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Orderly Charging and Discharging Group Scheduling Strategy for Electric Vehicles

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Abstract: To address the challenge of optimizing the real-time scheduling for electric vehicles on a large scale, a day-ahead–intraday multi-timescale electric vehicle cluster division strategy is proposed based on the different expected charging completion times of the accessed electric vehicles. In the pre-day phase, historical travel statistics are used to model and determine the moments when the electric vehicles are on-grid and off-grid. In the intraday phase, the EV clusters are carefully divided by real-time data collection, taking into full consideration the response willingness and ability of vehicle owners. For each scheduling period, a real-time optimal scheduling model for EV clusters based on the V2G mode is established by taking into account the constraints of the power grid, vehicle owners, batteries, and other parties. The model is divided into two layers to find the charging and discharging plans: the upper model aims to determine the aggregate charging and discharging power of the cluster during the current time period by targeting the distribution grid's minimum variance load curve within the scheduling interval; the lower model takes the lowest cost to the EV owner as the goal to find the charging and discharging plan of a single EV and, at the same time, introduces the scheduling penalty factor to adjust the difference with the cluster charging and discharging plan. The simulation outcomes indicate that the suggested approach successfully mitigates load fluctuations and has a good optimization effect and fast solution speed for dealing with large-scale EV access problems. The simulation results show that the proposed strategy can effectively smooth load fluctuations and can significantly reduce the difficulty of optimal real-time scheduling for electric vehicles on a large scale, and it has a better optimization effect and faster solution speed for dealing with large-scale electric vehicle access problems.

Keywords: electric vehicles; vehicle-to-grid (V2G); orderly charging and discharging; real-time optimization; grouping control; optimal scheduling; multiple timescales

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1. Introduction

As of June 2023, the national ownership of new energy vehicles reached 16.2 million, constituting 4.9% of the overall vehicle count. Within this figure, pure electric vehicles totaled 12.594 million, representing 77.8% of the overall new energy vehicle count. As a new type of controllable load, electric vehicles can serve as mobile energy storage devices when connected to the grid; they can not only obtain electricity from the grid but also provide energy to the grid through the price incentive mechanism to realize the networking of vehicles. However, with the increase in the number of electric vehicles, the disorderly charging of a large number of electric vehicles will have an impact on the power grid, which will lead to the increase in the load and voltage fluctuation of the power grid and affect the normal operation of the power grid [1,2]. Providing appropriate guidance for the charging of large-scale electric vehicles upon connection to the power grid can not only mitigate the negative impacts resulting from haphazard charging but also address issues such as the intensification of peak–valley differences and the compromised reliability and economic

efficiency of the distribution network; it can also provide auxiliary services for power grid optimization, realize peak shaving and valley filling [3], stabilize the power grid load, and reduce network loss [4] and, at the same time, bring certain economic benefits to the power grid and to car owners.

In recent years, scholars have made significant advancements both domestically and internationally in the research on the systematic management of charging and discharging for electric vehicles, as well as the vehicle-to-grid mode.

(1) n the intricate domain of electric vehicle (EV) scheduling, diverse temporal dimensions, which are notably embedded within the context of vehicle-to-grid (V2G) responsiveness, warrant scholarly investigation. Pioneering endeavors have delved into temporal intricacies via the prism of day-ahead optimal scheduling [5–7] and real-time optimal scheduling [8–10]. Leveraging historical data, the optimization scheduling [5] meticulously models and scrutinizes the travel parameters of EVs to prognosticate the temporal distribution of charging and discharging demands for the ensuing day. Reference [6] formulates day-ahead optimal charging schedules for EVs; these schedules are predicated on an integrated game model which is cognizant of the vehicle owners' interests. Reference [7] introduces an analytical approach deploying polyhedral approximation models to succinctly articulate the dispatchable region for large-scale EVs, thereby facilitating the involvement of EV aggregators in the distribution grid for effective day-ahead optimal scheduling.

Nevertheless, forecasting EV loads based on historical statistics has the potential for significant deviations between actual dispatch outcomes and day-ahead optimization projections. The extant optimization procedures necessitate adaptation in response to the actual access patterns of EVs, engendering challenges in devising charging and discharging strategies for individual EVs. Addressing the uncertainties surrounding factors such as the arrival and departure times of EVs, reference [8] propounds a real-time optimal scheduling strategy for large-scale electric vehicles, utilizing a dynamic non-cooperative game approach to formulate charging and discharging strategies for each electric vehicle within the cluster through the ADMM algorithm. Reference [9] proposes the concept of transferable charging/discharging margins for EVs, quantifying the flexibility of charging/discharging scheduling by considering dispatchable time/power and user willingness to participate. With the incremental proliferation of EVs connecting to the system in the future, real-time optimal scheduling requires heightened solution speeds and efficiency. Additionally, reference [10] concentrates on scheduling strategies for clusters of EVs, crafting charging plans attuned to real-time electricity markets via deep reinforcement learning methods and thereby enhancing scheduling intelligence while accounting for real-time dynamics and offering a novel perspective on EV charging strategy optimization.

Electric vehicles are different from traditional electric loads; they are connected to the grid at a time with a strong randomness [11,12] and use a single timescale to formulate the scheduling plan; thus, they cannot take into account the global nature of the scheduling process and accuracy.

(2) The investigation into the control methodologies of electric vehicle (EV) dispatch encompasses both individual and group dispatch strategies, with a focus on scale and the quantity of charging EVs. Reference [13] presents a decentralized two-layer charging strategy grounded in fuzzy data fusion, which enhances the charging cost optimization for an individual electric vehicle by utilizing the decision control variables obtained through fuzzy fusion. Reference [14] delves into charging demand and system load variations across different timescales, proposing an ordered charging/discharging model for two-tier EVs over extended time periods and thereby rationalizing the charging/discharging schedules for each EV. However, advancements in big data and artificial intelligence technology have prompted scholars to explore the effective management of charging and discharging behaviors from the perspective of EV clusters. This approach mitigates communication challenges, reduces algorithmic dimensions, and optimizes computational processes [15,16]. Reference [17] introduces a travel chain-based EV cluster charging and discharging capacity

calculation model, leveraging the spatial and temporal change probability characteristics of trip start and end points. This model guides the EV cluster to function as an energy storage system, promoting charging during off-peak hours. In addressing the unpredictability of current EV users' involvement in vehicle-to-grid (V2G) scheduling, reference [18] establishes an EV indicator evaluation model for the optimal scheduling of EV clusters. Reference [19] suggests a real-time scheduling method utilizing the charging end moment as a cluster characteristic; the method employs a two-layer optimization model to address optimal charging and discharging power concerns for both the entire cluster and individual EVs. However, all of the above clustering strategies subjectively define the optimal scheduling time of EV clusters, and if the load characteristics can be analyzed from the perspective of EV travel patterns, the difficulty of the solution can be greatly reduced, and the speed of the solution can be improved. At the same time user satisfaction must be considered when describing EV clusters [20,21] to ensure that owner needs are met while EV dwell time is effectively utilized. This holistic perspective underscores the evolving landscape of EV dispatch control methods, incorporating advancements in technology and user-centric considerations.

