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Research Article

Analysis of Smart Grid Optimal Scheduling considering the Demand Response of Different EV Owners

Xiaohua Zhang,[1,2] Chongyang Liao ,[1] Xingrui Chen,[1] Kuiheng Deng,[1] Bolin Chen,[1] and Yibo Gong[1]

[1]*School of Mechanical Engineering and Rail Transit, Changzhou University, Changzhou 213164, China*
[2]*Jiangsu Province Engineering Research Center of HighLevel Energy and Power Equipment, Changzhou University, Changzhou 213164, China*

Correspondence should be addressed to Chongyang Liao; 20085800070@smail.cczu.edu.cn

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The escalating growth of electric vehicle (EV) load has emphasized the growing importance of effective scheduling strategies. Due to the discrepancies among EV owners, their responses to scheduling can differ significantly. Therefore, to achieve better scheduling results, it is crucial to consider the impact of these discrepancies on the optimal scheduling. This paper proposes a classified scheduling method for different types of EV owners. According to charging and vehicle-to-grid (V2G) data of EV owners, the K-means clustering algorithm (K-means) is used to classify EV owners, and the demand response (DR) model is established based on the classification results. The DR model is designed to account for the diverse responses of different EV owners, and the price elasticity, time gap elasticity, and preference time elasticity are important factors in the model. This paper adopts the maximization of smart grid's revenue as the optimization objective through three approaches: (1) modifying the charging and V2G of EV; (2) obtaining V2G prices for all types of EV; and then (3) adjusting the power output of each unit. To evaluate the proposed method, the IEEE 10-unit system is employed for simulation, and the optimization problem is solved using the CPLEX solver. Compared to previous studies, the proposed classified scheduling method exhibits significant improvements in terms of revenue maximization, load distribution among different types of EVs, generation cost savings, and load variance reduction.

1. Introduction

Power generation and transportation are two of the largest sources of energy consumption in the space [1]. Fuel vehicle (FV) is the most widely used vehicle of transportation, and their low energy utilization efficiency has resulted in significant energy waste. The escalating adoption of electric vehicles (EVs) has resulted in a substantial shift of transportation load to the electrical grid. EVs have more advantages compared to FVs in terms of economy and environment [2]. Replacing FVs with EVs is an effective method to reduce carbon emissions [3]. Vehicle-to-grid (V2G) technology discharges EVs energy back to the smart grid [4]. Due to the large number of EVs, the application of V2G can alleviate the problem that electric energy is not difficult to store, but the cost is relatively high. Alizadeh et al. [5] developed a two-layer optimization model for the management of charging and discharging of EVs in parking lots, exploring the application value of V2G. With the development of battery technology, the cost of battery loss decreases rapidly, which has significantly promoted the popularity of V2G [6]. EVs with V2G can serve as flexible storage for smart grids, and Wei et al. [7], studying 300 EVs in three areas with two climate conditions, verified the environmental and economic benefits of V2G. Coupling a large number of EVs with V2G into a smart grid makes full decarbonization of transportation possible [8].

With the development of science and technology, the ability to collect data and extract valuable insights from massive amounts of data has been improved [9]. Various EV owners have different demands for EVs, and Roni et al. [10] conducted a study on EV charging in several areas in Seattle and found that the charging time of EVs in different regions varies. Based on power grid data, Yadav et al. [11] established an RBF-CNN-integrated model to predict short-term load and validated its results. Therefore, analyzing the behavior of EV owners is of critical importance. By analyzing the characteristics of EV owners, effective scheduling of EV charging can be achieved, which can improve the economy of the smart grid [12, 13].

Classifying EV owners is an effective way to distinguish EV owners' discrepancies. Cluster analysis is a crucial classification method based on the correlation of data [14], which divides the data into multiple clusters according to the distance between various data points. The K-means is the most commonly used clustering algorithm [15], and it has many advantages such as simplicity, convergence, scalability, and high efficiency. Ren et al. [16] used K-means to analyze probabilistic power flow. Al-Obaidi et al. [17] used the K-means clustering algorithm to divide EV owners into 9 clusters based on four dimensions: time, location, charging duration, and time gap between charges. Soltani et al. [18] conducted a double-layer clustering for EV owners, and EV owners were divided into two groups based on their charging patterns in the morning and evening. Then, each group was further divided based on whether they charge their EVs at their workplace or at home. The classification of EV owners is conducive to distinguishing the characteristics among them and then scheduling their charging and V2G activities based on their respective characteristics.

Electric power load scheduling plays a crucial role in ensuring stable smart grid operation [19, 20]. Price-based demand response models (PBDRMs) are widely used in smart grid schedule study, and price guidance is the simplest and most effective scheduling method [21]. Liu et al. [22] provided the elasticity curve of users, which reflects the sensitivity of nonresponsive users to changes in prices. EV charging and V2G demand can be influenced by price fluctuations in different time periods. A price elasticity matrix can be defined to reflect the response of EV charging and V2G to price in each period. The price elasticity of demand can be divided into two parts: (1) response to the price changes in this period, which is called self-elasticities, and (2) response to the price changes in the other period, which is called cross-elasticities [23]. To illustrate the response of hourly demand to hourly price changes, a 24×24 price elasticity matrix was defined to reflect the demand response (DR) to price changes in each period [24] and schedule the charging load of EV based on the price elasticity matrix [25]. The charging and V2G demand of EV owners are not only affected by the price but also by time. Lijesen [26] studied the impact of time on customers' DR and found that customers are more likely to accept schedules with minor changes in time, while they are less likely to accept schedules with significant changes in time, and various customers have different preferences for time [27]. The disorderly charging and V2G of EV will affect the reliability of the smart grid. Aalami et al. [28] established the demand response model of EV owners and calculated it for different power markets, effectively improving the reliability of the smart grid. Huang [29] employed a price elasticity matrix to quantify the impact of changes in electricity prices on EV charging and V2G behavior.

The above literature review highlights the research status of related fields. Previous studies in the field of classification and scheduling have made significant achievements. However, there is no integration of the results of these two fields when studying EV scheduling problems. Therefore, there is a need for further research to integrate classification and scheduling to better solve EV scheduling problems in the smart grid.

Previous studies usually used uniform prices to schedule all EV owners, but since EV owners have varied demand for EVs, they may have different responses to price changes. Applying the uniform pricing strategy to all EV owners may lead to some owners not responding to the schedule and not achieving the optimal scheduling effect. In contrast, a more targeted classified scheduling based on the characteristics of EV owners can better manage the diverse EV loads, thereby effectively reducing the gap between peak and off-peak periods and increasing grid revenue. This paper proposes a classified scheduling method that adjusts prices according to the characteristics of EV owners. The main contributions are as follows:

(1) To differentiate various types of EV owners and extract their characteristics, this paper employs the K-means algorithm to classify EV owners into different types based on charging and V2G data;

(2) To capture the varying responses of different EV owners to scheduling, this paper establishes DR models for different types of EV owners based on price elasticity, time preference elasticity, and time gap elasticity. By incorporating these factors, the models aim to reflect the diverse behaviors of EV owners in response to price changes;

(3) To demonstrate the significance of scheduling EV loads for the smart grid, the DR models of EV owners are incorporated into the smart grid model. The maximization of revenue is adopted as the optimization objective, and these prices are used to guide their charging and V2G demand.

In conclusion, this paper presents an optimal scheduling strategy for EV loads. Through the classification of EV owners and the implementation of dynamic pricing strategies, the study effectively addresses the diverse responses of EV owners. Moreover, the integration of DR models into the smart grid model optimizes revenue and guides charging behavior.

The structure of the remaining paper is outlined as follows. Section 2 introduces EV data simulation and cluster analysis. Section 3 establishes the model of smart grid scheduling with EV demand response. In Section 4, a case study is conducted based on the charging data of EV users. Section 5 presents the conclusions and further work of this study.

2. EV Data Simulation and Cluster Analysis

2.1. EV Data Simulation. EV charging and V2G behaviors exhibit a high degree of randomness. To further investigate the scheduling of EV loads, a large amount of relevant data is required. In particular, the application of V2G is only applied in microgrids, and its scale is relatively small. Therefore, this paper uses Monte Carlo simulation to generate a substantial amount of charging and V2G data for EVs. Based on these data, a classification approach is applied to categorize the EVs. As per the statistical data of the 2009 National Household Travel Survey (NHTS2009) [10], the distribution function of EV driving mileage conforms to the lognormal distribution is expressed as follows:

$$f(L) = \frac{1}{L\sigma_L\sqrt{2\pi}}\left[-\frac{(\ln L - \mu_L)^2}{2\sigma_L{}^2}\right], \tag{1}$$

where L represents the EVs' driving distance; σ_L is the standard deviation; and μ_L is the mean value. EV owners do not necessarily recharge their EVs every day. Most EV owners recharge their EVs every 3-4 days. Therefore, the charging demand of EV owners is equal to the product of the driving mileage and the energy consumption per unit mileage, multiplied by the number of days between recharging.

