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Optimal Scheduling and Compensation Pricing Method for Load Aggregators Based on Limited Peak Shaving Budget and Time Segment Value

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Abstract: Load-side peak shaving is an effective measure to alleviate power supply–demand imbalance. As a key link between a vast array of small- and medium-sized adjustable resources and the bulk power system, load aggregators (LAs) typically allocate peak shaving budgets using fixed pricing methods based on peak shaving demand forecasts. However, due to the randomness of supply and demand, fluctuations in peak shaving demand occur, making it a significant technical challenge to meet peak shaving needs under limited budget allocations. To address this issue, this paper first conducts a clustering analysis of various adjustable load characteristics to derive typical electricity consumption curves, and then proposes a differentiated calculation method for the value of multi-time-segment peak shaving. Subsequently, an optimization model for LA scheduling and compensation pricing is established based on the limited peak shaving budget and time-segment peak shaving value. While ensuring the economic benefits of LAs, the model also analyzes the impact of different peak shaving budget allocations on the scale of peak shaving that can be achieved. Finally, case studies demonstrate that, compared to traditional fixed compensation pricing, the proposed pricing method reduces scheduling costs by an average of 16.5%, while significantly improving the overall satisfaction of adjustable users.

Keywords: adjustable load; load aggregators; optimal scheduling; peaking value; budget; compensation pricing

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1. Introduction

In recent years, the rapid growth in the installed capacity of renewable energy has significantly exacerbated the challenges of peak shaving for power grids [1]. Load-side peak shaving is an effective supplementary measure to alleviate power supply–demand imbalance and facilitate the integration of green electricity. However, load-side adjustable resources consist of a large number of distributed adjustable loads. If the grid were to directly dispatch all individual loads, not only would the dispatch costs be extremely high, but the control process would also become overly complex. As a specialized demand response provider, the LA can integrate idle small- and medium-sized load-side resources and participate in distribution network control through multi-stakeholder consensus-based regulation. This approach enhances the resilience of the distribution network, allowing adjustable load-side resources to play a significant role in the peak shaving market. Currently, the main source of profit for LAs in peak shaving comes from the price difference between the economic incentives offered to users and the subsidies provided through contracts signed with the superior power grid [2]. Typically, LAs use fixed pricing methods to allocate peak shaving budgets based on forecasts of peak shaving demand [3]. Therefore, one of the critical technical challenges LAs face is how to reasonably design a user compensation mechanism under a limited peak shaving budget.

In recent years, numerous scholars both domestically and internationally have conducted extensive research on LAs, load-side optimal scheduling, and subsidy pricing.

In terms of LAs, the study in [4] proposed a robust optimization strategy for LA bidding in the main energy market based on controllable loads. The study in [5] established a multi-LA market bidding and grid economic dispatch model for grid frequency regulation services. The authors of [6] proposed a control framework and control methods for LAs targeting temperature-controlled loads such as air conditioners and water heaters. The research in [7] introduced a stochastic decision-making model for LAs in the day-ahead and real-time markets and evaluated the impact of implementing load reduction contracts on the aggregator's decision-making process.

In terms of load-side optimal scheduling, the study in [8] addresses the multi-time-scale characteristics of demand response (DR) resources, proposing a resource response evaluation system and utilizing membership functions to characterize the uncertainty of user response behavior. This leads to the construction of an optimal scheduling model for LAs that considers diverse user response behaviors. In [9], a master–slave game model is established between the profit of integrated energy parks and the energy usage of residential users, which is then transformed into a single-layer optimization model for finding a solution using the Karush–Kuhn–Tucker (KKT) conditions. The authors of [10] consider the adjustment characteristics of shiftable loads and interruptible loads, introducing an electric vehicle charging and discharging model to improve the utilization rate of wind and solar power and achieve the coordinated optimization of supply and demand. The study described in [11] takes into account the transaction model between the distribution system operator (DSO), LAs, and users, constructing a bi-level optimization model for the distribution system. The upper and lower models aim to maximize the profits of the DSO and LA, respectively, fully exploring the potential for user load adjustment. These studies primarily focus on the optimization of LA scheduling strategies. However, they do not fully account for the daily fluctuations in green electricity generation on the supply side, which directly impacts the allocation of the LA's budget when participating in the day-ahead peak shaving market.

In terms of subsidy pricing, ref. [12] modifies the peak, flat, and valley periods based on the peak shaving demand curve, and establishes a leader–follower game model, aiming to maximize the profits of the LA and the utility of users at the upper and lower levels, respectively. This approach ultimately leads to the optimization of the user subsidy price. The study in [13] analyzes various types of load models that consider user comfort and satisfaction, and establishes an optimized compensation pricing and energy consumption model for different users, taking into account the varying contributions of different types of users to demand response. Meanwhile, ref. [14] clusters adjustable load groups based on their characteristics and assigns subsidy prices according to priority levels. It is clear that, when balancing the interests of multiple stakeholders, most studies adopt a leader–follower game model. However, in practical applications, the complexity of these models poses a significant challenge to the broader implementation of the proposed pricing mechanisms. This is not only because the model structures may fail to satisfy the Karush–Kuhn–Tucker conditions [15,16], but also due to the excessive computational resources and time required to solve these models, further limiting their widespread adoption. Moreover, adopting a fixed pricing mechanism directly makes it difficult to effectively differentiate user value, thereby failing to fully incentivize users' potential for load adjustment. In conclusion, there is still room for improvement in the existing research on LA scheduling optimization. First, while some studies have examined the impact of the LA's user compensation mechanisms and budget on optimal scheduling, there remains a lack of in-depth exploration into how to accurately measure the peak shaving value of users across different time periods and how to allocate funds appropriately. In particular, given that the LA's available budget is limited and cannot be expanded indefinitely, it is essential to accurately evaluate the peak shaving value in different periods. Second, due to the inherent volatility of supply and demand, users' contributions to peak shaving vary across time segments, necessitating a more flexible compensation mechanism to balance the interests of both the load aggregator and the users.

In view of the above problems, this paper takes the minimum cost of LA peak shaving as the objective function, comprehensively considers the interaction between power dispatching center, LA, and load-side users, forms a typical user electricity consumption curve based on the cluster analysis of adjustable load regulation characteristics, and proposes a differentiated calculation method of multi-period peak load value to ensure the comfort of each user. An optimal scheduling and compensation pricing model of load aggregators based on the allocation of limited budget and the value of time segment peak adjustment is established. The practicability of the proposed method is verified by practical examples.

2. Flowchart of Optimization Scheduling and Compensation Pricing Method for Load Aggregators Based on Limited Peak Shaving Fund Allocation and Time-Based Peak Shaving Value

A flowchart of the proposed optimization scheduling and compensation pricing method for load aggregators, based on limited peak shaving fund allocation and the time-based peak shaving value, is shown in Figure 1. Electric vehicles currently account for more than 10% of the distribution area's load and can serve as distributed energy storage devices within industrial parks.

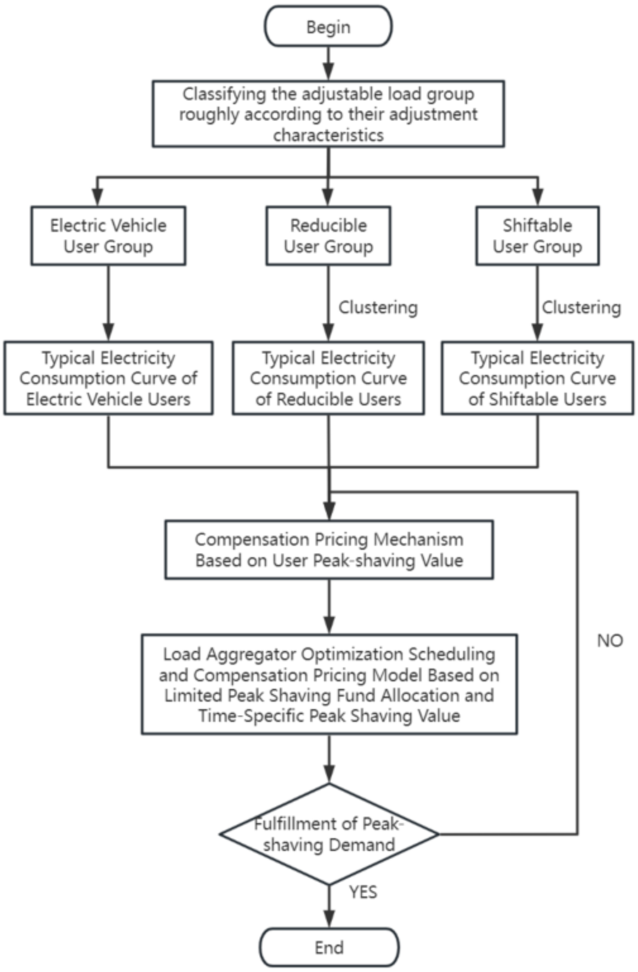


Figure 1. Flowchart of optimization scheduling and compensation pricing method for load aggregators based on limited peak shaving fund allocation and time-based peak shaving value.