This article describes the EV clustering strategy for day-ahead–intraday multi-timescales in the context of a large number of EVs connecting to the grid in an unorganized manner, which brings great difficulty in grid scheduling. The clustering strategy builds a charging model in the day-ahead phase based on the historical data, and it takes into account the charging willingness and travel plans of EVs in real time in the intraday phase, so that EVs' charging demands can be more accurately predicted and dispatched. The charging demands of EVs are considered. Based on the proposed clustering strategy, a two-layer model for the real-time optimal scheduling of EV clusters based on the V2G mode is established for EVs, with the upper-layer model soliciting the charging and discharging power of EV clusters; in the lower-layer model, the charging and discharging plan of a single EV is optimized with the objective of minimizing the cost to the EV owner and making it as consistent as possible with the upper-layer scheduling plan. Through the collaborative work between the upper and lower models, the effective management of EV clusters and the load scheduling of the power grid is realized; the charging cost is reduced; and more flexibility and choices are provided for EV users and power system managers. The primary contributions are outlined as follows:

- We propose the EV cluster segmentation strategy for the day-ahead–intraday multi-timescale; the strategy places EVs with similar attributes into the same cluster and adopts the unified expected completion time of the cluster instead of the expected completion time of each EV, to reduce the drawbacks brought about by the large differences in the entry and exit times of EVs.
- Considering the response willingness and ability of vehicle owners, we establish a two-layer model for the real-time optimal scheduling of EV clusters based on the V2G model to achieve effective management of the EV clusters and the load scheduling of the power grid, to reduce charging costs, and to provide more flexibility and choices for EV users and power system managers.

2. Electric Vehicle Cluster Layered Response Process

2.1. Electric Vehicle Cluster Response Architecture

As shown in Figure 1, the electric vehicle cluster control architecture is mainly composed of the grid corporation, the regional distribution network, the EVGMS (Electric Vehicle Grouping Management System), and the electric vehicles; this architecture is used to manage and coordinate the calculation and communication system of electric vehicle clusters. As the number of in-grid electric vehicles is continuously expanding, the massive storage and calculation of statistics make it vulnerable to a "dimensional disaster" if the regional power distribution network gathers and dispatches the demand for each electric vehicle directly. However, due to the large group of EVs in the regional distribution network, the intraday charging demand and load distribution show regularity; so, a day-

ahead–intraday multi-timescale clustering strategy is established to intelligently schedule and synchronize the charging and discharging activities of electric vehicles using the EV cluster management system, which reduces the algorithmic dimensions and accelerates the computation speed while taking into account the user's satisfaction.

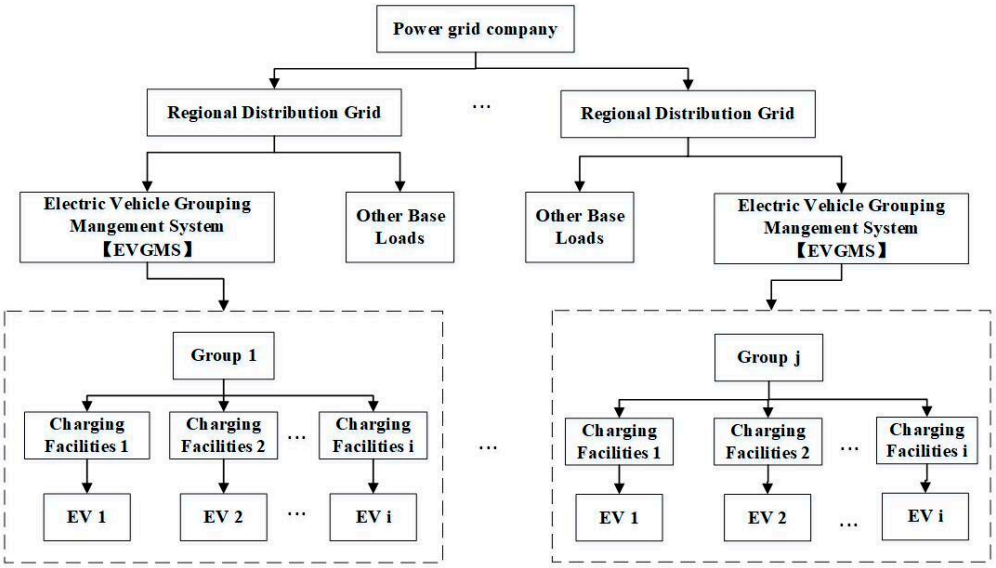

Figure 1. Electric vehicle cluster response architecture.

2.2. Electric Vehicle Cluster Hierarchical Response Process

This paper considers the electric vehicle cluster from the day-ahead and the real-time perspectives. In the previous period, the charging load of electric vehicles was simulated on the basis of historical traffic statistics, and the probabilistic statistical models were obtained for the moment when the electric vehicles were connected to the grid, $t_{a.i}$, and the moment when they left the grid, $t_{b.i}$. In the intraday phase, the EVGMS system takes into full consideration the willingness to respond and the response capacity by collecting information on EV charging and discharging willingness, access status, and the travel plan in real time. The EVGMS system collects information on EV charging and discharging willingness, access status, and the travel plan in real time and fully considers the response willingness and response capability. The EVs that are capable of and willing to participate in V2G are placed into the same cluster, with $t_{a.i}$ and $t_{d.i}$ as the cluster characteristic values, and the EVGMS system dispatches the cluster.

