drawback that conventional supervised learning fails when the training data are insufficient.

2) Compared with the existing PBDR modeling methods, the proposed XGBoost-based PBDR modeling method has lower errors. Moreover, the proposed optimal scheduling method has the lowest total cost, which proves that the proposed optimal scheduling method is beneficial for the operation of the distribution system.

3) The edge computing paradigm can effectively reduce the calculation time of optimal scheduling problems. Besides, the greater the number of users participating in DR is, the more significant the solution time reduction can be, which demonstrates that the edge computing paradigm is a feasible solution for optimal scheduling of the distribution system with large-scale users.

Note that the main work of this paper aims to propose a feasible method for optimal scheduling of the distribution system with large-scale users. For simplicity, the resource allocation of edge computing paradigm is not considered, and future work will take the collaborative optimization of energy and information resources into consideration. Besides, this paper assumes that the information interaction only exists between the control center and edge nodes, and the information exchange among edge nodes is not included, which is reasonable in the application scenario of this paper. The information interaction mechanism among multiple edge nodes and its typical application in the distribution system, e.g., distributed voltage control, should be evaluated further.

Appendix A

For the case that the XGBoost training data are sufficient, the content below can be skipped over. The actual situation is that, however, the ideal data are always insufficient for the XGBoost model, which relies heavily on the training data. For example, the current PBDR programs in China are mostly based on the TOU signals, and there is a problem of insufficient PBDR data in the early stage of the implementation of the RTP. Thus, it is necessary to extract the PBDR characteristic parameters of different users, which based on the existing TOU and corresponding PBDR data.

For user i, a bi-level PBDR parameter evaluation model is constructed as follows.

1) Upper level: PBDR feature evaluation

Based on TOU price and corresponding PBDR data, the parameter set of user i at time slot t is given by $\theta_{i,t}=\left\{\alpha_{i,1},\ \alpha_{i,2},\ \alpha_{i,0};\ r_i^u,\ r_i^d;\ L_{i,t}^{fix},\ \Delta L_{i,t}^{\max},\ \Delta L_{i,t}^{\min}\right\}$, where $t\in\mathcal{T}\equiv\{t{:}t=1,2,\ldots,T\}$; $\alpha_{i,1}$, $\alpha_{i,2}$, and $\alpha_{i,0}$ are the utility coefficients of user i; r_i^u and r_i^d are the up and down ramp rates for the load power regulation, respectively; $L_{i,t}^{fix}$ is the fixed power consumption of user i at time slot t; $\Delta L_{i,t}^{\max}$ and $\Delta L_{i,t}^{\min}$ are the upper and lower limits at time slot t for the load power regulation, respectively.

Let the actual load power of the user i with the TOU price at time t is $L_{i,t}^{real}$ and the optimized load power of the parameter evaluation model is $L_{i,t}$. Obtain a time series of pairwise price-consumption data $(p_t^{TOU},\ L_{i,t}^{real})$ from the existing historical data, and then the parameter evaluation model is constructed as:

$$\min_{\theta_{i,t},L_{i,t}}\sum_t\omega_t|L_{i,t}-L_{i,t}^{real}| \tag{A1}$$

where $\theta_{i,t}$ is the characteristic parameter; and ω_t is the weight coefficient.

2) Lower level: PBDR optimization

Based on the TOU price signal and the characteristic parameters $\theta_{i,t}$ given by upper level, the PBDR optimization problem of user i is given in (A2). Note that, the difference between the the results of optimized PBDR modeling and the actual PBDR modeling results is controlled by the upper level.

$$\max_{L_{i,t}} U_i = \sum_t (\alpha_{i,1} L_{i,t}^2 + \alpha_{i,2} L_{i,t} + \alpha_{i,0}) - \sum_t p_t^{TOU} L_{i,t} \tag{A2}$$

where U_i is the utility function of user i; the first term on the right side is the revenue while the second term means the payoff for the corresponding load power.

Let $\mathcal{T}_{-1} = \{t{:}t = 2, 3, \ldots, T\}$, Δt is the time interval, and $L_{i,t}$ is subject to:

$$L_{i,t} - L_{i,t-1} \le r_i^u \Delta t \quad \forall t \in \mathcal{T}_{-1} \tag{A3}$$

$$L_{i,t-1} - L_{i,t} \le r_i^d \Delta t \quad \forall t \in \mathcal{T}_{-1} \tag{A4}$$

$$L_{i,t} - L_{i,t}^{fix} \le \Delta L_{i,t}^{\max} \quad \forall t \in \mathcal{T} \tag{A5}$$

$$L_{i,t} - L_{i,t}^{fix} \ge \Delta L_{i,t}^{\min} \quad \forall t \in \mathcal{T} \tag{A6}$$

By solving the above bi-level optimization problem, the parameter vector of user i, i.e., $\boldsymbol{\theta}_i$, can be obtained. Then, the RTP signal is utilized as the electricity price signal, which is used to generate DR data considering RTP incentives.

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