3. Adjustable Load Characteristics and Clustering Method

Load-side users have diversity and variability, reflecting the differing response characteristics of various electricity consumers. Therefore, it is necessary to cluster users based on their load characteristics, allowing the LA to coordinate the scheduling of loads with similar attributes, thereby reducing the complexity of regulation. This paper primarily considers distributed energy storage devices in the form of electric vehicles (EVs) within the industrial park. Since most of these EVs belong to employees as private vehicles, they are excluded from the clustering process. However, shiftable and reducible loads, mainly consisting of mechanical equipment in the industrial park, are included in the clustering based on their adjustable characteristics.

In this paper, adjustable loads are broadly classified into three categories based on their response characteristics:

1. Type I Loads (Distributed Energy Storage): This refers to electricity loads located in different places that can flexibly adjust according to electricity demand or market price signals. These loads can be distributed across various areas, such as residential neighborhoods, commercial facilities, and industrial parks, typically including electric vehicle charging stations, smart household appliances, and industrial production equipment;
2. Type II Loads (Reducible Loads): This refers to equipment that responds to demand by reducing electricity consumption, primarily represented by industrial machinery, commercial air conditioning systems, and other high-power loads;
3. Type III Loads (Shiftable Loads): This refers to devices where the total load remains constant over a scheduling period, but the load can be flexibly adjusted across different time periods. Examples include certain industrial production equipment, washing machines, and water heaters.

3.1. Adjustable Loads Clustering

3.1.1. Adjustable Loads Clustering Index

The adjustable loads exhibit diversity and variability in their regulation characteristics. Therefore, it is necessary to cluster users based on these features. Compared to other clustering algorithms, the k-means clustering algorithm is more suitable for the practical needs of our study due to its adaptability in handling large volumes of load data in industrial parks and its relatively low computational complexity. Therefore, in this study, the k-means algorithm is applied to cluster reducible loads and shiftable loads, using the following features selected as the basis for clustering.

- Reducible loads:

The peak shaving method for this type of load involves directly restricting the current electricity consumption behavior of the equipment. Therefore, the clustering characteristic indicators for this type of load are as follows:

1. Primary and secondary reducible loads γ_1 [17]

The difference in load between the peak load and the loads of the two adjacent time periods in the daily load curve indicates the load reduction potential of user *i*. A larger value signifies a greater potential for user iii to reduce their load. The calculation method is as follows:

$$\gamma_1 = P_{peak}^{II}(i) - \min(P_{peak-1}^{II}(i), P_{peak+1}^{II}(i)) \tag{1}$$

In the formula, $P_{peak}^{II}(i)$ represents the typical peak value of the i-th dispatchable load during the day, and $P_{peak-1}^{II}(i), P_{peak+1}^{II}(i)$ represents the load values in the time periods adjacent to the peak.

2. Peak flexible load γ_2

The standard deviation of the load on a typical day indicates the flexibility of the load. A larger value signifies greater flexibility and a higher potential for the load to participate in real-time peak shaving. The calculation method is as follows:

$$\gamma_2 = \sqrt{\left(P^{II}_{peak}(i) - \overline{P^{II}(i)}\right)^2} \tag{2}$$

In the formula, $\overline{P^{II}(i)}$ represents the mean value of the i-th dispatchable load within a typical day.

- Shiftable Load:

Due to the occurrence of load shifting in and out within a single day, the clustering characteristic indicators for this type of load are as follows:

1. Daily Peak–Valley Difference Rate γ_3

The ratio of the difference between the peak and valley load on a typical day to the peak load indicates the shiftable potential. A larger value signifies a greater potential for shifting. The calculation method is as follows:

$$\gamma_3 = \left(P^{III}_{peak}(i) - P^{III}_{valley}(i)\right) / P^{III}_{peak}(i) \tag{3}$$

In the formula, $P^{III}_{peak}(i)$ and $P^{III}_{valley}(i)$ represent the peak and valley values of the i-th dispatchable load, respectively.

2. Load Volatility Rate γ_4

This refers to the variance of the load curve of user ii on a typical day divided by the mean. The greater the load volatility rate, the greater the potential for dispatchable load of user ii. The calculation method is as follows:

$$\gamma_4 = \sigma^{III}(i) / \mu^{III}(i) \tag{4}$$

In the formula, $\sigma^{III}(i)$ and $\mu^{III}(i)$ represent the variance and mean of the dispatchable load i on a typical day, respectively.

3.1.2. Adjustable Load Clustering

Based on the above clustering characteristics, the Euclidean distance is used to calculate the distance between each data point in the dataset and the centroid, clustering the two types of adjustable loads. The specific steps are as follows:

1. Determine the number of clusters (k) for the two types of adjustable loads and randomly select initial centroids;
2. Calculate the distance between each data point in the dataset and the centroids, assigning each point to the cluster associated with the nearest centroid;
3. Once all adjustable load data points have been classified, recalculate the centroids of each cluster;
4. If the distance between the newly calculated centroids and the original centroids is less than a predetermined threshold, the clustering is considered successful; otherwise, repeat steps 2 to 4.

After processing through the above clustering steps, the typical users participating in peak shaving will be clustered into m and l categories, thereby reducing the difficulty of LA regulation and maximizing the satisfaction of user energy demands.

4. Multi-Period Peak Shaving Value Differentiation Method

To fully assess the peak shaving value across different time periods and reduce LA's peak shaving costs, this paper proposes a multi-period peak shaving value differentiation method. This approach takes into account constraints such as peak shaving range, demand, budget, three types of load models, and user satisfaction. It enables the LA to more accurately evaluate the peak shaving value of users at various time periods and align it with user compensation pricing, thereby optimizing LA's operational efficiency while ensuring the users' basic electricity needs are met [18].

Constraints (5)–(7) represent the peak shaving capacity range for the three types of loads at a given time. Constraints (8)–(10) define the peak shaving capacity as the difference between the active power before and after peak shaving for the adjustable loads. Constraints (11)–(20) ensure the matching between the user response time and the indicated response participation amount.

$$-P_t^{I.\max} \leq \Delta P_t^I \leq P_t^{I.\max} \tag{5}$$

$$0 \leq \Delta P_{t,m}^{II} \leq P_{t,m}^{II.\max} \tag{6}$$

$$-P_{t,m}^{III.\max} \leq \Delta P_{t,m}^{III} \leq P_{t,m}^{III.\max} \tag{7}$$

$$\Delta P_t^I = P_t^{I,base} - P_t^I \tag{8}$$

$$\Delta P_{t,m}^{II} = P_{t,m}^{II,base} - P_{t,m}^{II} \tag{9}$$

$$\Delta P_{t,m}^{III} = P_{t,m}^{III,base} - P_{t,m}^{III} \tag{10}$$

In the equations, $P_t^{I,base}$, $P_{t,m}^{II,base}$, and $P_{t,m}^{III,base}$ represent the baseline daily electricity consumption power for the three types of adjustable loads. P_t^I, $P_{t,m}^{II}$, and $P_{t,m}^{III}$ denote the daily electricity consumption power curves after peak shaving for these three types of adjustable loads. ΔP_t^I, $\Delta P_{t,m}^{II}$, and $\Delta P_{t,m}^{III}$ represent the active power differences for Type I, Type II, and Type III adjustable loads before and after peak shaving during each time period, indicating the capacity for participating in the peak shaving market response.