Most EV owners charge V2G when they get home. Assuming that EV owners' get-home time is EV charging or V2G start time, according to NHTS2009 statistics, EV owners' get-home time meets the normal distribution which can be expressed as follows:

$$f(t) = \begin{cases} \dfrac{1}{\sigma_t\sqrt{2\pi}}\exp\left[-\dfrac{(t-\mu_t)^2}{2\sigma_t^2}\right](\mu_t - 12) < t < 24, \\ \\ \dfrac{1}{\sigma_t\sqrt{2\pi}}\exp\left[-\dfrac{(t-\mu_t+24)^2}{2\sigma_t^2}\right]0 < t < (\mu_t - 12), \end{cases} \tag{2}$$

where t represents the arrival time of an EV owner at home; σ_t is the standard deviation; and μ_t is the mean value. In this paper, it is assumed that the EV owner's arrival time at home is the starting time for charging.

This paper assumes that the distribution functions for the V2G demand and V2G starting times of EV owners are similar, with differences observed only in certain parameters. The charging, V2G demand, and V2G time of each EV can be obtained through Monte Carlo simulation based on the probability distribution.

As shown in Figure 1, the distribution functions for various parameters are inputted, including EV driving mileage, home arrival time, V2G demand, and V2G time. Based on these distribution functions, the charging and V2G load as well as their corresponding time durations are extracted for each EV owner. The charging demand of EV owners is prioritized over the V2G demand to ensure that their charging needs are met first. During the data simulation, the charging status is recorded for each time period, with a value of 1 indicating a charging demand and 0 indicating no charging demand. V2G operations are only performed during time periods with a charging status of 0. Once the charging and V2G data for all EV owners are extracted, the results are outputted, completing the data simulation process.

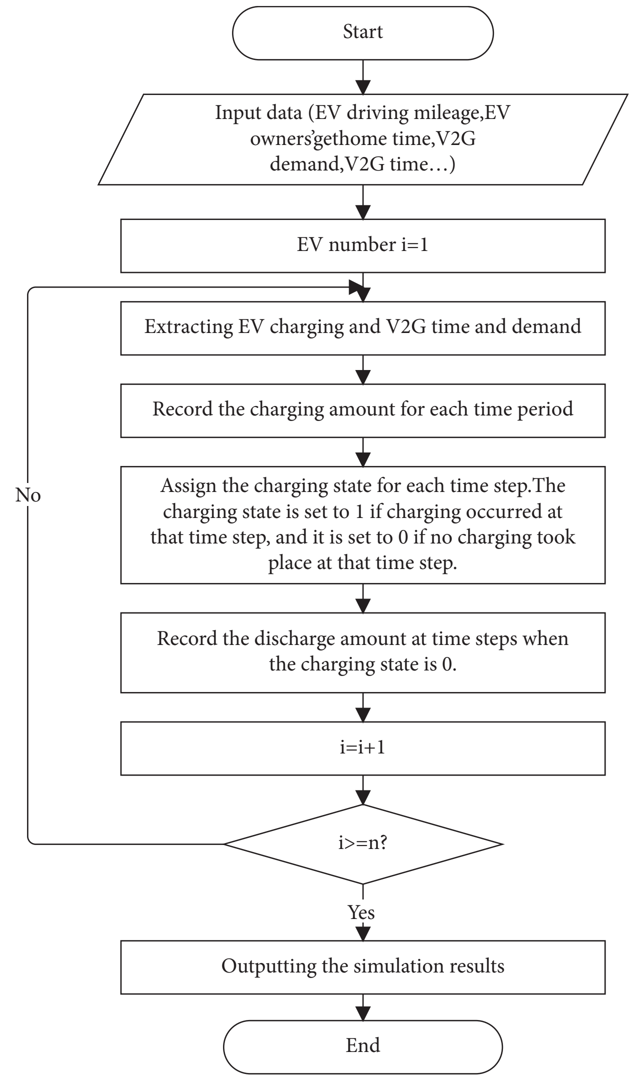


Figure 1: Flowchart of EV loads simulation based on Monte Carlo simulation.

2.2. Classification of EV Owners. Different EV owners exhibit different behavioral patterns, leading to varying demands for charging and V2G. By classifying EV owners, their behavioral characteristics can be highlighted, facilitating further analysis of EV owners. For the smart grid, the charging demand, charging time, V2G demand, and V2G time of EVs are crucial data. The charging demand directly affects the magnitude of the load, while the charging time determines the timing of the load. Moreover, the demand data provide insights into the behavioral patterns of EV owners, such as the intensity of EV usage inferred from the demand magnitude and the time periods of EV usage inferred from the demand time.

EV data are multidimensional and massive. K-Means is a suitable method for classifying such data due to its ability to handle multidimensional and massive datasets. K-Means follows two principles for data classification: (1) minimizing the distance between points in the same cluster and (2) maximizing the distance between different cluster centers. It has the advantages of a simple principle and fast convergence speed.

According to the charging time and demand data of EV owners, the EV owners are divided into a clusters by K-means, with the EV owners in the 1-th cluster being the 1-th type of EV owners and the EV owners in the a-th cluster being the a-th type of EV owners. Similarly, according to V2G time and demand data of EV owners, the EV owners are divided into av clusters by K-means, with the EV owners in the av-th cluster being the av-th type of EV owners. EV charging obtains electric energy from the smart grid, while V2G releases EV's stored electric energy to the smart grid. Since the two types of data are relatively independent, the clustering of EV owners is divided into charging clusters and V2G clusters; for example, EV charging is divided into i-th type, while V2G is divided into j-th type.

3. Modeling of Smart Grid Scheduling with EV Demand Response

3.1. DR Model of EV Owners. EV owners' DR refers to the EV owners adjusting their electricity consumption in response to changes in electricity prices. Guiding EV loads in a reasonable method can be of great help to the smart grid. The load demand of EV owners is mainly influenced by two factors: time and price. The impact of time on the load demand of EV owners can be further divided into two aspects: (1) Time preference elasticity of EV owners: different EV owners have different preferred time periods for charging and V2G. They are more willing to engage in charging or V2G activities during their preferred time periods. As a result, their response to price changes is more significant during these time periods, while it is relatively small outside of their preferred time periods. (2) Time gap elasticity of EV owners: time gap elasticity refers to the interval between price changes and the corresponding demand time periods. For example, when considering the impact of price changes at 10 o'clock on the demand at 6 o'clock, the time gap is 4 hours. The price impact on the load demand of EV owners is reflected in the fact that when prices change, consumers' demand for the product also changes accordingly, which is known as price elasticity.

The response of a single EV owner to price guidance is difficult to reflect; therefore, this paper takes a cluster of EV owners as the smallest unit for scheduling. The total charge and V2G demand of cluster a-th and av-th EV owners in this period are equal to the sum of all EV charging demand $d_a^0(t)$ and V2G demand $d_{av}^0(t)$ of this cluster, as shown in the following equations, respectively:

$$d_a^0(t) = \sum_{v=1}^{NV_a} d_a^V(t, v), \tag{3}$$

$$d_{\mathrm{av}}^0(t) = \sum_{v=1}^{\mathrm{NV_{av}}} d_{av}^V(t, v), \tag{4}$$

where $d_a^V(t, v)$ is the charging demand of cluster a-th v-th EV owner and $d_{\mathrm{av}}^V(t, v)$ is the V2G demand of cluster a-th v-th EV owner.

Taking the cluster center to represent the characteristics of this cluster EV owners, the charging and V2G time of the cluster center can represent the charging and V2G time preference of these cluster EV owners. The preference charging time elasticity $E_a^{\mathrm{TL}}(j)$ for cluster a-th EV owners at time j is stipulated as follows:

$$E_a^{\mathrm{TL}}(j) = \begin{cases} 1, & 0 \le \Delta t_a^{\mathrm{TL}}(j) \le 3, \\ 0.8, & 4 \le \Delta t_a^{\mathrm{TL}}(j) \le 8, \\ 0.6, & 9 \le \Delta t_a^{\mathrm{TL}}(j) < 12, \end{cases} \tag{5}$$

where $\Delta t_a^{\mathrm{TL}}(j)$ is the time gap between the a-th cluster center and the time of price change, and the time j may be later or earlier than time t, but the interval is within 12 hours; t_a is the charging time of a-th cluster center. $\Delta t_a^{TL}(j)$ is stipulated as follows:

$$\Delta t_a^{\mathrm{TL}}(j) = \begin{cases} j - t_a, & j - t_a > 0 \text{ and } j - t_a \le 12, \\ 24 - (j - t_a), & j - t_a > 0 \text{ and } j - t_a > 12, \\ t_a - j, & j - t_a < 0 \text{ and } j - t_a \le 12, \\ 24 - (t_a - j), & j - t_a < 0 \text{ and } j - t_a > 12. \end{cases} \tag{6}$$

The elasticity of preference V2G time $E_{\mathrm{av}}^{\mathrm{TL}}(j)$ and the scheduling time gap $\Delta t_{\mathrm{av}}^{\mathrm{TL}}(j)$ are similar to charging, so the preference V2G time elasticity for cluster av-th EV owners at time j is stipulated as follows:

$$E_{av}^{TL}(j) = \begin{cases} 1, & 0 \le \Delta t_{av}^{TL}(j) \le 3, \\ 0.8, & 4 \le \Delta t_{av}^{TL}(j) \le 8, \\ 0.6, & 9 \le \Delta t_{av}^{TL}(j) < 12. \end{cases} \tag{7}$$