In formulating the orderly charging and discharging strategy, the idea of real-time optimization is introduced into the group dispatching for the actual constraints and different characteristics of single electric vehicles, and a real-time response fractional group dispatching model designed for the orderly charging and discharging of electric vehicles in the V2G mode is established by comprehensively considering the constraints of the network, battery, and vehicle owner under the premise of ensuring the safe operation of the distribution network and the economic benefits of the vehicle owner. The model is divided into upper and lower layers to obtain charging and discharging scheduling plans for electric vehicles. The upper layer coordinates the charging and discharging power of the EV clusters in each period from the perspective of the EV clusters, to minimize the variance of the distribution network load curve in the scheduling time interval; the lower layer solves the economic cost to each electric vehicle owner within a cluster from the perspective of the optimal power allocation of the charging and discharging power of a single EV. Throughout the optimization process, each stratum utilizes the preceding optimization outcome from the counterpart layer as a known condition, facilitating information exchange between the two layers through several iterations.

The V2G real-time response group scheduling flow for electric vehicles is shown in Figure 2.

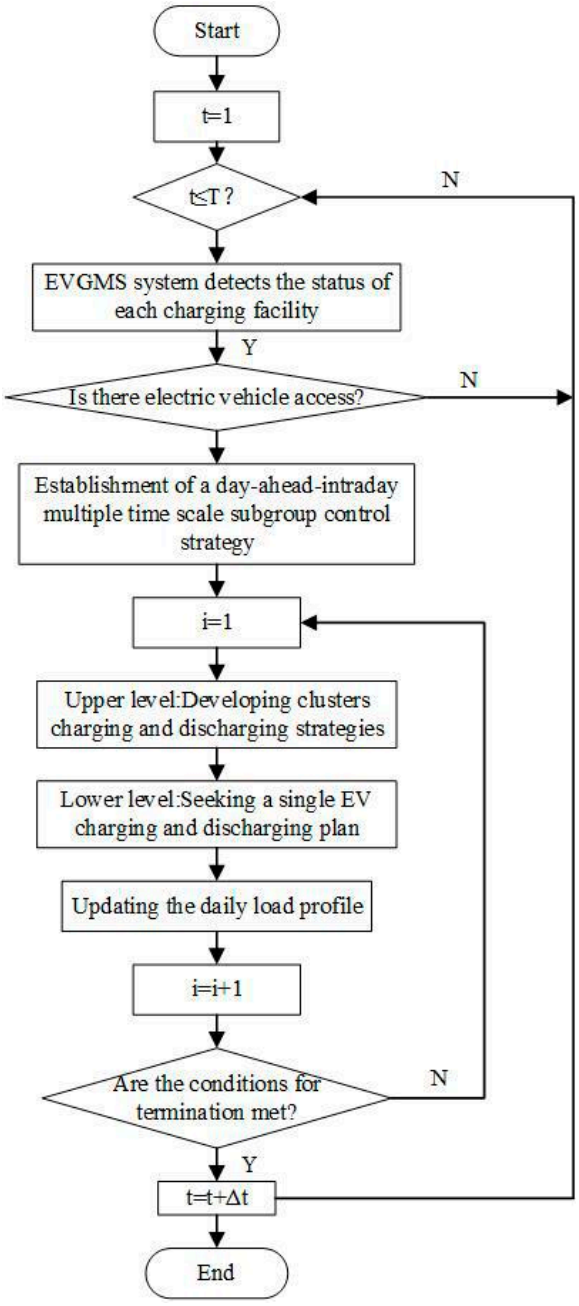

Figure 2. Electric vehicle group scheduling process.

YALMIP, as a MATLAB optimization toolbox, supplies the basic linear programming algorithms as well as the CPLEX, GLPK, and Lpsolve tools. YALMIP manages to model all problems uniformly. In particular, CPLEX has strong robustness, high optimization efficiency, and fast computation, which facilitates the solution of linear planning, quadratic planning, and the corresponding mixed-integer planning problems. CPLEX, an external solver by YALMIP, is used in this paper to solve the constructed two-layer optimization model. For each dispatch period, the optimization model yields the schedule of the electric vehicles. Ultimately, this paper takes the typical regional distribution grid load data as an example, and the model guarantees the economic operation of the grid and maximizes the

economic efficiency of vehicle owners based on meeting their travel needs. The validity is verified by using the above strategies.

3. Electric Vehicle Cluster Division Strategy

3.1. Day-Ahead Load Model

The charging load of an electric vehicle is subject to multiple constraints, including the power of the battery, the owner's usage habits, and the facilities for charging. The charging power and duration of the electric vehicle are largely determined by the time and the SOC that the electric vehicle is on/off the grid. This analysis is based on the results of the 2017 and 2018 U.S. Department of Transportation's National Household Travel Survey (NHTS), which replaces electric vehicle travel characteristics with traditional fuel-efficient vehicle travel characteristics. Using normalization of the statistical data [22,23], the probability density functions for the moments when the electric vehicles come home or leave home are obtained by satisfying [24]:

$$f_{t_{a.i}}(x) = \begin{cases} \frac{1}{\sigma_a\sqrt{2\pi}} exp\left[-\frac{(x+24-\mu_a)^2}{2\sigma_a^2}\right], 0 < x \le \mu_a - 12 \\ \frac{1}{\sigma_a\sqrt{2\pi}} exp\left[-\frac{(x-\mu_a)^2}{2\sigma_a^2}\right], \mu_a - 12 < x \le 24 \end{cases} \quad (1)$$

$$f_{t_{b.i}}(x) = \begin{cases} \frac{1}{\sigma_b\sqrt{2\pi}} exp\left[-\frac{(x-\mu_b)^2}{2\sigma_b^2}\right], 0 < x \le \mu_b + 12 \\ \frac{1}{\sigma_b\sqrt{2\pi}} exp\left[-\frac{(x-24-\mu_b)^2}{2\sigma_b^2}\right], \mu_b + 12 < x \le 24 \end{cases} \quad (2)$$

where $t_{b.i}$ the time at which the electric car leaves home at the beginning of the trip, and $t_{a.i}$ is the time at which the electric car returns home at the end of the last trip and is a random variable; μ_a and σ_a are the expectation and variance of the time when the electric vehicle i is connected to the grid, respectively. μ_d and σ_d are the expectation and variance of the expected time when the EV i is off the grid, respectively.

Assuming that the owner connects the electric vehicle to the grid immediately after returning home, the expected moment on the grid is $t_{a.i}$∼N (17.9,3.4^2), and the estimated time off the grid is $t_{b.i}$∼N (9.24,3.16^2).