$$\Delta P_t^I < M x_t^I \tag{11}$$

$$\Delta P_t^I > -M(1 - x_t^I) + \lambda \tag{12}$$

$$\Delta P_{t,m}^{II} < M x_{t,m}^{II} \tag{13}$$

$$\Delta P_{t,m}^{II} > -M(1 - x_{t,m}^{II}) + \lambda \tag{14}$$

$$\Delta P_{t,m}^{III} < M x_{t,m}^{III.1} \tag{15}$$

$$\Delta P_{t,m}^{III} > -M(1 - x_{t,m}^{III.1}) + \lambda \tag{16}$$

$$\Delta P_{t,m}^{III} > -M x_{t,m}^{III.2} \tag{17}$$

$$\Delta P_{t,m}^{III} < M(1 - x_{t,m}^{III.2}) - \lambda \tag{18}$$

$$x_{t,m}^{III} = x_{t,m}^{III.1} + x_{t,m}^{III.2} \tag{19}$$

$$\Delta P_t^{I,a} = \Delta P_t^I x_t^I \tag{20}$$

In the equations, x_t^I, $x_{t,m}^{II}$, and $x_{t,m}^{III}$ are the state variables for the participation of the three types of adjustable loads in the peak shaving ancillary market. $x_{t,m}^{III}$ is composed of two state variables, $x_{t,m}^{III.1}$ and $x_{t,m}^{III.2}$, for movable loads that can be shifted in and out. $\Delta P_t^{I,a}$ represents the amount of energy storage load scheduled positively by the LA (i.e., the energy level before peak shaving is greater than after peak shaving); M and λ represent the maximum and minimum values, respectively.

The sum of the peak shaving response capacities of different adjustable loads should meet the peak shaving demand issued by the power grid to achieve supply and demand balance. As shown below, P_t^{base} represents the daily peak shaving demand issued by the grid center, and P_t^f represents the amount of load that remains unresponsive.

$$P_t^{base} = \Delta P_t^I + \sum_m \Delta P_{t,m}^{II} + \sum_m \Delta P_{t,m}^{III} + P_t^f \tag{21}$$

Considering the multiple peaks that occur within a single day in the current power peak shaving market, the importance and urgency of peak shaving during different time periods vary. To more accurately reflect the peak shaving value at different times, this paper introduces a weighting coefficient for the peak shaving value in each time period. The calculation formula is as follows:

$$U_t^I = \left(P_t^{I,base} - P_t^{I,base,\min}\right) / \left(P_t^{I,base,\max} - P_t^{I,base,\min}\right) \tag{22}$$

$$U_{t,m}^{II} = \left(P_{t,m}^{II,base} - P_{t,m}^{II,base,\min}\right) / \left(P_{t,m}^{II,base,\max} - P_{t,m}^{II,base,\min}\right) \tag{23}$$

$$U_{t,m}^{III} = \left(P_{t,m}^{III,base} - P_{t,m}^{III,base,\min}\right) / \left(P_{t,m}^{III,base,\max} - P_{t,m}^{III,base,\min}\right) \tag{24}$$

In the equation, $P_t^{I,base,\max}$, $P_{t,m}^{II,base,\max}$, $P_{t,m}^{III,basse,\max}$, $P_t^{I,base,\min}$, $P_{t,m}^{II,base,\min}$, and $P_{t,m}^{III,base,\min}$ represent the peak and valley values of the daily load baseline for the m-th type of adjustable load among the three types of loads. U_t^I, $U_{t,m}^{II}$, and $U_{t,m}^{III}$ represent the peak shaving value executed by each user in each time period for each type of adjustable load.

To fully assess the peak shaving priority of different adjustable loads at various times and to assist the LA in more rationally allocating the peak shaving budget, this paper introduces the priority variation coefficients ρ_t^I, $\rho_{t,m}^{II}$, and $\rho_{t,m}^{III}$ for peak shaving. A larger coefficient indicates a higher peak shaving value for that time period, resulting in a larger share of funds from the peak shaving budget. The calculation formula is as follows:

$$\rho_t^I = U_t^I / \left(U_t^I + \sum_{m=1}^{m} U_{t,m}^{II} + \sum_{m=1}^{m} U_{t,m}^{III}\right) \tag{25}$$

$$\rho_{t,m}^{II} = U_{t,m}^{II} / \left(U_t^I + \sum_{m=1}^{m} U_{t,m}^{II} + \sum_{m=1}^{m} U_{t,m}^{III}\right) \tag{26}$$

$$\rho_{t,m}^{III} = U_{t,m}^{III} / \left(U_t^I + \sum_{m=1}^{m} U_{t,m}^{II} + \sum_{m=1}^{m} U_{t,m}^{III}\right) \tag{27}$$

For each type of adjustable load, the profit obtained from participating in peak shaving directly impacts its willingness to participate, as well as the LA's peak shaving budget. Traditional grid peak shaving pricing methods are relatively fixed, but as peak shaving demand fluctuates daily, this can lead to significant fluctuations in peak shaving costs. In this paper, the proposed peak shaving value-based pricing method can reduce the LA's forecasting bias when setting peak shaving prices and accurately fit the compensation pricing for each time period and typical user within a limited peak shaving budget [19].

$$c_t^I = \left(\rho_t^I C_{all} P_t^I\right) / \left(P_t^{I,base} \sum_{t=1}^{24} P_t^{base}\right) + \alpha^I c_t^{TOU} \tag{28}$$

$$c_{t,m}^{II} == \left(\rho_{t,m}^{II} C_{all} P_{t,m}^{II}\right) / \left(P_{t,m}^{II,base} \sum_{t=1}^{24} P_t^{base}\right) + \alpha^{II} c_t^{TOU} \tag{29}$$

$$c_{t,m}^{III} = \left(\rho_{t,m}^{III} C_{all} P_{t,m}^{III}\right) / \left(P_{t,m}^{III,base} \sum_{t=1}^{24} P_t^{base}\right) + \alpha^{III} c_t^{TOU} \tag{30}$$

In the equation, c_t^I, $c_{t,m}^{II}$, and $c_{t,m}^{III}$ represent the compensation pricing for each typical user; C_{all} denotes the peak shaving budget; α^I, α^{II}, and α^{III} are the adjustment coefficients for the compensation pricing of the three types of adjustable loads; and c_t^{TOU} represents the time-of-use electricity price.

5. Load Aggregator Optimization Scheduling and Compensation Pricing Model Based on Limited Peak Shaving Fund Allocation and Time-Specific Peak Shaving Value

5.1. Objective Function

The model aims to minimize the LA's peak shaving costs as the optimization objective. Under a limited peak shaving budget, it optimizes the peak shaving costs for three types of adjustable loads in order to meet the grid's peak shaving demand [20,21].

$$\min F = \sum_t c_t^I \Delta P_t^{I,a} + \sum_{t,m} c_{t,m}^{II} \Delta P_{t,m}^{II} + \sum_{t,m} c_{t,m}^{III} \left|\Delta P_{t,m}^{III}\right| + \sum_t \varepsilon P_t^f \tag{31}$$

In the formula, F represents the peak shaving cost of the LA, and ε is the penalty coefficient for the unmet peak shaving amount.

In constraint (31), the LA's scheduling cost is composed of the compensation costs of three types of adjustable loads and the penalty for unmet peak shaving demand. Among these, the compensation cost for shiftable loads exhibits nonlinear characteristics, primarily because shiftable loads involve both the shifting out and shifting in of electricity. To address this, an intermediate variable $Z_{t,m}^{III}$ is introduced, and through constraints (32) and (33), the nonlinear part is transformed into a linear form.

$$\Delta P_{t,m}^{III} \le Z_{t,m}^{III} \tag{32}$$

$$-\Delta P_{t,m}^{III} \le Z_{t,m}^{III} \tag{33}$$

At this point, the objective function (34) is as follows:

$$\min F = \sum_t c_t^I \Delta P_t^{I,a} + \sum_{t,m} c_{t,m}^{II} \Delta P_{t,m}^{II} + \sum_{t,m} c_{t,m}^{III} Z_{t,m}^{III} + \sum_t \varepsilon P_t^f \tag{34}$$

5.2. Constraint Conditions

The LA needs to comprehensively consider the regulation characteristics of different types of adjustable loads and, within the regulation constraints, determine the regulation scheme for load clusters based on the regulation potential of each load unit. To this end, this section develops the following constraints for the three types of adjustable loads:

1. Type I load (Distributed Energy Storage)

Currently, the charging behavior of electric vehicles when connecting to and disconnecting from the grid exhibits a high degree of randomness. Constraint (35) represents the time periods for electric vehicles connecting to or disconnecting from the grid. Specifically, the grid connection time period for electric vehicles should fall between T_1^I and T_2^I; therefore, the disconnection time period should be outside of this range. When the electric vehicle is in a disconnected state, its active power should be 0. The formula is as follows:

$$T_1^I \le T_{in}^I \le T_2^I \tag{35}$$

The state of charge of electric vehicles should satisfy constraints (36)–(38). The state of charge varies with the charging power, remaining below the maximum capacity of the battery, while also limiting the magnitude of the charging power and the battery's charging and discharging states.

$$SOC_{t+\Delta t}^I = SOC_t^I + P_{t,ch}^I \eta \Delta t \tag{36}$$

$$SOC_t^{\min} \leq SOC_t^I \leq SOC_t^{\max} \tag{37}$$

$$0 \leq P_{t,ch}^I \leq y_t P_{t,ch}^{I,\max} \tag{38}$$

In the formula, SOC_t^I represents the state of charge of the electric vehicle at time t, η is the charging efficiency of the electric vehicle, $SOC_t^{\min}$ and $SOC_t^{\max}$ are the minimum and maximum states of charge of the electric vehicle, respectively, and $P_{t,ch}^I$ is the charging power of the electric vehicle load at a certain moment. y_t is the grid connection/disconnection state variable for electric vehicles; when y_t is 0, it indicates that the electric vehicle is disconnected from the grid, and when y_t is 1, it indicates that it is connected to the grid. The regulation characteristics of electric vehicle loads impose certain requirements on the state of charge (SOC) when the vehicle is disconnected from the grid. Therefore, this model introduces constraint (39) to ensure that the total SOC of the electric vehicle is not less than 75% at the time of disconnection. The specific formula is as follows:

$$SOC_{t=T_2^I} \geq 0.75 SOC_t^{\max} \tag{39}$$

2. Type II load (reducible load)

Type II load is reducible load, which is an important component of the electricity ancillary services market. The LA can adjust this type of load during appropriate time periods based on the adequacy of the regional power supply, thereby achieving the goal of peak shaving. This type of load mainly includes large power loads such as industrial equipment and commercial air conditioning. The maximum number of reductions should satisfy constraint (40), and the maximum reduction duration should satisfy constraint (41).

$$\sum_t x_{t,m}^{II} \leq N_{\max} \tag{40}$$

$$\sum_{t=1}^{t+T_{\max}^{II}} \left(1 - x_{t,m}^{II}\right) \geq 1 \tag{41}$$

In the equations, $N_{\max}$ represents the maximum number of reductions for t for the reducible load, and $T_{\max}^{II}$ represents the maximum duration of sustained reduction for the reducible load.

3. Type III load (shiftable load)

Type III load has a high degree of controllability, allowing for a certain proportion of load shifting based on the adequacy of regional power supply. This means that within a scheduling period, the total amount of electricity supplied to users remains constant, while the timing of supply can be adjusted. This type of load mainly includes certain industrial production equipment, washing machines, water heaters, and similar devices. There are two main constraints associated with this type of load: first, the total amount of shifted load across different time periods within a single day must equal zero; second, the minimum continuous operating time constraint for shiftable loads must be satisfied.

$$\sum_{t,m} \Delta P_{t,m}^{III} = 0 \tag{42}$$

$$\sum_{t=T_{in}^{III}}^{T_{in}^{III}+T_{\min}^{III}-1} x_{t,m}^{III} \geq T_{\min}^{III}\left(x_{t,m}^{III} - x_{t-1,m}^{III}\right) \tag{43}$$

In the equations, $T_{\min}^{III}$ represents the minimum continuous operating time for the shiftable load.

4. Constraints on the willingness of adjustable load users to participate

The willingness of users to participate in load aggregation for peak shaving is mainly determined by two factors: first, the degree to which their electricity demand is met, and second, whether the benefits obtained from participating in power peak shaving align with their expectations.

$$C_t^I = c_t^{TOU} P_t^{I,base} \tag{44}$$

$$C_{t,m}^{II} = c_t^{TOU} P_{t,m}^{II,base} \tag{45}$$

$$C_{t,m}^{III} = c_t^{TOU} P_{t,m}^{III,base} \tag{46}$$

$$R_t^I = 1 - \left(\Delta P_t^I c_t^{TOU}\right) / C_t^I \tag{47}$$

$$R_{t,m}^{II} = 1 - \left(\Delta P_{t,m}^{II} c_t^{TOU}\right) / C_{t,m}^{II} \tag{48}$$

$$R_{t,m}^{III} = 1 - \left(\Delta P_{t,m}^{III} c_t^{TOU}\right) / C_{t,m}^{III} \tag{49}$$

In the equations, C_t^I, $C_{t,m}^{II}$, and $C_{t,m}^{III}$ represent the electricity costs for load-side users before participating in the peak shaving market, while R_t^I, $R_{t,m}^{II}$, and $R_{t,m}^{III}$ represent the satisfaction levels of the three types of load users.

6. Case Study Analysis

In the practical case study model of this paper, a hybrid park is selected as the research subject for case analysis. The park includes electric vehicle loads, reducible loads, and shiftable loads.

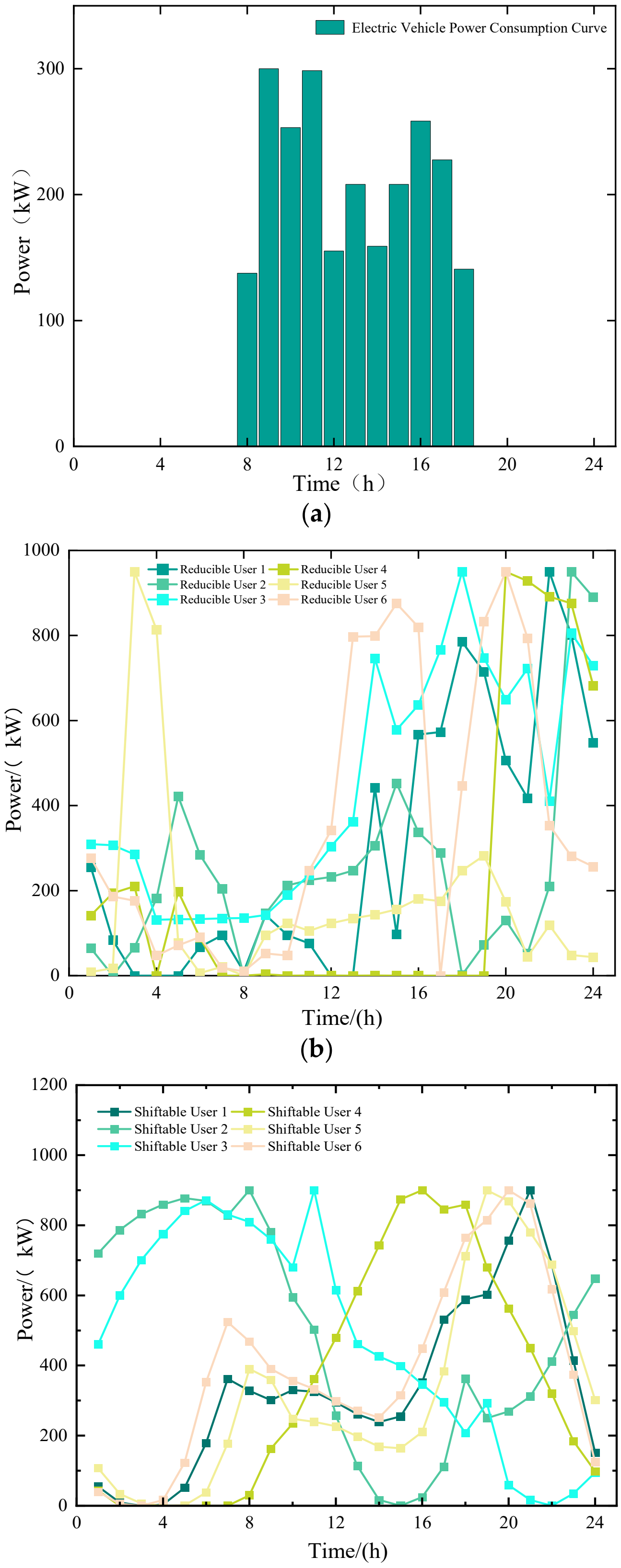
6.1. Basic Scenario Settings for the Case Study