EV owners also have different responses to price change times [26]. The response of demand time t to the scheduling time j is shown as follows:

$$E_{\Delta T}(t, j) = \gamma \Delta t^{-\mu}(t, j), \tag{8}$$

where γ and μ are two constant coefficients; Δt is the scheduling time gap; the calculation for Δt is similar to that of $\Delta t_a^{\mathrm{TL}}(j)$; and it is stipulated as follows:

$$\Delta t(t,j)=\begin{cases} t-j, & t-j>0 \text{ and } t-j\leq 12,\\ 24-(t-j), & t-j>0 \text{ and } t-j>12,\\ j-t, & t-j<0 \text{ and } t-j\leq 12,\\ 24-(j-t), & t-j<0 \text{ and } t-j>12. \end{cases} \tag{9}$$

The response of EV owners' demand to scheduling time gap can be reflected by a 24×24 matrix, and this matrix reflects the fact that EV owners have lower responsiveness to price changes with longer scheduling time gaps, while their responsiveness to price changes is higher with shorter scheduling time gaps, and the scheduling time gap matrix is shown as follows:

$$\begin{bmatrix} E_{\Delta T}(1,1) & E_{\Delta T}(1,2) & \cdots & \cdots & E_{\Delta T}(1,24)\\ E_{\Delta T}(2,1) & E_{\Delta T}(2,2) & \cdots & \cdots & \cdots\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ \cdots & \cdots & E_{\Delta T}(t,j) & \cdots & \cdots\\ \cdots & \cdots & \cdots & \cdots & \cdots\\ E_{\Delta T}(24,1) & \cdots & E_{\Delta T}(24,j) & \cdots & E_{\Delta T}(24,24) \end{bmatrix}. \tag{10}$$

The charging price elasticity $E_a(t,j)$ reflects the response of EV owners to price. The charging price elasticity of cluster a-th EV owners of the demand time t versus price change time j can be defined as follows:

$$E_a(t,j)=\frac{\rho_0(j)}{d_a^0(t)}*\frac{\partial d_a(t)}{\partial \rho_a(j)}, \tag{11}$$

where $\rho_0(j)$ is the initial charging price at time j, which is equal to the initial electricity price, and $d_a^0(t)$ is the initial charging demand of cluster a-th EV owners at time t.

The load at each hour will be affected by the corresponding price variation at that hour, and the response of EV owners' charging demand to price changes throughout the day can be represented as a 24×24 matrix. In this matrix, each element of the matrix represents the degree of change in EV owners' charging demand in response to a price variation at a particular hour.

$$\begin{bmatrix} E_a(1,1) & E_a(1,2) & \cdots & \cdots & E_a(1,24)\\ E_a(2,1) & E_a(2,2) & \cdots & \cdots & \cdots\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ \cdots & \cdots & E_a(t,j) & \cdots & \cdots\\ \cdots & \cdots & \cdots & \cdots & \cdots\\ E_a(24,1) & \cdots & E_a(24,j) & \cdots & E_a(24,24) \end{bmatrix}. \tag{12}$$

The diagonal elements of this matrix are the self-elasticities that reflect the response of charging demand to price change in the current period, and the off-diagonal elements are mutual elasticity that reflect the response of charging demand to price change in other periods.

V2G price elasticity $E_{\mathrm{av}}(t,j)$ of av-th EV owners can be defined as follows:

$$E_{\mathrm{av}}(t,j)=\frac{\rho_{V2G}^0(j)}{d_{av}^0(t)}*\frac{\partial d_{av}(t)}{\partial \rho_{av}(j)}, \tag{13}$$

where $\rho_{V2G}^0(j)$ is the initial V2G price at time j and $d_{\mathrm{av}}^0(t)$ is the initial V2G demand of cluster av-th EV owners at time t.

Similar to the EV owners' charging price elasticity matrix, the EV owners' V2G price elasticity matrix is shown as follows:

$$\begin{bmatrix} E_{av}(1,1) & E_{av}(1,2) & \cdots & \cdots & E_{av}(1,24)\\ E_{av}(2,1) & E_{av}(2,2) & \cdots & \cdots & \cdots\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ \cdots & \cdots & E_{av}(t,j) & \cdots & \cdots\\ \cdots & \cdots & \cdots & \cdots & \cdots\\ E_{av}(24,1) & \cdots & E_{av}(24,j) & \cdots & E_{av}(24,24) \end{bmatrix}. \tag{14}$$

3.2. Modeling of DR for EV Owners' Charging and V2G.

According to Section 3.1, the charging demand of EV owners will be affected by the price change, scheduling time gap, and preference time. The DR model of cluster a-th EV owners charging can be expressed as follows:

$$\begin{bmatrix} \Delta d_a(1)\\ \Delta d_a(2)\\ \vdots\\ \Delta d_a(j)\\ \cdots\\ \Delta d_a(24) \end{bmatrix}=\begin{bmatrix} E_a(1,1) & E_a(1,2) & \cdots & \cdots & E_a(1,24)\\ E_a(2,1) & E_a(2,2) & \cdots & \cdots & \cdots\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ \cdots & \cdots & E_a(t,j) & \cdots & \cdots\\ \cdots & \cdots & \cdots & \cdots & \cdots\\ E_a(24,1) & \cdots & E_a(24,j) & \cdots & E_a(24,24) \end{bmatrix}\cdot\begin{bmatrix} E_{\Delta T}(1,1) & E_{\Delta T}(1,2) & \cdots & \cdots & E_{\Delta T}(1,24)\\ E_{\Delta T}(2,1) & E_{\Delta T}(2,2) & \cdots & \cdots & \cdots\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ \cdots & \cdots & E_{\Delta T}(t,j) & \cdots & \cdots\\ \cdots & \cdots & \cdots & \cdots & \cdots\\ E_{\Delta T}(24,1) & \cdots & E_{\Delta T}(24,j) & \cdots & E_{\Delta T}(24,24) \end{bmatrix}$$
$$\times\begin{bmatrix} E_a^{\mathrm{TL}}(1),\\ E_a^{\mathrm{TL}}(2),\\ \vdots,\\ E_a^{\mathrm{TL}}(j),\\ \cdots,\\ E_a^{\mathrm{TL}}(24). \end{bmatrix}\cdot\begin{bmatrix} \Delta\rho_a(1)\\ \Delta\rho_a(2)\\ \vdots\\ \Delta\rho_a(j)\\ \cdots\\ \Delta\rho_a(24) \end{bmatrix}. \tag{15}$$

The left side of equation (15) is the changing of cluster a-th EV owners' charging demand, and the right side contains the price elasticity matrix, scheduling time gap elasticity matrix, and preference charging time elasticity. It can be seen that the DR model proposed in this paper not only considers the impact of price on demand but also considers the impact of price change time on demand. The charging demand $\Delta d_a(t)$ of cluster a-th EV owners in time t is expressed as follows:

$$\Delta d_a(t) = \sum_{j=1}^{24} E_a(t,j) * E_{\Delta T}(t,j) * E_a^{\mathrm{TL}}(j) * \Delta\rho_a(j), \quad (16)$$

where $\Delta\rho_a(j)$ is the change of charging a price for cluster a-th EV owners at time j.

The charging demand $d_a(t)$ of cluster a-th EV owners at time t after scheduling is equal to the initial demand added to the demand change, and it is expressed as follows:

$$d_a(t) = d_a^0(t) + \Delta d_a(t). \quad (17)$$

Also, the charging price $\rho_a(t)$ of cluster a-th EV owners at time t after scheduling is equal to the initial demand added to the demand change, and it is expressed as follows:

$$\rho_a(t) = \rho_0(j) + \Delta\rho_a(t). \quad (18)$$

The DR model of cluster av-th EV owners V2G is similar to charging, so the V2G demand change $\Delta d_{\mathrm{av}}(t)$ is expressed as follows:

$$\Delta d_{\mathrm{av}}(t) = \sum_{j=1}^{24} E_{\mathrm{av}}(t,j) * E_{\Delta T}(t,j) * E_{\mathrm{av}}^{\mathrm{TL}}(j) * \Delta\rho_{\mathrm{av}}(j), \quad (19)$$

where $\Delta\rho_{\mathrm{av}}(j)$ is the change of V2G price for cluster av-th EV owners at time j.

The V2G demand $d_{\mathrm{av}}(t)$ of cluster av-th EV owners at time t after the schedule is expressed as follows:

$$d_{\mathrm{av}}(t) = d_{\mathrm{av}}^0(t) + \Delta d_{\mathrm{av}}(t). \quad (20)$$

Also, the V2G price $\rho_{\mathrm{av}}(j)$ of cluster av-th EV owners at time t after the schedule is expressed as follows:

$$\rho_{\mathrm{av}}(j) = \rho_{V2G}^0(t) + \Delta\rho_{\mathrm{av}}(j). \quad (21)$$