3.2. Intraday Real-Time Demand

Before the electric vehicle is plugged into the grid, the vehicle owner is expected to alert the EVGMS about their travel plans and charging and discharging schedule (including their participation or non-participation in the V2G dispatch, off-grid time $t_{b.i}$, and off-grid expected charge status $S_{e.i}$). Simultaneously, the EVGMS obtains such information about the electric vehicle as on-grid moment $t_{\mathrm{a.i}}$, state of charge $S_{a.i}$, battery capacity B_i, etc., from the Battery Management System (BMS) [25]. The EVGMS, acting as a hub for the information exchange and command transmission, reports the collected feedback to the regional distribution network and the grid company. In turn, the regional distribution dispatch department issues dispatch orders and makes charge/discharge plans for the cluster as a whole based on the current load demand of the grid and the information reported by the EVGMS system. The electric vehicle V2G responsiveness k is related to its on-/off-grid time and the shortest charging time $t_{min.i}$ from maximum power to full charge:

$$k = \frac{\Delta t}{t_{min.i}} = \frac{t_{b.i} - t_{a.i}}{t_{min.i}} \quad (3)$$

$$t_{min.i} = \frac{(S_{e.i} - S_{a.i})B_i}{P^+_{i.max}} \quad (4)$$

Electric Vehicles have V2G responsiveness when $k > 1$, and the larger the value of k, the more flexible and dispatchable the electric vehicle can be. However, in actual operation,

the V2G response capability is limited by a value of k greater than 1. In consideration of the vehicle owner's subsequent travel requirements, this paper uses $k > 1.2$ as the criterion to measure the V2G capability of an electric vehicle [26].

3.3. Partition Rules for Electric Vehicle Clusters

As shown in Figure 3, in view of the stochastic nature of electric vehicle grid access, electric vehicles are divided into two categories: those that participate in V2G dispatching and those that do not, based on the real-time intraday collection of vehicle owner demand. The EVGMS system then calculates whether the electric vehicle is V2G-responsive or not. Electric vehicles that fail to have V2G responsiveness are charged directly. Finally, for EVs with the capability and willingness to participate in V2G dispatching, a clustering strategy is developed according to the day-ahead load model.

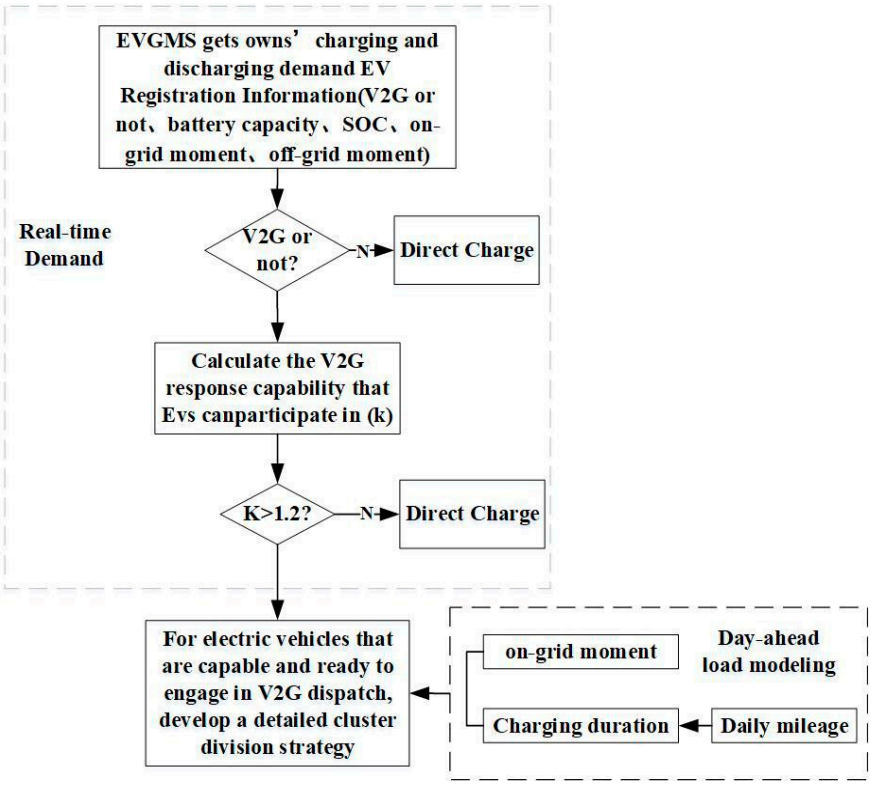

Figure 3. Electric vehicle group rules.

In the process of optimal scheduling, the expected completion time of each EV $t_{b.i}$ is replaced by the uniform expected completion time of the cluster $T_{b.j}$, which eliminates the variability of the off-grid time of each EV in the cluster, and the EVGMS will complete the charging and discharging demand of vehicle owners before $T_{b.j}$ in order to make the number of EVs in each sub-group similar. In this article, the EV clusters are divided by "equal integration" within the confidence level of 80% based on the probability.

4. Electric Vehicle Cluster Optimization Model

For electric vehicles that choose not to partake in dispatching or lack the capability to do so, direct charging is employed, with a consistent charging power while connected to the grid. The expression is as follows:

$$P_{i.t}^{+} = min\left(P_{i.max}^{+}, \frac{(S_{e.i} - S_{a.i})B_i}{t_{b.i} - t_{a.i}}\right) \tag{5}$$

where $P_{i.max}^{+}$ indicates the maximum charging power.

4.1. Upper Layer Model

4.1.1. Objective Functions

The total charging and discharging power of cluster j in period t is obtained by minimizing the variance of the total load curve of the distribution network from $T_{a.j}$ at the start of unified dispatch to $T_{b.j}$ after unified dispatch.

$$F_1 = \frac{1}{T_{b.j} - T_{a.j}} \sum_{t=T_{a.j}}^{T_{b.j}} \left(P_{basic.t} + \sum_{j=1}^{J} P_{j.t}^{\pm} - P_{avg} \right)^2 \tag{6}$$

$$P_{avg} = \frac{1}{T_{b.j} - T_{a.j}} \sum_{t=T_{a.j}}^{T_{b.j}} \left(P_{basic.t} + \sum_{j=1}^{J} P_{j.t}^{\pm} \right) \tag{7}$$

where F_1 is the distribution network total load variance; J is the total number of clusters; $P_{j.t}^{\pm}$ is the charging and discharging power of cluster j in time t; P_{basic} is the distribution network base load other than electric vehicle charging and discharging; and P_{avg} is the average load of the distribution network in the total period.

