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Retraction

Retracted: Multiobjective Optimization Scheduling of Sequential Charging Software for Networked Electric Vehicles

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] X. Liu, X. Wang, F. Ren, M. Zhang, H. Khatter, and A. alam, "Multiobjective Optimization Scheduling of Sequential Charging Software for Networked Electric Vehicles," *Journal of Sensors*, vol. 2022, Article ID 6968470, 8 pages, 2022.

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Research Article

Multiobjective Optimization Scheduling of Sequential Charging Software for Networked Electric Vehicles

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In order to reduce the adverse effects of disordered charging of electric vehicles on the safe and stable operation of the distribution network, a multiobjective optimal scheduling method for the sequential charging software of networked electric vehicles is proposed. Aimed at minimizing charging costs and peak-to-valley differences in distribution network loads, its scheduling strategy will continuously roll and update EV charging schemes over time. The results show that the actual response data collected by the Internet of Vehicles app has corrected the probability distribution of the user's choice of charging mode and response behavior. On the fifth day, the user's actual charging response curve is close to the theoretical curve obtained by the optimization algorithm, and the expected charging is basically achieved. Calculations showed that the variance of the total load curve after charging decreased by 24.8 from 169.35 to 127.39. The proposed orderly charging strategy can effectively reduce the charging cost of electric vehicle users and the peak-to-valley difference of the distribution network load, play a good role in peak-valley filling, improve the convergence accuracy of the algorithm, and obtain the optimal solution of the problem.

1. Introduction

In recent years, the Beijing-Tianjin-Hebei region and the northeast region appear to have large-scale haze weather; it is necessary to accelerate the promotion of new energy vehicles or automobiles and accelerate their industrial layout, actively promote all applications, and enhance the structural transformation. State Grid and China Southern Power Grid have also actively mobilized and advocated to actively develop energy conservation and electric energy, replace many tasks, actively develop the work of exchanging electricity for coal, increase investment in transmission lines, actively transform lines, and improve transmission capacity. The government will give priority to promoting new energy vehicle technology in the relevant regional urban agglomerations of Shenyang Economic Development Zone and then actively expand the promotion efforts to promote the application of new energy vehicles in the province, establish new energy vehicle-related supporting equipment, and cooperate with the State Grid Corporation to improve electric vehicles. Charging-related supporting equipment is utilized to promote the comprehensive development of the new energy vehicle industry. It is expected that in the next 20 years, the development of new energy electric vehicles will achieve a blowout effect, and the new energy electric vehicle domain and industry will usher in a great development and also enter a period of rapid development. Large-scale electric vehicles, like small capacitors or power supplies, will constantly exchange energy with the power grid, which will inevitably have a greater impact on the power grid. This kind of charging not only has a certain randomness in time and space, so this kind of disordered charging will bring some negative effects to the energy management of the power grid. This randomness and intermittency will be very significant. To further consider, a large number of disordered mobile charging loads in a regional power grid will affect the whole trend of the regional power grid and its load distribution, as well as the influence of whether the regional power grid leads to peak load. Such mobile loads can lead to increased load on the regional grid, busier lines, increased investment, and operating costs [1]. As an emerging load, the access of electric vehicles to the power grid will have a series of impacts on the power system. For example, the peak-to-valley difference of the load will be further increased, the load of the distribution network will be partially overloaded, the local line voltage of the power grid will be too low, and the line loss will increase. Large distribution network transformer capacity exceeds the limit and other issues. With the large-scale popularization of electric vehicles, the uncertainty of the time and space of electric vehicles in the network will become prominent. A large number of studies have shown that the orderly access of electric vehicles to the grid has much less impact on the power system than the disorderly access to the grid.