To ensure that the charging and V2G behavior of EV owners are feasible, certain parameters should be considered. First, it is necessary to ensure that the charging and V2G price fluctuations for EV owners are within a reasonable range, as shown in equations (22) and (23); second, in order to meet the demands of different types of EV owners, the charging and V2G load fluctuations of each type of EV owner should be limited, as shown in equations (24) and (25); finally, constraints on the total EV charging and V2G load should be enforced, as shown in equations (26) and (27), respectively:

$$\rho_a^{\min} \le \rho_a(t) \le \rho_a^{\max}, \quad (22)$$

$$\rho_{\mathrm{av}}^{\min} \le \rho_{\mathrm{av}}(t) \le \rho_{\mathrm{av}}^{\max}, \quad (23)$$

$$d_a^{\min}(t) \le d_a(t) \le d_a^{\max}(t), \quad (24)$$

$$d_{\mathrm{av}}^{\min}(t) \le d_{\mathrm{av}}(t) \le d_{\mathrm{av}}^{\max}(t), \quad (25)$$

$$d_{\mathrm{ch}}^{\min}(t) \le \sum_{a=1}^{k} d_a(t) \le d_{\mathrm{ch}}^{\max}(t), \quad (26)$$

$$d_{V2G}^{\min}(t) \le \sum_{\mathrm{av}=1}^{\mathrm{kv}} d_{\mathrm{av}}(t) \le d_{V2G}^{\max}(t), \quad (27)$$

where $\rho_a^{\min}$ is the lower limit of charging a price for cluster a-th EV owners; $\rho_a^{\max}$ is the upper limit of charging a price for cluster a-th EV owners; $\rho_{\mathrm{av}}^{\min}$ is the lower limit of V2G price for cluster av-th EV owners; and $\rho_{\mathrm{av}}^{\max}$ is the upper limit of V2G price for cluster av-th EV owners. $d_a^{\min}(t)$ is the lower limit of charging demand for cluster a-th EV owners; $d_a^{\max}(t)$ is the upper limit of charging demand for cluster a-th EV owners; $d_{\mathrm{av}}^{\min}(t)$ is the lower limit of V2G demand for cluster av-th EV owners; and $d_{\mathrm{av}}^{\max}(t)$ is the upper limit of V2G demand for cluster av-th EV owners. $d_{\mathrm{ch}}^{\min}(t)$ is the lower limit of the sum of charging demand for all EV owners; $d_{\mathrm{ch}}^{\max}(t)$ is the upper limit of the sum of charging demand for all EV owners; $d_{V2G}^{\min}(t)$ is the lower limit of the sum of V2G demand for all EV owners; and $d_{V2G}^{\max}(t)$ is the upper limit of the sum of V2G demand for all EV owners.

3.3. Optimization Objectives of Smart Grid Scheduling with EV Demand Response. This paper adopts to maximize the revenues of smart grid, and the revenues C of smart grid are expressed as follows:

$$\operatorname{Max} C = \sum_{t=1}^{24}\left(\rho_0(j) * P_{\mathrm{Load}}(t) - C_i^{\mathrm{gen}}(t) + \rho_a(t) * \sum_{a=1}^{k} d_a(t) - \rho_{\mathrm{av}}(t) * \sum_{\mathrm{av}=1}^{\mathrm{kv}} d_{\mathrm{av}}(t)\right), \quad (28)$$

where $P_{\mathrm{Load}}(t)$ is the base load of the smart grid and $C_i^{\mathrm{gen}}(t)$ is the output cost of unit i. The objective function can be divided into two parts: revenue and cost. Revenue includes both basic load and EV charge sales revenue, while cost includes output and V2G cost.

The output cost of unit i consists of fuel and start-up costs. The output cost of unit i is shown as follows:

$$C_i^{\mathrm{gen}}(t) = a_i + b_i * P_i(t) + c_i * P_i^2(t) + \left(U_i(t) - U_i(t-1)\right) * S_i(t), \quad (29)$$

where a_i, b_i, and c_i are three different coefficients of fuel cost; $P_i(t)$ is the output of unit i; $U_i(t)$ is the state variable of unit i, 1 is start, 0 is off; and $S_i(t)$ is the start-up cost of unit i.

To ensure the stable operation of the smart grid, it is necessary to impose constraints on the generator units. These constraints include the output limits of the generator unit, as shown in equation (30); the load balance constraint, the sum of the generator unit output and the V2G output of EVs, equals the sum of the base load and the charging load of EVs, as shown in equation (31); the constraint on spinning reserve of generation units refers to the additional capacity provided by generation units within a certain period of time to ensure the stability operation for smart grid, as shown in equation (32); the constraint on the ramp rate of the generator unit, the output increase, and decrease of the generator unit should be within the rated range, as shown in equation (33); after starting or stopping the generator unit, it needs to meet a certain time requirement before it can start or stop again, as shown in equations (34) and (35).

$$P_i^{\min} \le P_i(t) \le P_i^{\max}, \tag{30}$$

$$\sum_{i=1}^{n} P_i(t) + \sum_{a=1}^{k} d_a(t) = P_{\text{Load}}(t) + \sum_{\text{av}=1}^{\text{kv}} d_{\text{av}}(t), \tag{31}$$

$$\sum_{i=1}^{n} P_i^{\max} + \sum_{\text{av}=1}^{\text{kv}} d_{\text{av}}(t) \ge \sum_{i=1}^{n} R_i(t) + P_{\text{Load}}(t) + \sum_{a=1}^{k} d_a(t), \tag{32}$$

$$\Delta P_i^{\text{down}} \le P_i(t) - P_i(t-1) \le \Delta P_i^{\text{up}}, \tag{33}$$

$$\left[U_i(t) - U_i(t-1)\right] * \left[T_i^{\text{off}}(t) - T_{i,\min}^{\text{off}}\right] \ge 0, \tag{34}$$

$$\left[U_i(t-1) - U_i(t)\right] * \left[T_i^{\text{on}}(t) - T_{i,\min}^{\text{on}}\right] \ge 0, \tag{35}$$

where $P_i^{\min}$ is the minimum output of unit i, $P_i^{\max}$ is the maximum output of unit i; $P_{\text{Load}}(t)$ is the base load at time t; $R_i(t)$ is spinning reserve of unit i at time t; ΔP_i^{down} is the maximum output ramp-down rate for unit i; and ΔP_i^{up} is the maximum output ramp-up rate for unit i.

4. Numerical Studies

In this paper, IBM's CPLEX is used to find the optimal solution. A total of 7,000 EVs are assumed to be integrated into the IEEE 10-unit power system [30], and the generator units' data are given in Table 1. The battery capacity of an EV is set as 100 kWh, the charging power is 6–30 kW, and the V2G power is 6–15 kW. We assumed that the basic load does not respond to electricity price changes. The exchange rate between USD and RMB in this paper is 1 : 7.

Considering that V2G has not yet been implemented, the following Study A and Study B are included: Study A only considers the charging load of EVs, and the scheduling effects are analyzed. To demonstrate the advantages of the proposed classification-based scheduling method, two cases are designed, Case 1 uses the nonclassification method, and Case 2 uses the proposed classification method to schedule the charging load of EV owners. Study B considers the charging load and V2G load of EVs, the scheduling effects are simulated after the implementation of V2G, two cases are designed, Case 3 uses the nonclassification method to schedule the charging load and V2G load of EV owners, and Case 4 uses the proposed classification method to schedule the charging load and V2G load of EV owners.

4.1. Classification of EV Owners. Figure 2 shows the clustering effects of EV owners' charging under different numbers of clusters, as illustrated in Figures 2(a)–2(d). Regardless of the number of EV owner clusters created, the charging periods for cluster centers are consistently distributed in the morning, noon, or night, fulfilling the classification criteria. In terms of charging demand, according to the NHTS2009 statistics, the amount of EV owners with light and medium charging demand is more significant, so the classification of these EV owners should be more detailed. When the number of clusters is 4 or 6, the classification of charging demand is not detailed enough. However, when the number of clusters is 8 or 9, the classification of EV owners' charging demand is more accurate. To further compare the two, we can examine their respective silhouette coefficients. The silhouette coefficient is used to evaluate the effectiveness of clustering. Its values range from −1 to 1, where positive values indicate that data points within a cluster are more similar to each other than to data points in other clusters, and negative values suggest that data points might be better assigned to other clusters. A higher silhouette coefficient indicates a tighter and more effective clustering result. By comparing the silhouette coefficients at different numbers of clusters, we can determine the optimal number of clusters and select the best clustering result. The vertical coordinate indicates the number of categories, and the horizontal coordinate indicates the size of the silhouette value. When number of clusters is 9, the silhouette coefficient has a lot of negative values, which indicates that many data points do not fit the cluster very well.

After comparison, it can achieve the best classification effect when the number of clusters is 8. According to Figure 2(c), clusters 3-th and 5-th are lightly charging EV owners, clusters 4-th, 6-th, 7-th, and 8-th are medium charging EV owners, and clusters 1-th and 2-th are heavy charging EV owners. In terms of charging time, clusters 3-th and 7-th EV owners charge in the morning, clusters 4-th and 8-th EV owners charge at the noon, and 5-th and 6-th EV owners charge at all periods.

Figure 3 shows the clustering effects of EV owners' V2G under different numbers of clusters, as illustrated in Figures 3(a)–3(d). In terms of V2G time, when the number of clusters is 9, the distribution of cluster centers becomes confused, and when the numbers of clusters are 8 and 6, the cluster centers are distributed in the morning, noon, or night. When the number of clusters is 4, the cluster centers are distributed in the morning and night. In terms of V2G demand, when the cluster is 6, the classification effect is best.

Table 1: IEEE 10-unit parameter.