Using the adjustable load data from a typical workday in an industrial park as an example, the system operates on a 24 h dispatch cycle, with a dispatch time interval of 1 h. The peak shaving budget for the load aggregator is set between CNY 6000 and 12,000, and the penalty coefficient for non-response is 1.5 yuan/kWh. It is assumed that there are 100 electric vehicles in the industrial park, each with a battery capacity of 50 kWh. The initial total energy of the electric vehicle fleet is 2500 kWh, the charging power is 5 kW, and the charging efficiency is 0.9. The electric vehicles connect to the grid at 9:00 and disconnect at 19:00. The typical daily electricity consumption curve for electric vehicle users in the industrial park is shown in Figure 2a [22]. The park's reducible loads consist of 4000 air conditioning units, and the typical reducible user curve after clustering is shown in Figure 2b. The maximum number of reduction events per day for reducible loads is eight, and the maximum continuous reduction time is 5 h per day. The park's shiftable loads consist of 6000 fans and other related indoor electrical equipment. The typical shiftable user curve after clustering is shown in Figure 2c. The minimum continuous operation time for shiftable loads is 2 h. The satisfaction levels for electric vehicle users, reducible load users, and shiftable load users must reach 0.75, 0.6, and 0.6, respectively, to qualify for participation in market transactions.

The peak shaving demand curve is shown in Figure 3 [23], and the time-of-use electricity prices are listed in Table 1.

Table 1. Time-of-use price.

Types	Time Periods	Electricity Selling Prices /[CNY∗(kW∗h)$^{-1}$]
Peak hours	9:00–12:00, 15:00–18:00	1.17
Off-peak hours	6:00–8:00, 13:00–14:00 19:00–20:00	0.7
Valley hours	0:00–5:00, 21:00–24:00	0.328



(**a**)

(**b**)

(**c**)

Figure 2. Three kinds of adjustable load typical daily electricity curves: (**a**) daily electricity consumption curve of typical electric vehicle users; (**b**) typical daily electricity usage curve of reducible users after clustering; (**c**) typical daily electricity usage curve of shiftable users after clustering.

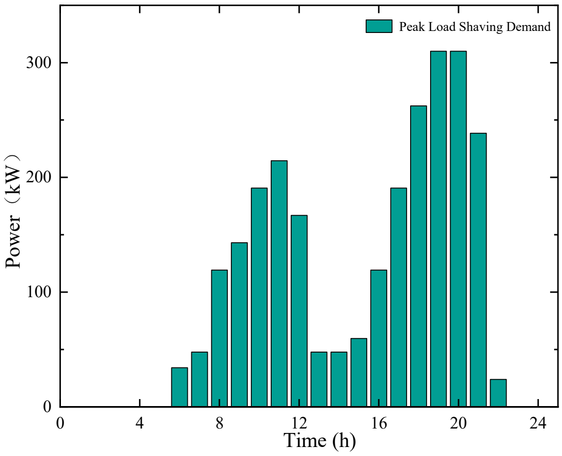


Figure 3. Peak shaving demand curve of the park.

In this paper, the following five scenarios are set up to compare the load dispatch optimization results, fund utilization, and other aspects, in order to verify the superiority of the proposed model. The scenarios are as follows:

Scenario S1: Fixed compensation pricing is assumed, where the compensation prices for adjustable resources are based on the peak shaving compensation rates in Zhejiang Province from July to September 2023. The compensation prices for electric vehicles, reducible loads, and shiftable loads are 0.85 CNY/kWh, 1 CNY/kWh, and 0.95 CNY/kWh, respectively.

Scenario S2: Compensation prices for typical users are set based on the peak shaving value of each time period, with a peak shaving budget of CNY 6000.

Scenario S3: Compensation prices for typical users are set based on the peak shaving value of each time period, with a peak shaving budget of CNY 8000.

Scenario S4: Setting compensation prices for various typical users based on their peak shaving value during different time periods, with a peak shaving budget of CNY 10,000.

Scenario S5: Setting compensation prices for various typical users based on their peak shaving value during different time periods, with a peak shaving budget of CNY 12,000.

This study employed a system configured with an Intel Core i5-12400F processor, 8x2GB DDR4 RAM, 1024GB SSD storage, and an NVIDIA GeForce GTX 4060ti graphics card, running on a Windows 11 Professional 64-bit operating system. The simulation and optimization work were conducted using GAMS version 45.

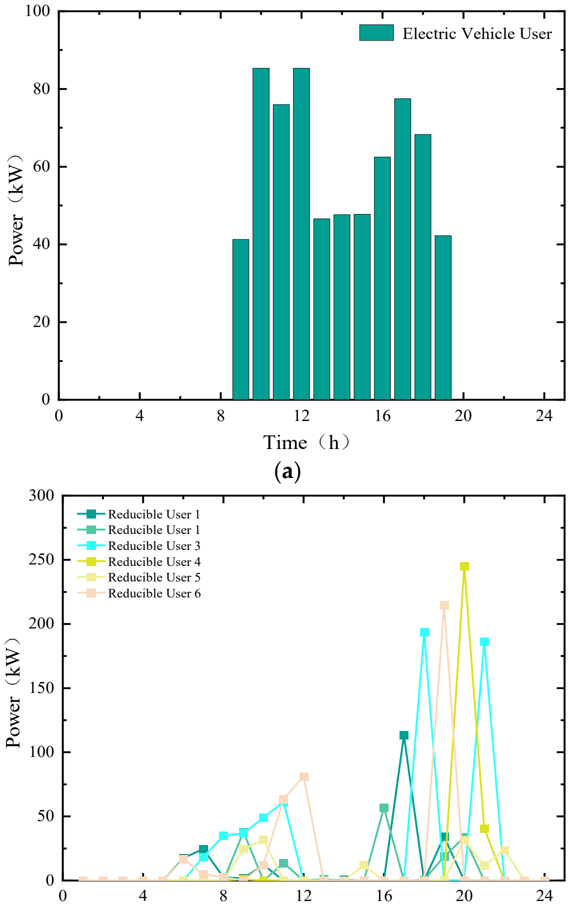
6.2. Scenario Optimization Results

1. Optimization results for Scenario S1

Based on the aforementioned optimization model and the baseline scenario, the optimization results of the electricity consumption curves for three types of adjustable loads before and after peak shaving are as follows:

In Scenario S1, the total dispatching cost for LA is approximately CNY 2463.5, with the compensation cost for electric vehicles being around CNY 578.48, the compensation cost for reducible loads being CNY 1766.4, and the compensation cost for shiftable loads being CNY 0. Shiftable loads do not participate in the market. This is due to the greater complexity involved in their market engagement compared to the other two types of adjustable loads, as shiftable loads require both an “out” and “in” time period to ensure user electricity needs are met. Additionally, the LA must compensate shiftable users for both “in” and “out” time periods, which reduces the relative convenience and cost-effectiveness of shiftable loads compared to other adjustable loads. Furthermore, Scenario S1 utilizes a fixed compensation price, which limits the adaptability of the adjustable load groups to changes in the peak shaving market, further reducing the priority for scheduling shiftable loads to participate in peak shaving. Ultimately, this results in shiftable users opting out of the peak shaving market.

Figure 4a,b illustrate the market participation of various types of typical adjustable users in Scenario S1. As shown in Figure 2, electric vehicle users exhibit high levels of market participation, reaching peak engagement during the two peak shaving demand periods of 8:00–12:00 and 17:00–21:00. However, due to the relatively low electricity consumption of electric vehicles, the primary participants in the peak shaving market remain the reducible load users, especially between 17:00 and 21:00, during which users 1, 3, and 6 alternate in-depth participation to meet peak shaving needs. Among the three types of adjustable resources, reducible loads have the largest scheduling scale and the fewest scheduling constraints compared to electric vehicle loads and shiftable loads, allowing them to participate in the market at nearly any time. However, since only electric vehicle and reducible load users participate in the market under this scenario, user satisfaction for both types of users appears relatively imbalanced post-peak shaving compared to pre-peak shaving.



(**a**)

(**b**)

Figure 4. Typical adjustable user participation in market in Scenario S1: (**a**) power curve of typical electric vehicle users participating in peak shaving market; (**b**) power curve of typical reducible users participating in peak shaving market.