4.1.2. Constraints

(1) Power Balance Constraints for Distribution Network Nodes

$$P_{g.m} - P_{j.t}^{\pm} - P_{basic.m} = U_m \sum_{m=1}^{k} U_n (G_{mn} cos\theta_{mn} + B_{mn} sin\theta_{mn}) \tag{8}$$

$$Q_{g.m} - Q_{j.t}^{\pm} - Q_{basic.m} = U_m \sum_{m=1}^{k} U_n (G_{mn} cos\theta_{mn} + B_{mn} sin\theta_{mn}) \tag{9}$$

Here, k is the total number of nodes; $P_{g.m}$ and $Q_{g.m}$ are the active and reactive power of node m; $P_{j.t}^{\pm}$ and $Q_{j.t}^{\pm}$ are, respectively, the active and reactive power charged and discharged by electric vehicles; $P_{basic.m}$ and $Q_{basic.m}$ are the basic load requirements of the distribution network other than the charging and discharging of electric vehicles; U_m and U_n are the voltage amplitude; θ_{mn} is the phase angle difference of voltage; and G_{mn} and B_{mn} are the real part and imaginary part of the node conduction matrix.

(2) Node Voltage Deviation Constraints

$$|U_m U_n (G_{mn} \cos\theta_{mn} + B_{mn} \sin\theta_{mn}) - U_m^2 G_{mn}| \le P_{max.mn} \tag{10}$$

$$U_{min.m} \le U_m \le U_{max.m} \tag{11}$$

where $P_{max.mn}$ is the maximum active power of the power transmission line mn, and $U_{max.m}$ and $U_{min.m}$ are the maximum and minimum voltage constraints.

(3) The SOC Constraints for Clusters

The aggregate of the charge and discharge power cannot surpass the total charging demand of cluster j during any period t1 from the start of the optimization period.

$$D_j = \sum_{t=T_{a.j}}^{T_{b.j}} \eta_j P_{j.t}^{\pm} \Delta t = \sum_{i=1}^{I} (S_{e.i} - S_{a.i}) B_i \tag{12}$$

$$\sum_{t=T_{a.j}}^{t_1} \eta_j P_{j.t}^{\pm} \Delta t \le D_j \tag{13}$$

$$t_{a.i} < t \le t_{b.i} \tag{14}$$

where B_i is the battery capacity; η_j is the cluster charge/discharge efficiency; and D_j is the total charge/discharge demand of cluster j during optimal scheduling.

(4) Charge/Discharge Power Constraints for Clusters

$$\sum_{i=1}^{I} P_{i.max}^{-} \le P_{j.t}^{\pm} \le \sum_{i=1}^{I} P_{i.max}^{+} \tag{15}$$

where $P_{i.max}^{+}$ and $P_{i.max}^{-}$ are the upper and lower limits of the charging and discharging power that the battery is capable of withstanding to ensure battery safe operation.

4.2. Lower Layer Model

4.2.1. Objective Functions

With the optimization objective of minimizing the cost to each electric vehicle i owner in cluster j, the charging and discharging strategy of a single electric vehicle is formulated under the premise of satisfying the owner's demand.

$$F_2 = \sum_{i=1}^{I}\left(C_i^{+} + C_i^{B} - C_i^{-}\right) + \sum_{t=T_{a.j}}^{T_{b.j}} \alpha \left| P_{j.t}^{\pm} - \sum_{i=1}^{I} P_{i.t}^{+} + \sum_{i=1}^{I} P_{i.t}^{-} \right| \tag{16}$$

$$C_i^{+} = \sum_{t=T_{a.i}}^{T_{b.i}} \omega_t P_{i.t}^{+} \Delta t \tag{17}$$

$$C_i^{-} = \sum_{t=T_{a.i}}^{T_{b.i}} \omega_t P_{i.t}^{-} \Delta t \tag{18}$$

$$C_i^{B} = \sum_{t=T_{a.i}}^{T_{b.i}} \left(P_{i.t}^{+} + P_{i.t}^{-}\right) \lambda_{i.t} \Delta t \tag{19}$$

where F_2 is the cost of the V2G response for the electric vehicle owner, including the charging cost C_i, the cost of battery loss ${C_i}^B$, and the gain from discharge ${C_i}^-$ of the electric vehicle i; $P_{i.t}^{\pm}$ is the charging and discharging power of electric vehicle i in time period t; I is the quantity of electric vehicles in the cluster; and ω_t is the t -period tariff, and for the convenience of analysis, the tariffs are considered to be the same in this paper; $\lambda_{i.t}$ is the battery loss coefficient; and α is the penalty factor for scheduling deviation.

The charge/discharge power and the battery temperature varied less when the electric vehicle was connected to an AC charger. For this situation, the paper treats $\lambda_{i.t}$ as a function of the current discharge depth $DOD_{i.t}$ and the frequency of charging/discharging cycles $l_{i.t}$ to establish the loss model of power battery [27,28].

$$\lambda_{i.t} = \frac{c_b B_i + c_r}{l_{i.t} B_i DOD_{i.t}} \tag{20}$$

$$DOD_{i.t} = 1 - S_{i.t} \tag{21}$$

The SOC of electric vehicle i in time period t is shown by the following equation:

$$S_{i.t} = S_{a.i} + \frac{\sum_{t=T_{a.i}}^{t} \eta_i^{+} P_{i.t}^{+} \Delta t}{B_i} - \frac{\sum_{t=T_{a.i}}^{t} P_{i.t}^{-} \Delta t}{\eta_i^{-} B_i} \tag{22}$$

where c_b is the acquisition cost for each capacity of the battery and c_r is the renewal budget.