Unit	1	2	3	4	5	6	7	8	9	10
$P_i^{\max}$ (MW)	455	455	130	130	162	80	85	55	55	55
$P_i^{\min}$ (MW)	150	150	20	20	25	20	25	10	10	10
a_i	1000	970	700	680	450	370	480	660	665	670
b_i	16.19	17.26	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
c_i	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.0079	0.00413	0.00222	0.00173
$T_{i,\min}^{\text{on}}$ (h)	8	8	5	5	6	3	3	1	1	1
$T_{i,\min}^{\text{off}}$ (h)	8	8	5	5	6	3	3	1	1	1
Initial	8	8	−5	−5	−6	−3	−3	−1	−1	−1
$S_i(t)$($)	4500	5000	550	560	900	170	260	30	30	30

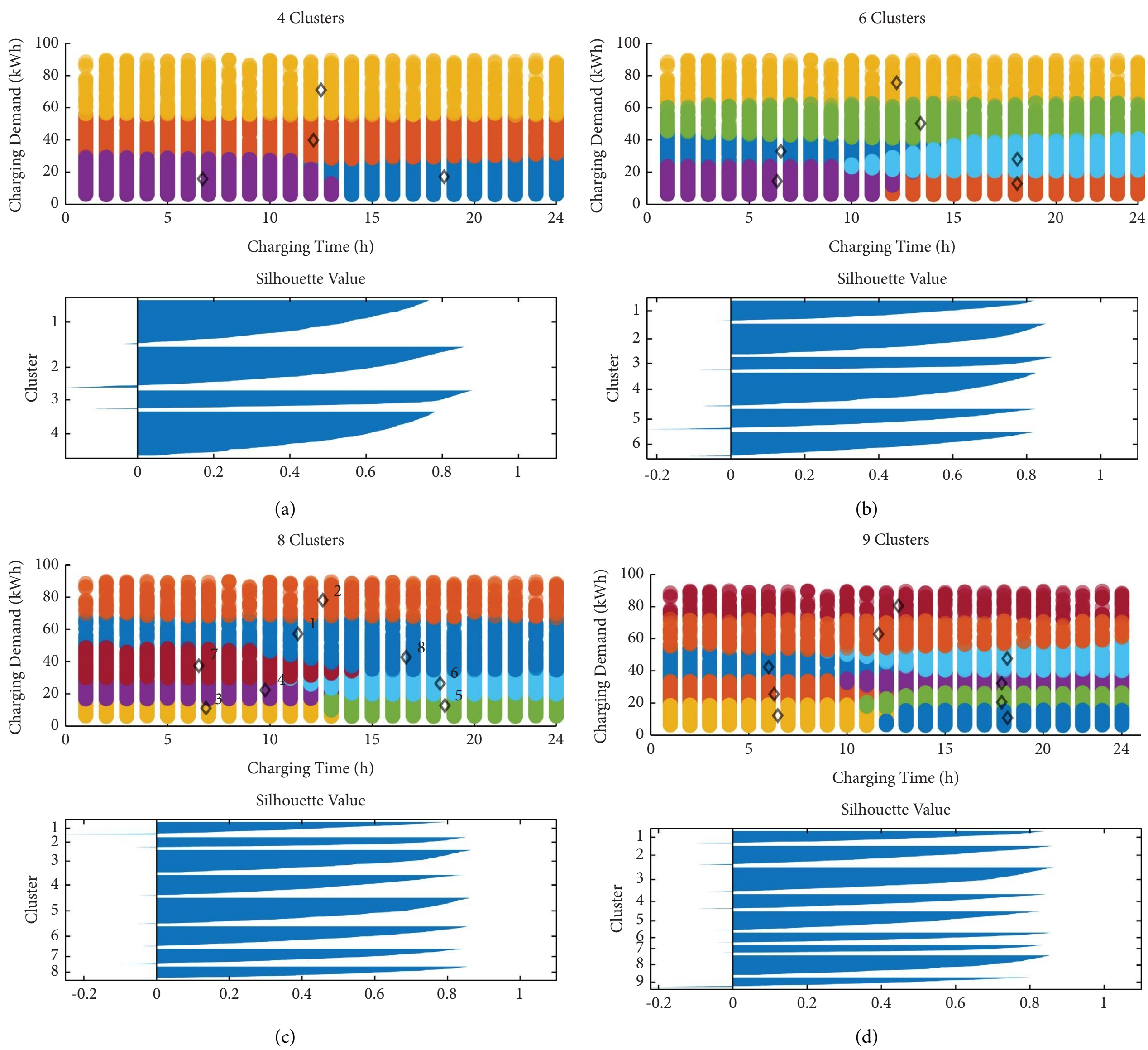


Figure 2: EV owners' charging classification effects under different numbers of clusters. (a) 4 clusters. (b) 6 clusters. (c) 8 clusters. (d) 9 clusters.

When the number of clusters is 8 or 6, the classification effect is better. The silhouette coefficient has a lot of negative values when the number of clusters is 8, so this paper selects the number of clusters to be 6. In the 6 clusters, clusters 2-th, 3-th, and 5-th are light V2G EV owners, and clusters 1-th, 4-th, and 6-th are heavily V2G EV owners. In terms of V2G time, clusters 3-th and 4-th are EV owners V2G in the morning, clusters 2-th and 6-th are EV owners V2G at the noon, and clusters 1-th and 5-th are EV owners V2G at the night.

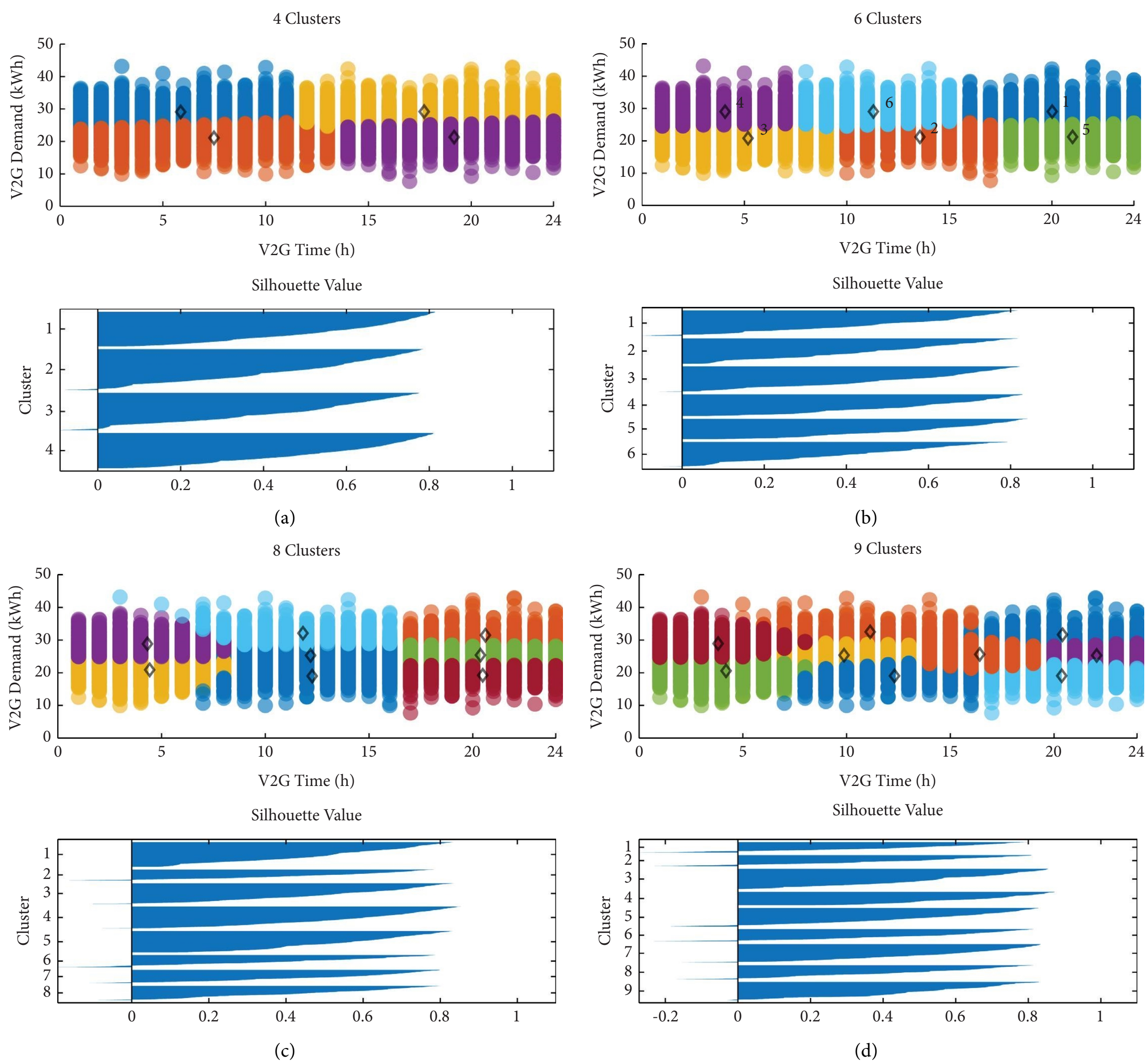


FIGURE 3: EV owners' V2G classification effects under different numbers of clusters. (a) 4 clusters. (b) 6 clusters. (c) 8 clusters. (d) 9 clusters.

4.2. Study A: EV Charging Schedule. Study A only considers EV charging, and it is divided into case 1 and case 2. (1) Case 1: unclassified scheduling for EV charging; (2) case 2: classified scheduling for EV charging.

This paper uses Monte Carlo simulation to simulate the charging load of 7000 EVs, accounting for about 2% of the base load. The basic load and EV charging load are shown in Figure 4. According to Figure 4, the base load has two load peak periods at 10:00–14:00 and 18:00–20:00 and two load valley periods at 1:00–4:00 and 21:00–24:00. So, a day can be divided into the six periods: the first valley period (1:00–4:00); the first transition section (5:00–9:00); the first peak period (10:00–14:00); the second transition section (15:00–17:00); the second peak period (18:00–20:00); and the second valley period (21:00–24:00).