2. Optimization results for the differentiated value of multi-period peak shaving scenarios

The following are the optimization results of scenarios S2, S3, S4, and S5:

- Optimization results for Scenario S2:

The participation of three adjustable loads in the peak shaving market and the pricing results for each time period in Scenario S2 are as follows.

- Optimization results for Scenario S3:

The participation of three adjustable loads in the peak shaving market and the pricing results for each time period in Scenario S3 are as follows.

- Optimization results for Scenario S4:

The participation of three adjustable loads in the peak shaving market and the pricing results for each time period in Scenario S4 are as follows.

- Optimization results for Scenario S5:

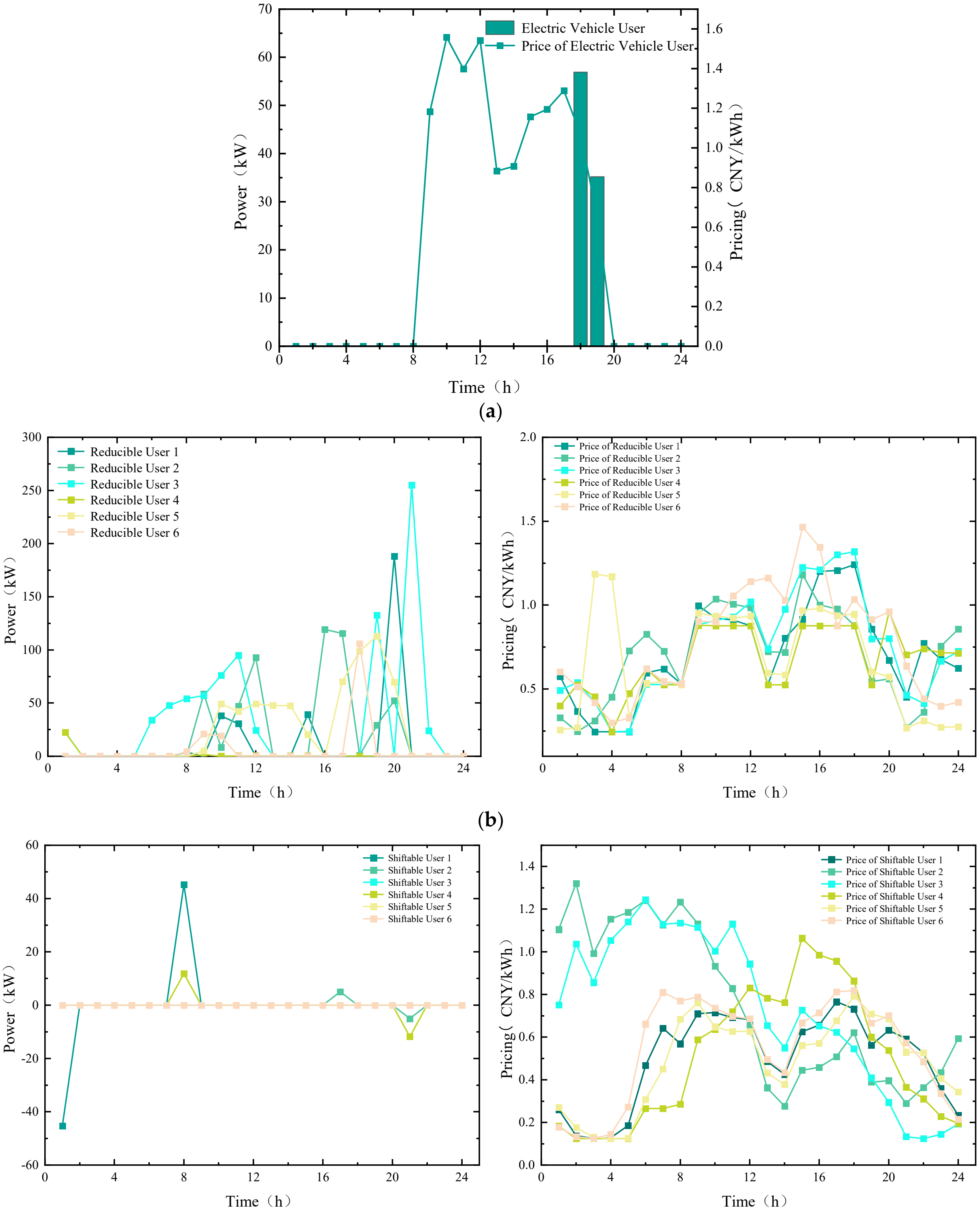
With a peak budget of CNY 12,000, the three adjustable loads participate in the peak market and the pricing results for each time period are shown below.

By comparing Figures 4–8, it can be observed that the compensation pricing curves for the same user exhibit similar fluctuation trends. This is because, in Scenarios S2 to S5, compensation pricing is primarily influenced by factors such as users' market participation levels, pre-peak shaving power consumption, the peak shaving value at each time period, peak shaving budget, and time-of-use electricity pricing. Among these, the primary variable across Scenarios S2 to S5 is the peak shaving budget, which has a relatively limited impact on compensation pricing. However, this does not imply that the peak shaving budget is unimportant. On the one hand, the final compensation price for users results from an optimization that considers multiple factors, including market participation level, pre-peak shaving power consumption, time-period-specific peak shaving value, and the budget for peak shaving. On the other hand, when the peak shaving budget is too low, the user compensation pricing derived from the pricing formula is also comparatively low. Since the model sets a minimum threshold for typical users, those falling below this threshold will be unable to participate in the peak shaving market, ultimately preventing the LA from meeting peak shaving requirements. However, even among users of the same type, differences in compensation pricing exist. For instance, during the 3:00–4:00 time period, the compensation price for user 5, a typical reducible user, is approximately 1.41 CNY/kWh, significantly higher than other reducible users. As shown in Figure 2b, during this period, user 5's electricity demand peaks, while other reducible users are mostly at low consumption levels. By referencing the peak shaving value Formulas (22)–(27), it can be seen that a user's peak shaving value is not only related to their own electricity demand but also to the demand of other users during the same period. Therefore, user 5's peak shaving value is the highest during this period, indicating that, compared to other users, user 5 has the greatest potential to participate in the peak shaving market during this time.

As shown in Table 2, which presents the daily costs and costs for each typical user under different budgets, the daily cost increases progressively with the rise in the peak shaving budget. This is because the user's compensation pricing is positively correlated with the budget.