By fitting the experimental data [29], there is a linear relationship between $l_{i.t}$ and $DOD_{i.t}$: the greater the depth of $DOD_{i.t}$, the lower the number of $l_{i.t}$.

$$l_{i.t} = 694 DOD_{i.t}^{-0.795} \tag{23}$$

4.2.2. Constraints

(1) The SOC Constraints for Electric Vehicles [30]:

$$S_{min.i} \le S_{i.t} \le S_{max.i} \tag{24}$$

$$S_{e.i} = S_{a.i} + \frac{\sum_{t=T_{a.i}}^{T_{b.i}} \eta_i^+ P_{i.t}^+ \Delta t}{B_i} - \frac{\sum_{t=T_{a.i}}^{T_{b.i}} P_{i.t}^- \Delta t}{\eta_i^- B_i} \tag{25}$$

(2) Charge/Discharge Power Constraints for Electric Vehicles:

$$-\sum_{i=1}^{I} P_{i.t}^- \eta_i^- \delta_{i.t}^- \le P_{j.t}^{\pm} \le \sum_{i=1}^{I} P_{i.t}^+ \eta_i^+ \delta_{i.t}^+ \tag{26}$$

$$P_{i.min}^{\pm} \le P_{i.t}^{\pm} \le P_{i.max}^{\pm} \tag{27}$$

where ${\eta_i}^{\pm}$ is the charging/discharging efficiency of the electric vehicle i. $\delta_{i.t}^{\pm}$ is the charging/discharging state or not of the electric vehicle i in time period t; when $\delta_{i.t}^{\pm} = 1$, the electric vehicle is in the charge/discharge state; $P_{i.max}^{\pm}$ and $P_{i.min}^{\pm}$ are the upper and lower limits of the charging and discharging power of the electric vehicle i.

(3) Charge/Discharge State Constraints for Electric Vehicles:

$$\delta_{i.t}^- + \delta_{i.t}^+ \le 1 \tag{28}$$

(4) Charge/Discharge Time Constraints for Electric Vehicles:

$$T_{a.j} \le t_{a.i} < t_{b.i} \le T_{b.j} \tag{29}$$

5. Example Analysis

5.1. Parameter Settings

In this paper, as an example, the IEEE33 node distribution network (shown in Figure 4) is divided into three regions to simulate the proposed electric vehicle cluster orderly charging and discharging scheduling model and the cluster allocation method. In the simulation, we select a reference power of 10 MVA, a reference voltage of 12.66 kV, and an allowable voltage offset of ±5% at the load node [26].

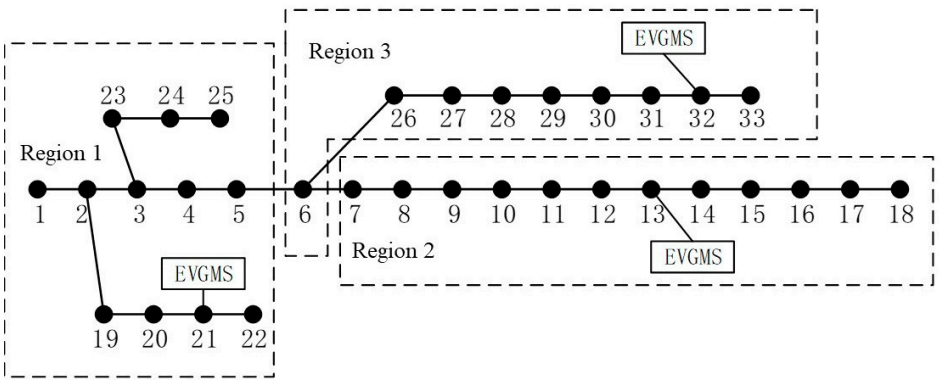

Figure 4. IEEE33 node distribution network.

The simulation time is from 00:00 to 24:00, and the time interval Δt = 30 min, totaling 48 time periods. It is assumed that the charge/discharge load and the other fundamental loads of the electric vehicle stay the same in the current period.

Assume that the distribution network serves a total of 1000 cars, with random access to three nodes, 13, 21, and 32, during the simulation. The mainstream BYD E6 series electric

vehicles were employed as the subject of the study. c_b = 2000 CNY/kWh, c_r = CNY 50,000. Battery specifications: B_i = 82 kWh, mileage of 400 km, power consumption of 20.5 kWh per 100 km, $P_{i.max}{}^{\pm}$ = 7 kW, and $\eta_i{}^{\pm}$ = 0.95. The upper and lower charge states of the battery during charging and discharging are 1/0.2, $S_{a.i}$~N (0.5,0.1^2), and $S_{e.i}$ = 0.95. It is assumed that 90% of the vehicle owners are inclined to engage in the V2G response process and have no subsequent travel plans once they are connected to the grid.

According to this paper, the average price of electricity for different voltage levels (as shown in Table 1) is taken as the average of the peak and valley periods for general industry and commerce in Beijing city. Moreover, the study assumes that the charge and discharge prices are the same. The examples described in this paper were implemented in MATLAB R2016b on a computer with an i7-9750H CPU, 144 HHz main frequency, and 16 GB of RAM.

Table 1. The division of peak and valley periods in Beijing and their electricity prices.

Type	Peak Hour	Steady Hour	Valley Hour
Hours	110:00–15:00 18:00–21:00	7:00–10:00 15:00–18:00 21:00–23:00	23:00–7:00
Tariffs (CNY/kWh)	1.28	0.76	0.29

5.2. Analytics of Simulation Results

To compare the real-time cluster dispatching strategy with the disorderly charging model, the load curve in this paper is shown in Figure 5. In particular, disorderly charging refers to the practice where an electric vehicle, upon connection to the grid, charges directly at maximum power until it reaches a need.

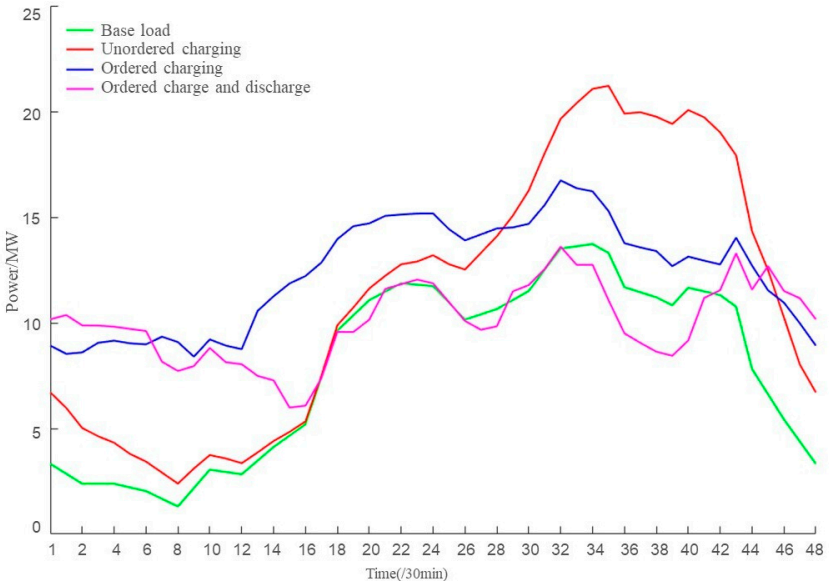

Figure 5. Cluster optimization effect.