In terms of EV load, comparing the EV load before scheduling and after scheduling, the scheduling effect for EV owners is significant. In the first valley period, the initial EV charging load is about 8300 kW, and the load increases to nearly 9000 kW after unclassified scheduling and increases to nearly 10500 kW after classified scheduling, respectively. From the first transition period to the first peak period, the initial EV charging load increases significantly from 8200 kW to 9200 kW and then stabilizes at 9000 kW, expanding the load gap of the peak between valleys. The effect of unclassified charge scheduling is small during this period, and the EV charging load slightly decreases at the end of the first peak period, while the EV charging load significantly reduces after the classified scheduling at the first peak period, and the lowest point is only 7600 kW.

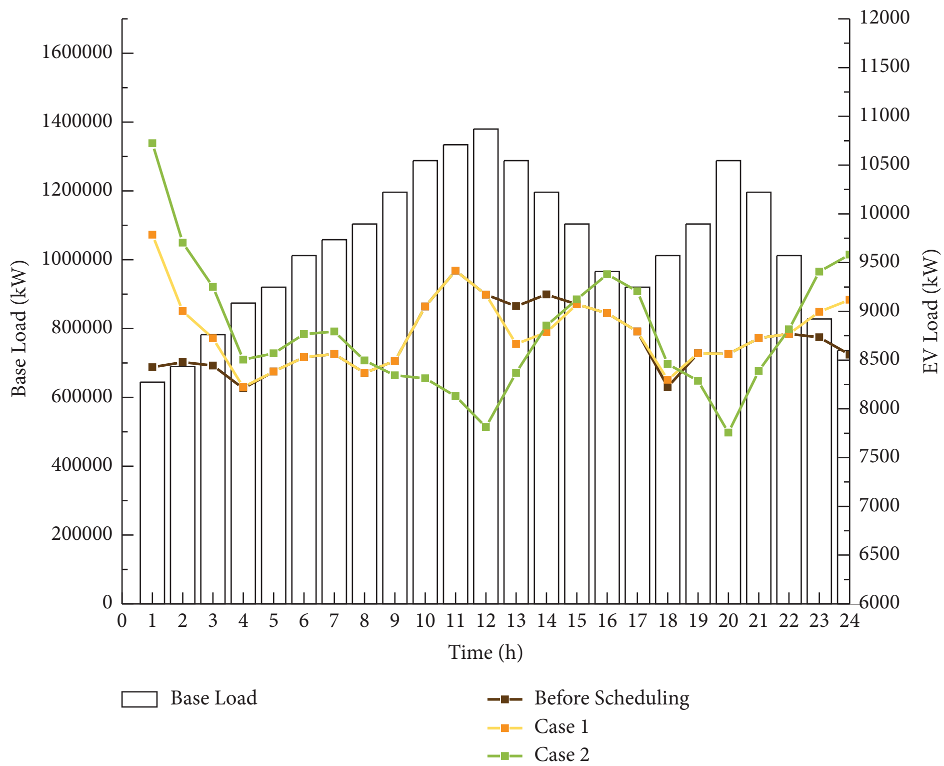


FIGURE 4: Base load and EV load. The bar plot represents the basic load, and the point plot represents the EV charging load.

The initial EV charging load has a fluctuation in the second transition period, second peak period, and second valley period, decreasing to 8100 kW at 18:00, and stabilizing around 8700 kW at other periods. The EV charging load increases to 9200 kW in the second transition section, then decreases to 7600 kW in the second peak period, and rapidly increases to 9000 kW in the second valley period after classified scheduling. The EV charging load gap between the peaks with valley effectively decreases after scheduling. Moreover, classified scheduling is superior to unclassified scheduling in all periods.

The payoff and load data of Study A are presented in Table 2. The "revenue" column represents the revenue generated from selling electricity in the smart grid. The "output cost" column represents the cost of power generation from the generator units. The "charging load" column indicates the total load from EV charging. The "load variance" column represents the variance of the total load in the smart grid. The revenue of case 2 increases ¥1×10^5 than case 1. In terms of output cost, the output costs of the case 1 and the case 2 are close, and the output cost of case 2 is slightly lower than case 1 about ¥1×10^4. The charging load of case 1 decreases 5000 kWh compared to before scheduling. The output costs of case 1 and case 2 are close, but the charging load of case 2 is larger, and it can be seen that the load distribution of case 2 has better economic benefits. Variance can reflect the dispersion of data. Load variance reflects the fluctuation of load, and the variance of case 2 is 7×10^7 smaller than that of case 1. When EV charging load only accounts for 2% of the base load, it shows that the classified scheduling achieves good results in reducing the gap of the peak between valleys.

The charging price of EV owners is shown in Figure 5, and the initial charging price is set as 0.3 ¥/kWh. According to Figure 5, case 1's range of price change is small. The price slightly drops in the first and second valleys and slightly rises in the first and second peaks. In terms of case 2, the charging prices of clusters 1-th, 2-th, 3-th, and 7-th have significant fluctuation in a day, while the charging prices of clusters 4-th, 5-th, 6-th, and 8-th fluctuate slightly. The charging prices of clusters 1-th and 2-th EV owners sharply rise before 13:00, especially at 11:00 and 12:00, the charging price of cluster 2-th EV owners closes to the upper limit of 0.6 ¥/kWh, and the charging price of cluster 1-th EV owners drops sharply to the lower limit of 0.2 ¥/kWh after 15:00. The charging price of cluster 2-th EV owners drops sharply at 13:00 and drops sharply to the lower limit of 0.2 ¥/kWh after 14:00. The charging prices of the clusters 3-th and 7-th EV owners drop sharply almost to the lower limit before 12:00. After 14:00, the charging price of these two clusters rises significantly, especially the charging price of the cluster 3-th EV owners rises to 0.58 ¥/kWh at 17:00, and the charging price of the cluster 7-th EV owners rises to 0.51 ¥/kWh at 20:00. The charging price of cluster 4-th EV owners rises to 0.35 ¥/kWh from 10:00 to 14:00 and drops to 0.23 ¥/kWh. The charging price of cluster 5-th EV owners drops slightly from 05:00 to 09:00 and rises after 12:00, and the price peak is at 20:00. The charging price of cluster 6-th EV owners rises from 5:00 to 9:00 and gets the highest point 0.36 ¥/kWh at 12:00. The charging price of cluster 8-th EV owners drops all the time.

Table 2: Payoff and load data of Study A.

	Revenue (¥)	Output cost (¥)	Charging load (kWh)	Load variance
Before scheduling	4.202×10^7	3.989×10^6	208740	5.25×10^{10}
Case 1	4.296×10^7	3.893×10^6	206652	5.218×10^{10}
Case 2	4.307×10^7	3.892×10^6	211036	5.211×10^{10}

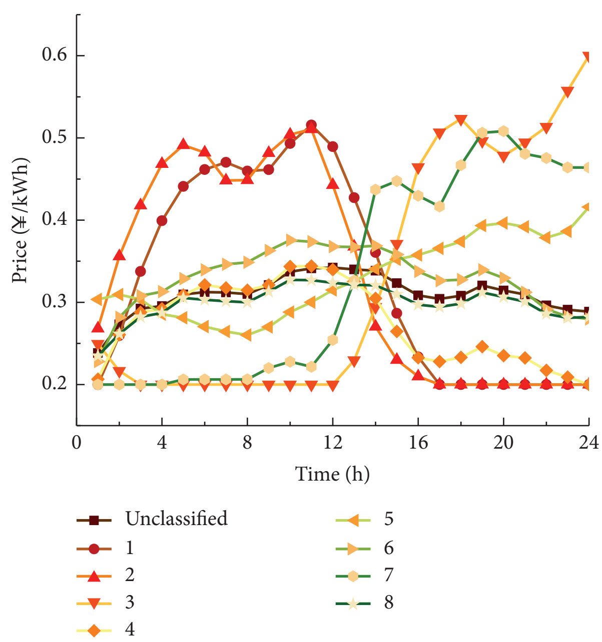


Figure 5: Charging price of EV owners. The initial charging price is set as 0.3 ¥/kWh. The curves in different colors are the charging prices of different EV owners.

Two trends can be seen from the charging prices of various EV owners: (1) the price increases during the period that the load of these EV owners is concentrated, and the price reduces during the period that the load of these EV owners is less; (2) the price will increase in peak periods and will reduce in valley periods.

Figure 6 shows the load changes of various EV owners after scheduling where Figure 6(a) is the EV charging load stack diagram after unclassified scheduling and Figure 6(b) is the EV charging load stack diagram of case 2. It can be seen in Figure 6(a) that the loads of clusters 1-th, 2-th, 3-th, 4-th, and 7-th EV owners are concentrated in a certain period, while the loads of clusters 5-th, 6-th, and 8-th EV owners are widely distributed in all periods. The loads of clusters 1-th, 2-th, and 4-th EV owners are mainly concentrated in the first valley period, the first transition period, and the first peak period. It can be observed that the load periods of different types of EV owners remain almost unchanged, indicating the insufficient scheduling capability of unclassified scheduling. After classified scheduling, the loads of clusters 1-th, 2-th, and 4-th EV owners have more than 10% increase in the first valley and about 10% decrease in the first peak. The loads of clusters 3-th and 7-th EV owners transfer some loads to the first valley period, first transition section, and first peak period. Cluster 3-th EV owners transfer 1000 kW load to the first valley period and 1200 kW load to the first peak period. Cluster 4-th EV owners transfer 1200 kW load to the first valley period and 400 kW load to the first peak period. The loads of clusters 5-th, 6-th, and 8-th EV owners transfer from two peak periods to two valley periods.