Electric vehicles are directly connected to the grid for charging through the charging infrastructure, and the actual indirect carbon emissions produced are not significantly superior to traditional fuel vehicles, and it is difficult to reduce the dependence on fossil fuels. In this case, there are two ways to achieve low carbon in the true sense: one is to vigorously develop the renewable energy power generation system, coordinate the scheduling of electric vehicle charging and renewable energy power generation in the power grid, and improve the grid's consumption of renewable energy. The second is to directly establish the connection between the charging and discharging facilities and the distributed renewable energy power generation system, so as to realize the local consumption and utilization of renewable energy. Judging from the current development situation, it is very difficult to adjust the primary energy structure of the power grid. Through the on-site integration of renewable energy and electric vehicles, the utilization rate of renewable energy can be effectively improved and carbon emissions can be reduced.

A great deal of research has been done on the method of orderly charging of electric vehicles, and a variety of optimization methods of orderly charging have been developed from different aspects. From the perspective of research and skill, orderly charging can be divided into the following: (1) single electric vehicle charging control, (2) charging control of multiple electric vehicles, and (3) charging control of electric vehicles in the regional power grid. According to the power flow direction, it can be divided into the following: (1) single direction charging control, which only considers the one-way charging from the power grid to the electric vehicle and does not consider the reverse feeding of electric vehicles to the power grid. (2) After the V2G Fangk electric vehicle is connected to the power grid, the electric energy flows bidirectionally between the battery and the power grid, involving the case that the electric vehicle feeds the electric energy to the power grid.

Wang et al. established a mathematical model for orderly charging of electric vehicles in charging stations, aiming at maximizing the operating income of charging stations and taking the capacity of distribution transformers and maximizing the satisfaction of users' charging needs as constraints [2]. The charging strategy is that in every fixed period, the EV charging control system calls the orderly charging optimization program to calculate and determine the charging and stopping status of each charger within J periods in the future according to the parking status of EV in the charging station, user demand, grid load, and electricity price information. On the basis of summarizing the influence of EV charging on the power grid, Long established the influence of user behavior on charging. According to the power curve fitted by the measured smart electric power data, an orderly charging method for electric vehicles is proposed. Under the premise of ensuring the safety of the power grid and meeting the charging needs of users, the electric vehicles are charged by using the valley power as much as possible to reduce the fluctuation of the power grid load, so as to improve the economy of the power grid operation [3]. Charging of electric vehicles is also affected by the power grid and human behavior, so the orderly charging method should meet the needs of both the power grid and users: it should not only provide sufficient electricity for users but also reduce the operating cost of the power grid as much as possible. After the user connects the electric car to the charging pile, the user sets the charging completion time. Before this time, the calculation model of charging through pool gas is completed to judge whether it can participate in orderly charging; thus, according to the battery SOC, battery power curve, and grid load situation, the optimal charging start time is calculated, the charging power is superimposed on the grid load curve, and the EV is charged after the waiting time is up. For the research on the coordination of multiple charging stations in the regional power grid, the literature based on the particle swarm optimization (PSO) algorithm established a mathematical model of load stabilization for charging and discharging of electric vehicles. Liu et al. built the technical management and market operation mode of regional electric vehicles. Established on the existing system grid structure, an intelligent charging method was proposed, and they compared and studied the scale of grid-connected electric vehicles in three cases: blind charging, response to peak and valley TOU price, and intelligent charging; it shows that on the premise of ensuring the safety and stability of the system, the largest grid-connected charging of electric vehicles can be achieved through its intelligent charging method [4]. Ponnam and Swarnasri established the load characteristics of EV charging and the influence of different charging modes on the power grid. On this basis, a multitime scale mathematical model for collaborative scheduling of electric vehicles with wind power is established. Based on the planning and measured data of North China Power Grid and Northwest Power Grid, the feasibility of dispatching EV charging to smooth the equivalent load fluctuation of the power grid and consume the excess wind power at night is analyzed [5].