From Figure 5, it can be seen that a certain peak-to-valley differential already exists in the conventional load during a single day of operation, where the load peak-to-valley difference is 12.42 MW and the standard deviation is 4.18 MW. However, disorderly charging further exacerbates the peak load during hours 31–44 (15:00–21:00), where the load peak-to-valley difference is 18.82 MW and the standard deviation is 6.28 MW. Random charging causes enormous pressure on the grid for real-time dispatch. By using the optimization strategy in the article, the peak-to-valley load difference can be reduced to

7.29 MW, while the standard deviation drops to 1.83 MW. From the load curve, it is clear that the charging load of electric vehicles is mainly concentrated in the "Valley" period (e.g., 0–16, 44–48), while in the "Peak" period, the electric vehicle cluster feeds back to the grid in the form of discharge. Such a process dramatically smooths out the volatility of the load curve and achieves peak shaving. In addition, without considering the discharge, the load peak-to-valley difference is 8.34 MW and the standard deviation is 2.58 MW. Compared to random charging, the optimization of EV clusters by the EVGMS system is advantageous.

Figure 6 illustrates the power response curves of three different nodes which are randomly accessed by electric vehicles during the dispatch time interval, as well as the load curves of the region where the nodes are located. As the figure shows, by adopting the charging and discharging strategy in this paper, each of the access nodes for electric vehicles can perform according to a charging and discharging schedule, while calming the regional load curve fluctuations.

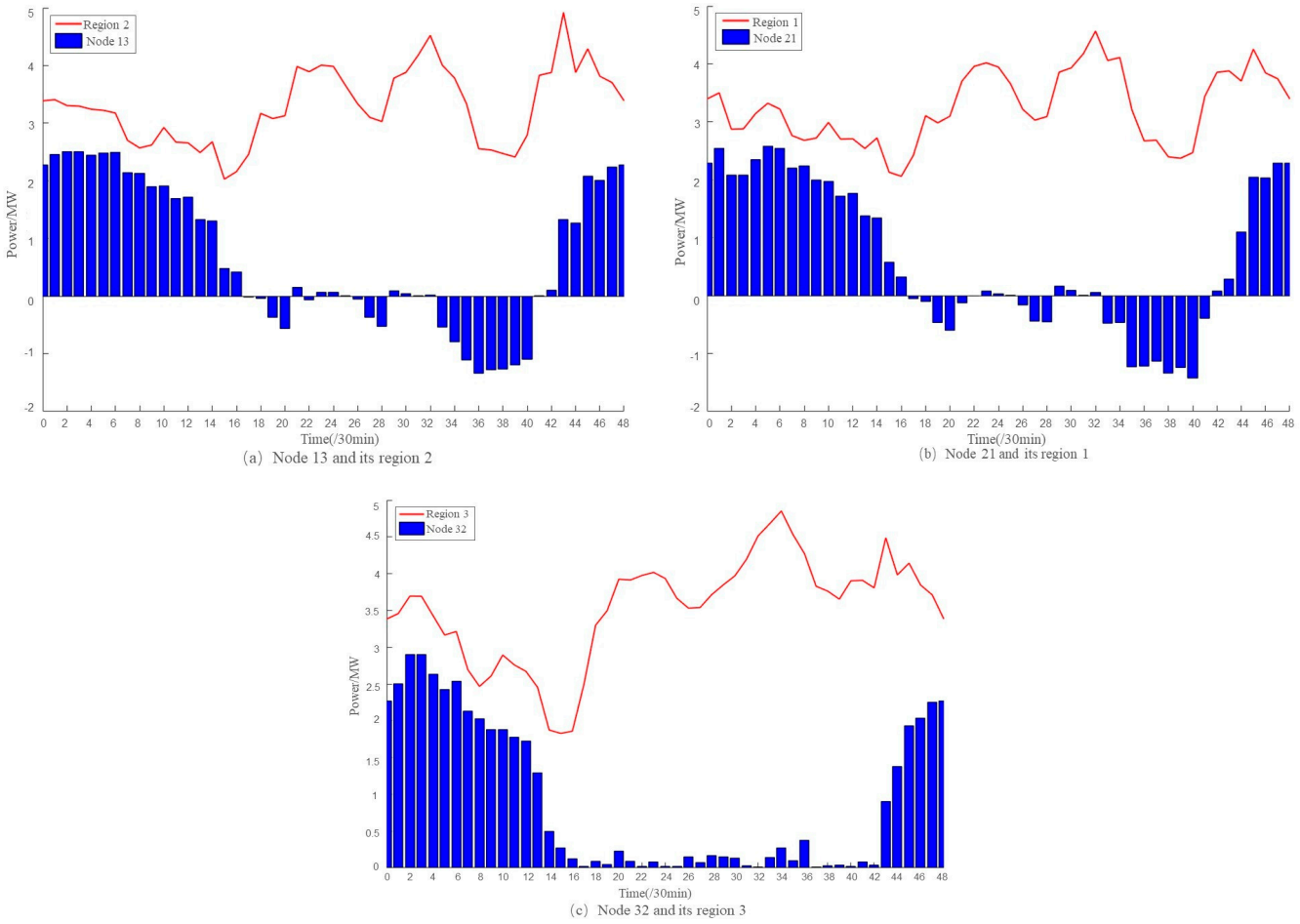

Figure 6. Electric vehicle clusters connected to nodes 13, 21 and 32 and regional load curve.

Figure 7 randomly selects three clusters whose scheduling times are 17:00–10:00, 15:00–8:30, and 24:00–6:30, respectively. As can be seen, the scheduling commands issued by EVGMS and the real-time response of each cluster are basically matched. Of these, the clusters with dispatch hours of 24:00–6:30 take full advantage of the low valley tariffs to recharge, whereas the clusters whose dispatch times are 17:00–10:00 and 15:00–8:30 discharge at peak load times, which not only feeds power back into the grid but also provides revenue for the vehicle owner.