By considering the price and load variations of different types of EV owners, it can be observed that unclassified scheduling has a limited range of price changes due to the need for the responses of various types of EV owners. On the other hand, classified scheduling only needs to consider the response of a specific type of EV owner, allowing for larger price variations. As a result, unclassified scheduling exhibits weaker scheduling capability because it lacks the ability to effectively guide different types of EV owners in shifting their loads to other time periods.

4.3. Study B: EV Charging and V2G Scheduling. Study B considers EV charging and V2G, and it is divided into case 3 and case 4: case 3: unclassified scheduling for EV charge and V2G; case 4: classified scheduling for EV charge and V2G.

Electric energy flows from the electric grid to EVs during EV charging. Therefore, guiding EV owners to increase charging during valley periods and decrease charging during peak periods is very useful for reducing the gap between peak and valley periods.

As shown in Figure 7, the charging scheduling effect of case 3 is poor, and the charging load decreases to 7700 kW in the first valley period and increases to 10000 kW in the first peak period. The gap between peak and valley periods will aggravate after unclassified scheduling while case 4 has a good scheduling effect on the charging load. The load increases during the first valley period, reaching a peak of around 10500 kW, and then decreases to 7500 kW during the first and second peak periods. It then increases again to 9500 kW during the second valley period.

Electric energy flows from the EVs to the electric grid during EV V2G, so guiding EV owners to decrease V2G in the valley periods and increase V2G in the peak periods is very useful to reduce the gap between peaks with valley periods. In the first valley period, the V2G decreases to 3600 kW after classified scheduling. In terms of case 3, the V2G increases to 7000 kW in the first transition period and decreases to 4500 kW in the second transition period. In contrast, the V2G fluctuation of case 4 is smoother.

Table 3 displays the payoff and load data from Study B, wherein V2G load represents the total load of EVs V2G. The revenue for Case 4 has improved by about ¥1.1×10^6 compared to Case 3. Meanwhile, the output cost of Case 4 is ¥1×10^5 less than Case 3. From Study B, it can be deduced that the disparities in both revenue and output cost between Case 3 and Case 4 are more pronounced than those in Study A. While the charging and V2G load for Case 3 are lower

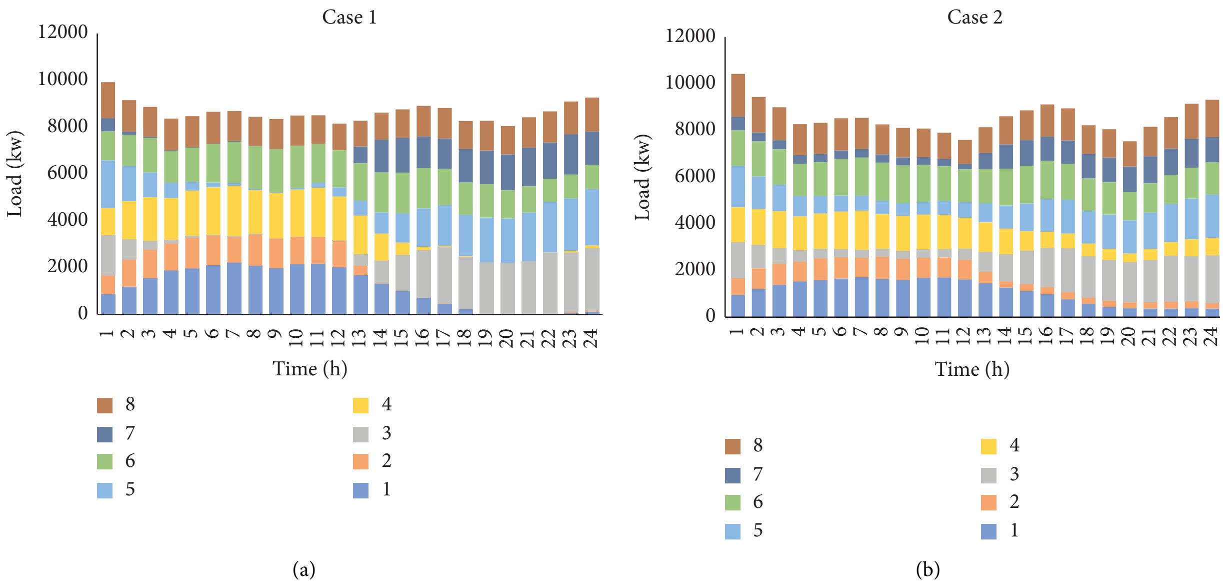


Figure 6: Stacking diagram of charging loads of EV owners. (a) The charging load stack diagram after unclassified scheduling. (b) The charging load stack diagram after classified scheduling.

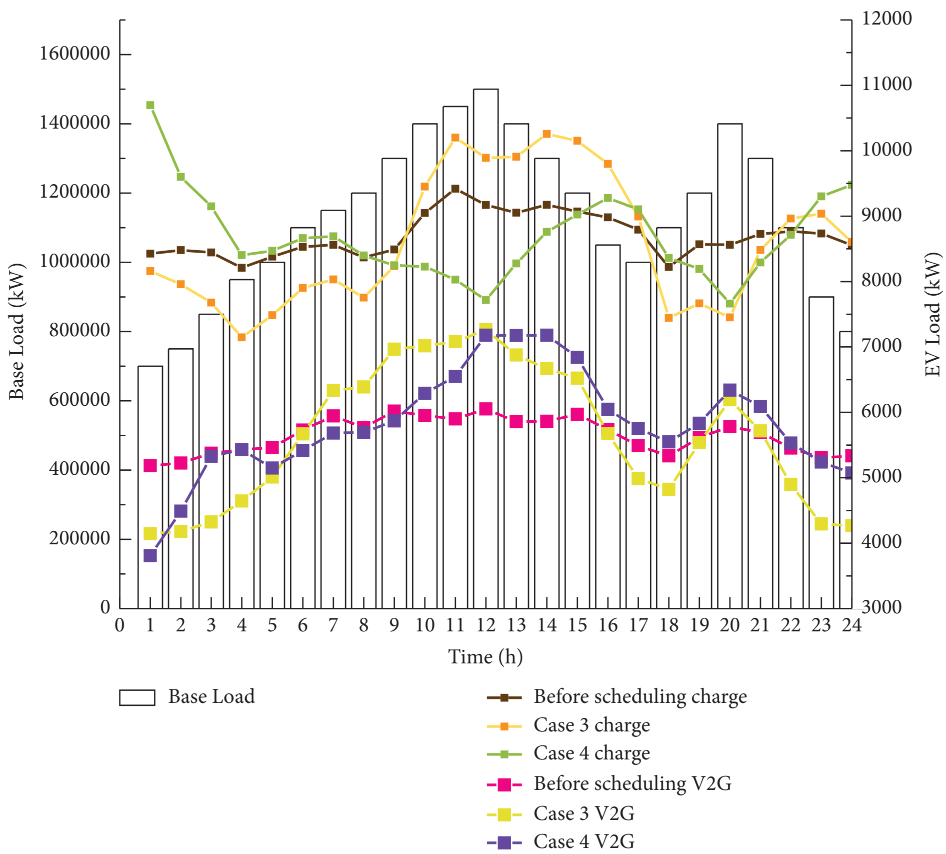


Figure 7: Base load, EV charge, and V2G load. The bar plot represents the base load, and the point plot represents the EV charging and V2G load.

than those of Case 4, the output cost of Case 3 is higher than that of Case 4. This underscores the advantage of classified scheduling in economic benefits. Additionally, the load variance in Case 4 is approximately 1% less than that in Case 3, indicating that classified scheduling has advantages in narrowing the gap between peak and valley periods. From

Table 3: Payoff and load data of Study B.