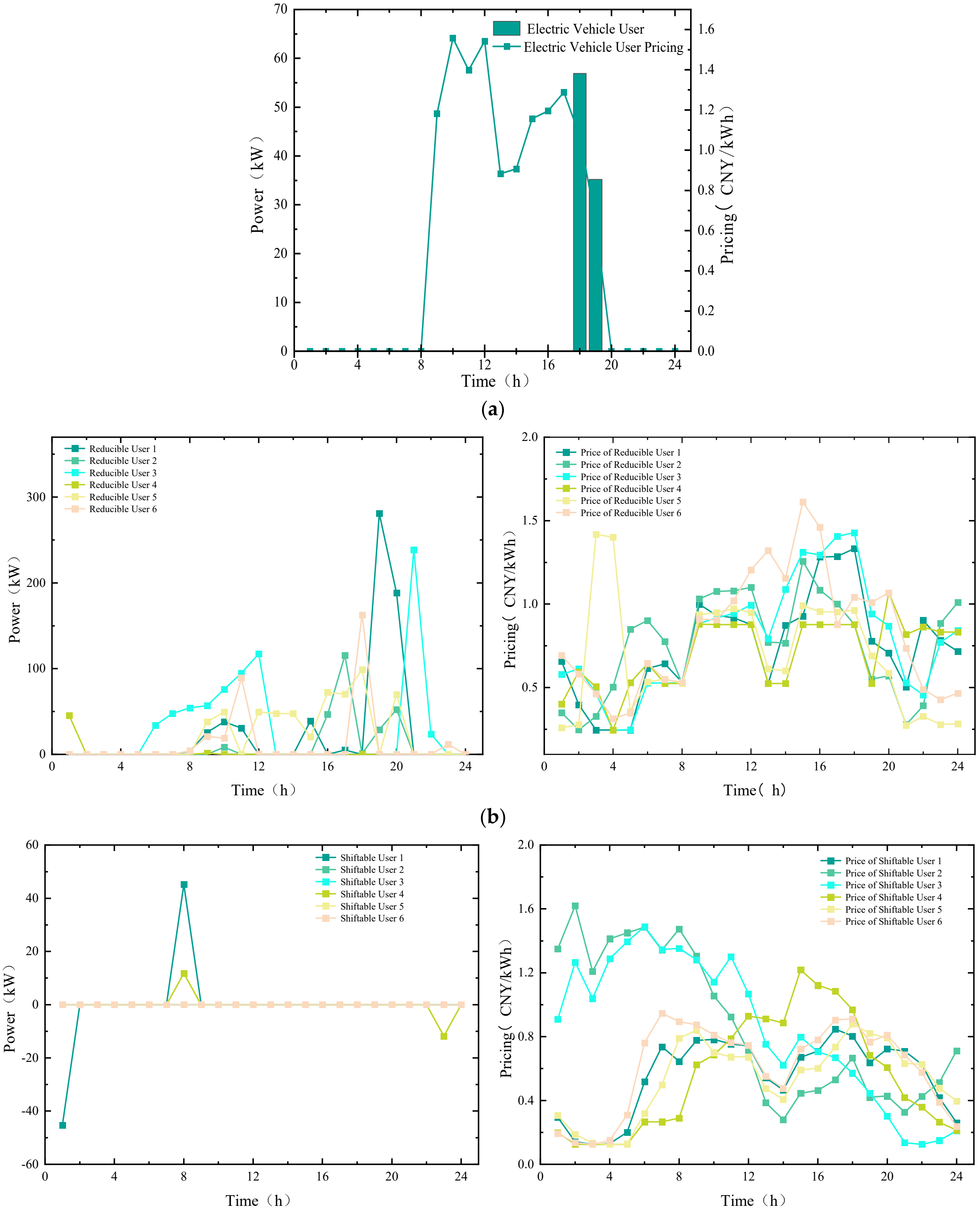
Table 2. Costs for a single day and for each typical user under various peak shaving budgets in Scenarios S2–S5.

Cost/CNY Scenarios	Single Day	Electric Vehicle Users	Adjustable Users	Flexible Users
S2	1968.5	21.36	1907.75	39.44
S3	2028.7	83.62	1895.98	49.17
S4	2094.5	0	2045.5	48.99
S5	2138.0	25.48	2047.56	64.96



(**c**)

Figure 5. Scenario S2 can adjust the user's participation in the market and pricing: (**a**) power and pricing curves of typical electric vehicle users participating in the peak shaving market; (**b**) power and pricing curves of typical reducible users participating in the peak shaving market; (**c**) power and pricing curves of typical shiftable users participating in the peak shaving market.

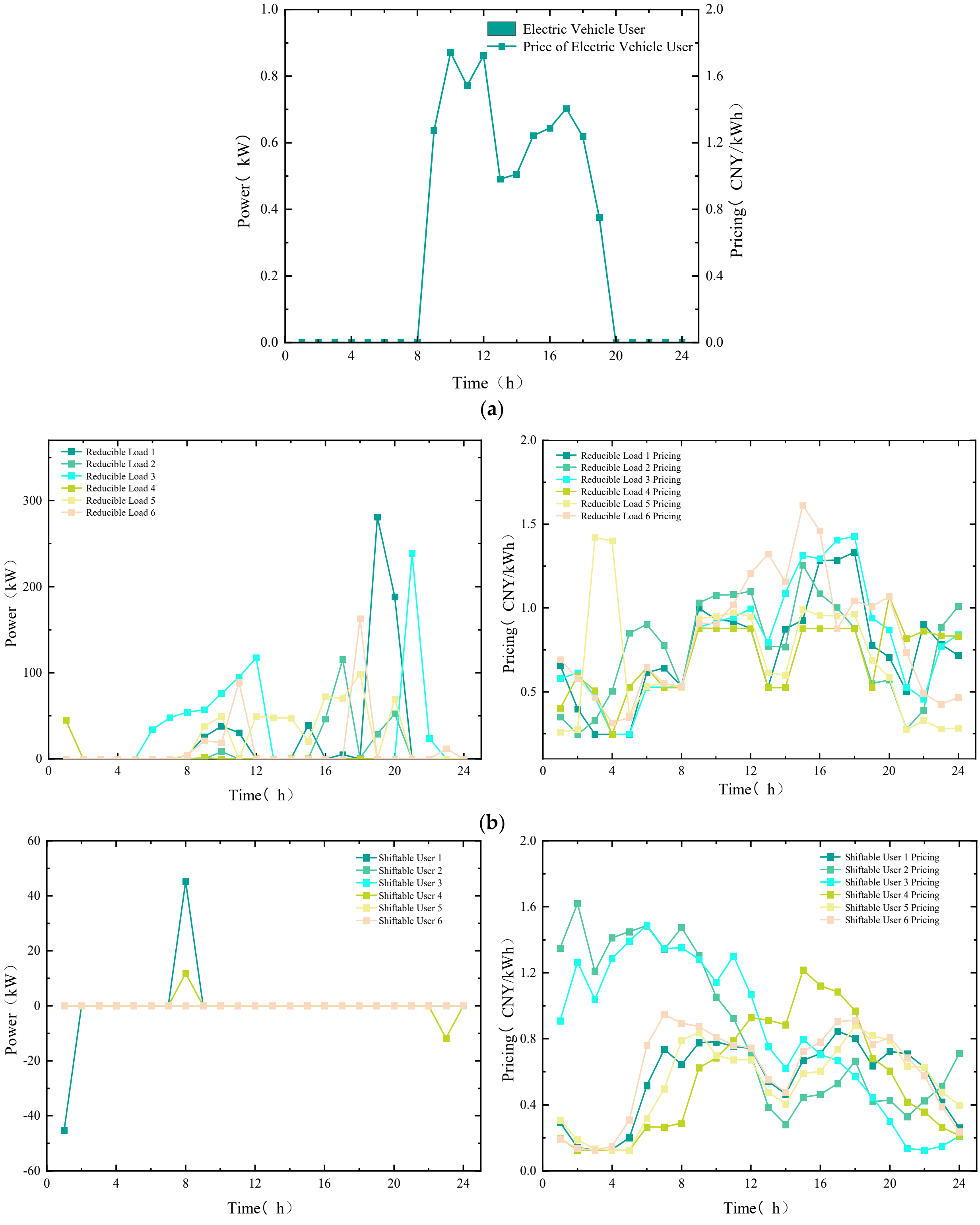


(**a**)

(**b**)

(**c**)

Figure 6. Scenario S3 can adjust the user's participation in the market and pricing: (**a**) power and pricing curves of typical electric vehicle users participating in the peak shaving market; (**b**) power and pricing curves of typical reducible users participating in the peak shaving market; (**c**) power and pricing curves of typical shiftable users participating in the peak shaving market.



(**a**)