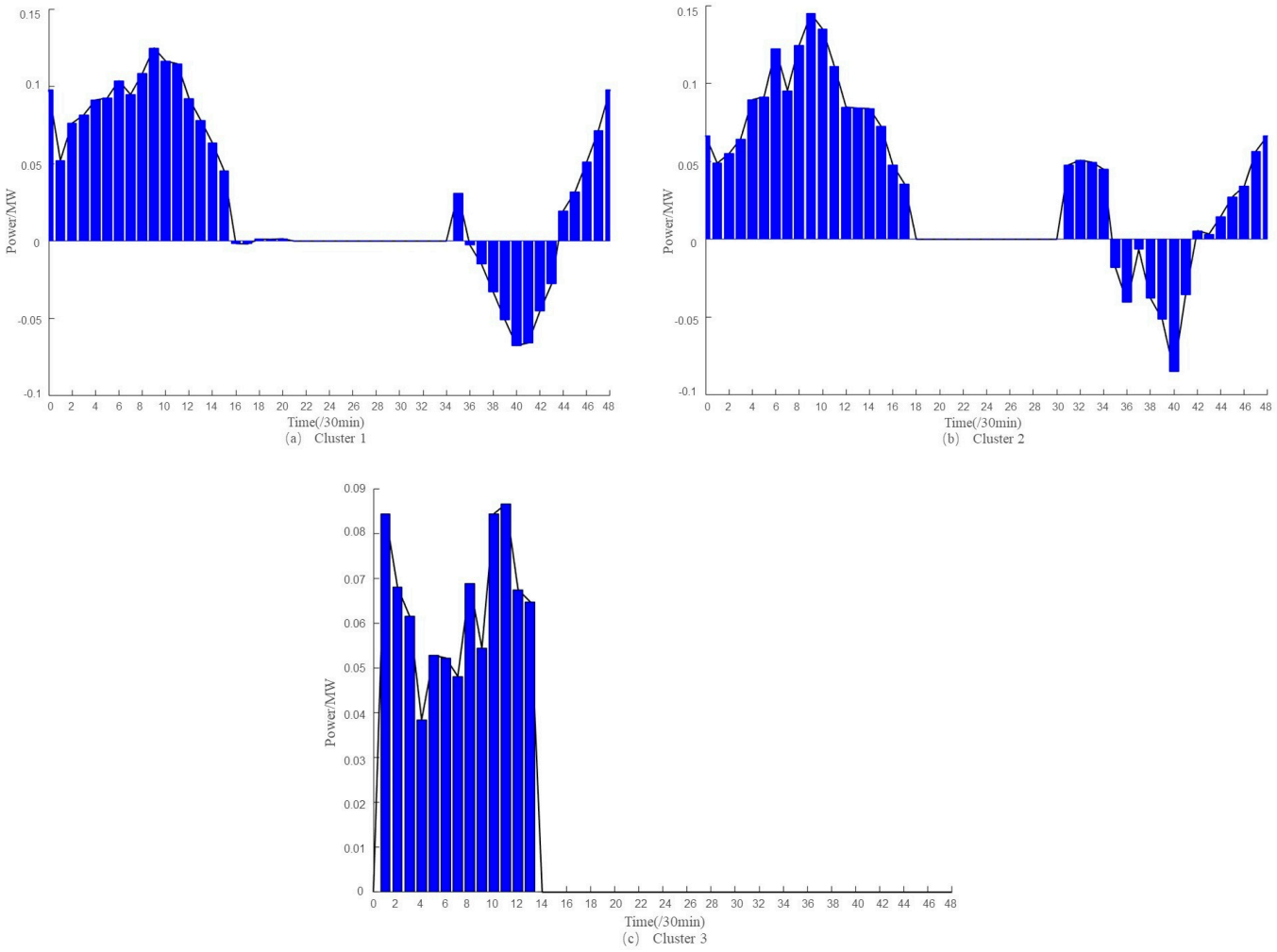

Figure 7. Clusters and curve.

In terms of the economic benefits to vehicle owners, the average cost of a single charge is CNY 15.64 when charging irregularly. On the other hand, with the optimized strategy, under the assumption that the average loss of a single discharge is CNY 0.28, it costs an average of CNY 9.26 to charge and discharge in an orderly manner, which is 39.24% less than random charging. Regardless of the discharge, the typical cost to the owner of an electric vehicle with only sequential charging control is CNY 10.31, which is 10.18% higher than the average cost of sequential charging and discharging. Consequently, the cluster-sequenced charging and discharging scheduling strategy reduces the peak-to-valley load differential and simultaneously takes into account the economic profit of the electric vehicle owners.

6. Conclusions

Against the background of a large number of EVs connecting to the grid in an unorganized manner, there are great difficulties involved in grid scheduling.

(1) We propose a multi-timescale EV cluster division strategy for the day-ahead and intraday phases, which better solves the drawbacks of the EV cluster as a whole and the single EV as the scheduling object in the power grid at the current stage. First, in the day-ahead phase, EV charging loads are modeled based on historical EV travel data; in the intraday phase, EVs with similar attributes are placed into the same cluster by collecting EV access and departure times from the grid and real-time demand. This kind of clustering can ensure the user's traveling demands and thus has strong practical application significance.

(2) We established a two-layer, real-time optimal scheduling model for EVs that are capable of and willing to participate in V2G. First of all, in the upper layer model, the electric vehicle cluster charging and discharging power are obtained to minimize the variance of the load curve of the distribution network; in the lower model, the charging and discharging schedules of individual EVs are optimized to minimize the cost to the EV owners and are made to be as consistent as possible with the upper scheduling schedule. This cluster scheduling strategy is compared with disordered charging; the proposed model makes full use of the low grid load rate to charge EVs and keep the system at a higher and more stable load rate, while ensuring the safe operation of the distribution network and user satisfaction.

The simulation results show that the model has a good optimization effect and a fast solution speed for dealing with large-scale electric vehicle access problems. In order to consider customer satisfaction, the model effectively smooths the load fluctuation, and the economy of the electricity consumption by vehicle owners is also effectively improved. In the subsequent research work, issues such as the leakage of the vehicle owners' privacy will be emphasized.

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