	Revenue (¥)	Output cost (¥)	Charging load (kWh)	V2G load (kWh)	Load variance
Case 3	4.17×10^7	3.97×10^6	206652	135469	5.21×10^{10}
Case 4	4.28×10^7	3.87×10^6	208740	139534	5.17×10^{10}

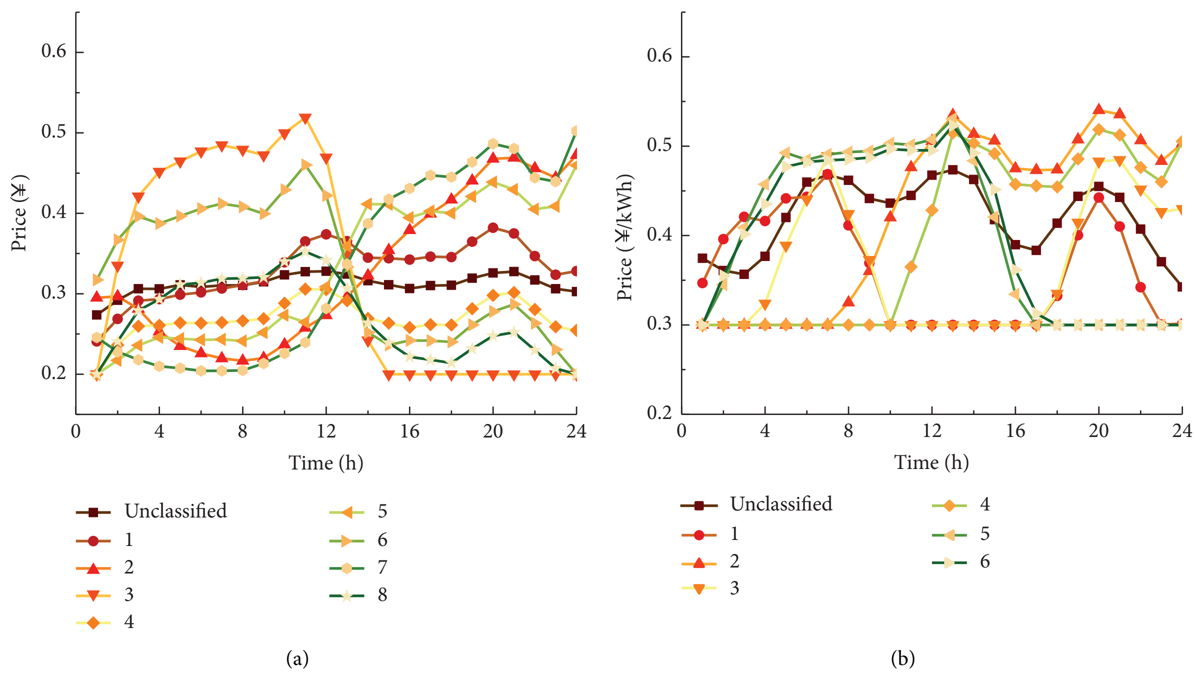


Figure 8: Charging and V2G price of EV owners. The initial charging price is set as 0.3 ¥/kWh, and the initial V2G price is set as 0.4 ¥/kWh. (a) The charging price of EV owners. (b) The V2G price of EV owners.

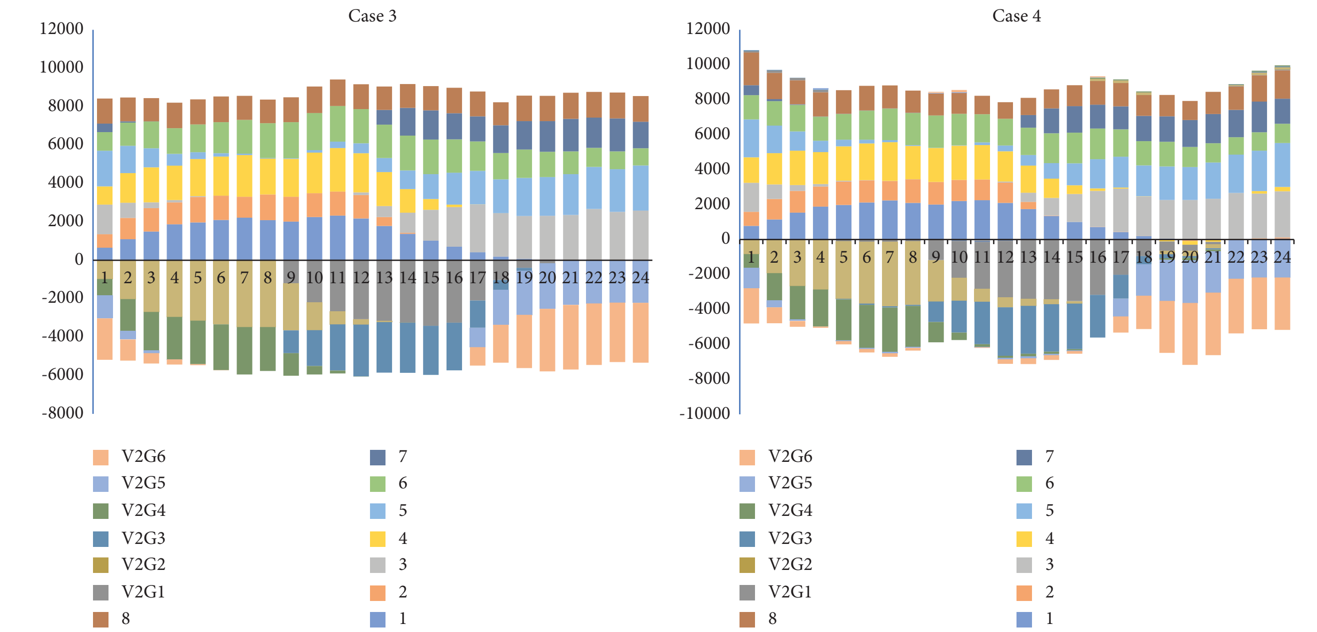
the above observations, it can be concluded that after classified scheduling, the distribution of EV charging load and V2G load becomes more reasonable, leading to a reduction of generation costs and an increase in the smart grid revenue.

As shown in Figure 8(a), the charging price of case 3 in valley periods rises by 0.02–0.05 ¥/kWh, and it leads to anincrease in the peak valley difference of EV charging load.

As shown in Figure 8(b), the V2G price of case 3 drops by 0.04 to 0.07 ¥/kWh in the first and second valley periods and rises by 0.01 to 0.03 ¥/kWh in the first and second peak periods. After unclassified scheduling, the distribution of V2G is close to the basic load. The V2G price change range of case 4 is −0.1–0.16 ¥/kWh. The V2G price of clusters 1-th and 4-th EV owners decreases to the lower limit of 0.3¥/kWh during the first valley period, and the V2G price of clusters 5-th and 6-th EV owners decreases to the lower limit too in the second peak period. By comparing case 3 and case 4, it can be seen that classified scheduling has more significant potential in scheduling.

Figure 9 shows the charging and V2G load changes of various EV owners after scheduling where Figure 9(a) is the charging and V2G load stack diagram after unclassified scheduling and Figure 9(b) is the EV charging and V2G load stack diagrams after the classified schedule, respectively. It can be seen from Figure 9(a) that the clusters 1-th and 3-th EV owners' V2G are mainly distributed in the first and second peak periods, the V2G of clusters 2-th and 6-th EV owners is mainly distributed in the first and second valley periods, the V2G of cluster 4-th EV owners is mainly distributed in the first valley period and the first peak period, and the V2G of cluster 5-th EV owners is mainly distributed in the first and second valley periods and the second peak period. As shown in Figure 9(b), after the classified schedule, during the first valley period, the V2G of cluster 2-th EV owners decreases to 1390 kW, accounting for about 20% of the initial V2G. During the first peak period, the V2G of cluster 2-th EV owners increased by 2479 kW, the V2G of cluster 4-th EV owners increased by 565 kW, the V2G of cluster 5-th EV owners increased by 993 kW, and the V2G of cluster 6-th EV owners increases by 3394 kW. During the second peak period, the V2G of the clusters 2-th and 4-th EV owners increased, including 2155 kW of cluster 2-th EV owners and 957 kW of cluster 4-th EV owners. During the second valley period, the V2G of clusters 5-th and 6-th EV owners decreased, including 925 kW of clusters 5-th EV owners and 3157 kW of clusters 6-th EV owners.

From the above data, it can be seen that classified scheduling allows for more targeted pricing strategies based on the characteristics of different EV owners, thereby



(a) (b)

Figure 9: Stacking diagram of charging and V2G loads of EV owners. (a) The charging and V2G load stack diagram after unclassified scheduling. (b) The charging and V2G load stack diagram after classified scheduling.

improving its ability to schedule EV loads. As a result, the distribution of EV charging load and V2G load becomes more reasonable. This more rational distribution of EV charging load and V2G load helps to reduce generation costs and increase the revenue of the smart grid. The advantages of classified scheduling are evident in various aspects, showcasing its benefits in multiple aspects.

5. Conclusion

This paper addresses the issue of insufficient scheduling capability of existing unclassified EV load scheduling methods by proposing a method for classifying EV load scheduling based on the characteristics of EV owners. To better reflect the response of different types of EV owners to scheduling, this paper expands upon the traditional price elasticity model by incorporating time preference time elasticity and time gap elasticity, comprehensively capturing the diverse responses of different EV owners to scheduling. Through comparative analysis of relevant data, this paper achieves the following improvements compared to previous studies:

(1) Expanded the boundaries of the traditional model: This paper extends the traditional EV owner DR model by considering the different responses of EV owners to time and price.

(2) Proposed an improved scheduling method tailored for EV loads: The proposed classified scheduling method in this paper demonstrates stronger scheduling capability for EV loads compared to traditional unclassified scheduling methods (demonstrated in Section 4.2). With EV load accounting for only 2%, there was an increase of 0.25% in revenue of the smart grid. The classified scheduling method formulates more targeted prices based on the characteristics of different types of EV owners, significantly improving the scheduling capability during preferred time periods and expanding the range of adjustable time.

(3) By comparing Study A & Study B in Section 4, this paper showcases the stronger potential application of classified scheduling after the implementation of V2G. With the increasing interaction between EVs and the smart grid, the advantages of classified scheduling over unclassified scheduling are also enhanced.

In addition, future work could further explore the following two aspects:

(1) The load characteristics of some EV owners may change, and it is necessary to further consider the transitions between different types of EV owners.

(2) Since V2G is still in the theoretical research stage and lacks real-world data on EV charging and V2G load after V2G implementation, future research based on real data can further explore the usage characteristics of EV owners.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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