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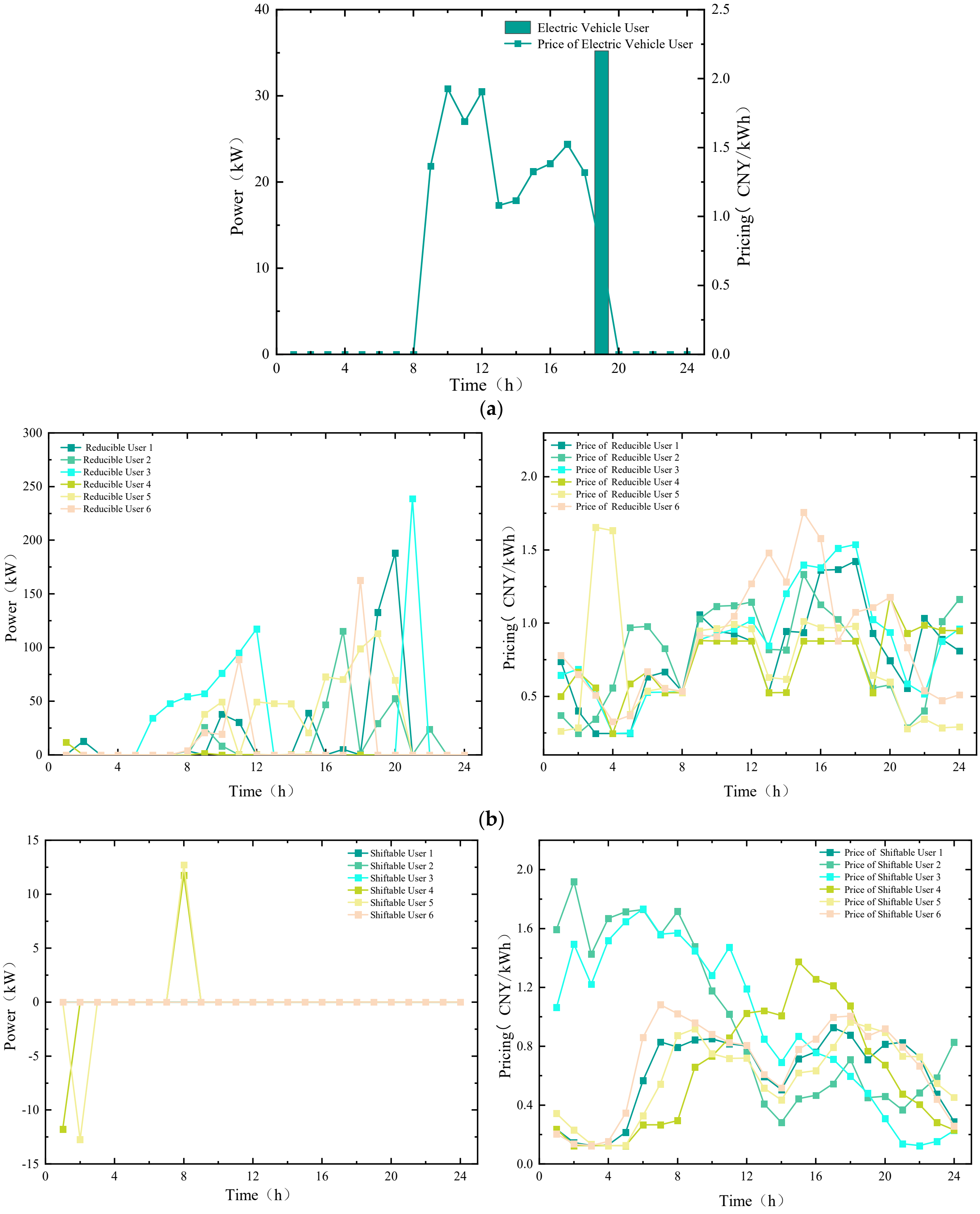
(**c**)

Figure 7. Scenario S4 can adjust the user's participation in the market and pricing: (**a**) power and pricing curves of typical electric vehicle users participating in the peak shaving market; (**b**) power and pricing curves of typical reducible users participating in the peak shaving market; (**c**) power and pricing curves of typical shiftable users participating in the peak shaving market.



(**a**)

(**b**)

(**c**)

Figure 8. Scenario S5 can adjust the user’s participation in the market and pricing: (**a**) power and pricing curves of typical electric vehicle users participating in the peak shaving market; (**b**) power and pricing curves of typical reducible users participating in the peak shaving market; (**c**) power and pricing curves of typical shiftable users participating in the peak shaving market.

For the LA, to meet the peak shaving demand shown in Figure 3, a peak shaving budget of at least CNY 2000 is required.

As shown in Table 2, with an increase in the peak shaving budget, the scheduling costs for reducible and shiftable users also gradually rise. In conjunction with the peak shaving value Formulas (22)–(27), it can be observed that user compensation pricing is positively correlated with the peak shaving budget. Therefore, as the peak shaving budget increases and users' market participation levels remain relatively stable, the compensation costs for users incrementally increase. At budget levels of CNY 10,000 and CNY 12,000, the participation of electric vehicle users is relatively low. In the previous two budget scenarios, electric vehicle users mainly participated in the market during the 18:00–19:00 period. This is because, as the peak shaving budget increases, the compensation price for electric vehicle users also rises. However, based on the peak shaving value Formulas (22)–(27), it can be seen that the user's compensation price is negatively correlated with their level of market participation. At this time, reducible users, with a wider range of adjustment, offer more economically favorable compensation prices compared to electric vehicle users. Therefore, the LA would allocate a large portion of reducible resources during this time period. In contrast, users with shiftable loads primarily participate in the market during the late-night to early-morning hours to meet the demands of the electricity market.

6.3. Comparative Analysis of Pricing Methods

In order to better compare the effects of different user compensation pricing methods on the LA, we introduce three evaluation criteria: scheduling costs, unmet peak shaving demand, and average user satisfaction. The results are presented in Tables 3 and 4 below:

Table 3. Scheduling costs and unresponsiveness of Scenarios S1–S5.

Scenarios	Scheduling Cost/Yuan	Unmet Peak Shaving Demand/kW
S1	2463.5	64.76
S2	1968.57	0
S3	2028.79	0
S4	2094.51	0
S5	2138.02	0

Table 4. Comparison of average user satisfaction.

Scenarios / User Type	S1	S2	S3	S4	S5
Electric vehicle	0.71	0.98	0.95	1	0.98
Reducible load 1	0.91	0.88	0.88	0.86	0.85
Reducible load 2	0.95	0.91	0.86	0.91	0.89
Reducible load 3	0.92	0.89	0.88	0.88	0.89
Reducible load 4	0.89	0.80	0.80	0.79	0.79
Reducible load 5	0.93	0.82	0.83	0.83	0.80
Reducible load 6	0.93	0.88	0.92	0.90	0.92
Shiftable load 1	1	1.02	1.02	1.02	1.02
Shiftable load 2	1	1	0.99	0.99	1
Shiftable load 3	1	1	1	1	1
Shiftable load 4	1	0.98	0.98	0.99	0.99
Shiftable load 5	1	1	1	1	1.01

As shown in Tables 3 and 4, the scheduling costs under different budgets in Scenarios S2–S5 are, on average, 16.5% lower than those in the fixed pricing Scenario S1. This indicates that the pricing method based on peak shaving value orientation is more economically advantageous. Moreover, in the fixed pricing Scenario S1, there was a lack of user response at 8:00, while in Scenarios S2–S5, users actively responded to market peak shaving demands. This further demonstrates that the pricing methods in Scenarios S2–S5 are more effective in tapping into user potential and in balancing the interests between the higher-level grid, LA, and electricity users.

In terms of user satisfaction, compared to Scenario S1, electric vehicle users' satisfaction increased by an average of 38% in Scenarios S2–S5, while the satisfaction of reducible load users and shiftable load users decreased by 7% and 0.3%, respectively. This indicates that the pricing methods in Scenarios S2–S5 significantly improve electric vehicle user satisfaction, albeit with a slight decrease in the satisfaction of reducible and shiftable load users, leading to a more balanced overall user satisfaction.

In conclusion, the differentiated multi-period peak shaving value calculation method proposed in this paper is more reasonable than the fixed pricing in Scenario S1, as it takes into account both the LA's scheduling costs and user comfort, providing practical reference value.

7. Conclusions

This paper addresses the issue of an LA's inability to accurately and reasonably measure user peak shaving value under limited peak shaving funding to meet peak shaving demands. It comprehensively considers the adjustment characteristics of dispatchable loads and proposes a differentiated calculation method for the peak shaving value of adjustable users. This method provides LAs with a user compensation pricing mechanism that is both economical and practical. Case studies further validate the effectiveness of the constructed pricing mechanism.

1. This paper introduces indicators for the adjustment characteristics of primary and secondary dispatchable loads and conducts cluster analysis on adjustable resources, effectively reducing the technical difficulties faced by LAs in subsequent scheduling processes.
2. This paper takes minimizing peak shaving scheduling costs as the optimization objective and employs an optimized scheduling and compensation pricing model for load aggregators based on limited peak shaving funding and time-period peak shaving values. Compared to traditional fixed compensation pricing, the scheduling costs are, on average, reduced by 16.5%, while the satisfaction of electric vehicle users increases by an average of 38%. In contrast, the satisfaction of dispatchable and shiftable load users decreases by only 7% and 0.3%, respectively. This approach significantly reduces scheduling costs while enhancing overall user satisfaction.

However, this paper does not yet consider the discharge behavior of electric vehicles or the potential impacts of their random charging and discharging patterns on the model. Future research will further explore these factors to enhance the current pricing model.

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