Based on the above research results, there is still a lack of optimal scheduling methods for EV photovoltaic charging stations. Compared with conventional charging stations, photovoltaic charging stations not only are equipped with photovoltaic power generation system inside the station but also need to be equipped with energy storage system of a certain capacity considering the fluctuation and intermittent characteristics of photovoltaic power generation. In this case, on the one hand, photovoltaic power generation should be used as much as possible to reduce the cost of electricity purchase from the grid; on the other hand, it is necessary to consider the service life of the energy storage system and reduce the cyclic energy storage as much as possible. Therefore, the optimization scheduling method of conventional charging stations cannot be fully applicable. Aiming at the photovoltaic charging station system of electric vehicles, this paper studies the multiobjective optimal scheduling method of the photovoltaic charging station system with the goal of reducing the electricity purchase cost and the circulating power of the battery pack. The network needs to be scalable: given that there may be billions of devices connected to any given blockchain network, the network must be able to expand its ability to handle transactions and requests. The network needs to support the discovery and transaction of general-purpose assets: there are many tradable digital assets and resources (such as data) on IoT devices, not just money. There is therefore also a need for ways to discover these assets. The network needs to support selective storage: given all the limitations of IoT devices, they will only be able to participate in a small subset of the network, and what each device stores and processes must be carefully selected.

2. Structure of the Internet of Vehicles System

The IoV system is mainly composed of two parts, which realize information interconnection through Bluetooth communication.

(1) A vehicle status information monitoring system centered on an electronic control unit (ECU). The system mainly uses voltage, current, and temperature sensors and counters the voltage, current, temperature, and charging and discharging times of the electric vehicle battery through the ampere-hour integration method. Calculate the real-time SOC (state of charge) of the battery

(2) A user response-interactive system centered on the Internet of Vehicles app. The system mainly realizes the following functions: (A) push information to users during the recommended charging period of EVs, and make statistics on user response; (B) by connecting the app and charging device through the wireless network, users can upload the charging scheme to the charging pile through the app to realize charging control of EV. (C) Through the mobile network, vehicle position information, charging pile status information, and real-time road traffic information can be obtained. Users can select charging piles according to their travel willingness, and the app can provide users with the charging navigation scheme [6, 7].

The system consists of a photovoltaic battery pack, energy storage battery pack, central control unit, DC-DC converter, AC-DC converter, DC bus, and charging pile, as shown in Figure 1.

(1) Photovoltaic battery pack: it is composed of solar panels in series and parallel. Photovoltaic cells absorb solar energy and emit direct current, which is connected to the system through a DC-DC converter and is the main power source for charging electric vehicles in the station

(2) Energy storage battery pack: it is composed of lead-acid batteries in series and parallel and plays an energy storage and adjustment role in the system

(3) DC-DC converter: use unidirectional DC-DC to realize the connection between photovoltaic cells and DC bus and charging pile and DC bus, and use bidirectional DC-DC to connect energy storage battery pack and DC bus

(4) AC-DC converter: it connects the AC distribution network and the DC bus and is a necessary conversion module for the distribution network to charge the system

(5) Central controller: collects the electrical information of each part and controls the energy flow between each component

(6) Charging pile: it is an electric vehicle charging terminal, which can flexibly charge electric vehicles during parking time

3. Vehicle Connected Framework

3.1. Pushing Process of the Internet of Vehicles App. The push process of the Internet of Vehicles app is based on the prediction of the current day load data and the optimization model to get the theoretical value of push volume within each time interval. The current day is divided into several push periods, the push volume of each push period is determined, and push is carried out at the first end of each push period. The user's SOC value determines the priority of his/her push; that is, the smaller the SOC value, the higher the probability of being pushed. If the user does not respond, it will be pushed in the next recommended charging period. If the user responds to push, the user is prompted to select the charging pile, and the vehicle position information and real-time road traffic information obtained by the Internet of Vehicles app are used to carry out path planning for the user. After arriving at the charging pile, the user connects the mobile phone to the charging pile through the wireless network and sets the charging mode and charging requirements on the app. The charging mode is divided into quick charging and regular charging, and the charging requirements are divided into three types: (1) the end time of charging is the constraint; that is, the user sets the end time of charging in advance and does not make requirements on the amount of charging; (2) the charging amount is the constraint; that is, the user requires the electric quantity to reach its set value at the end of charging and does not make

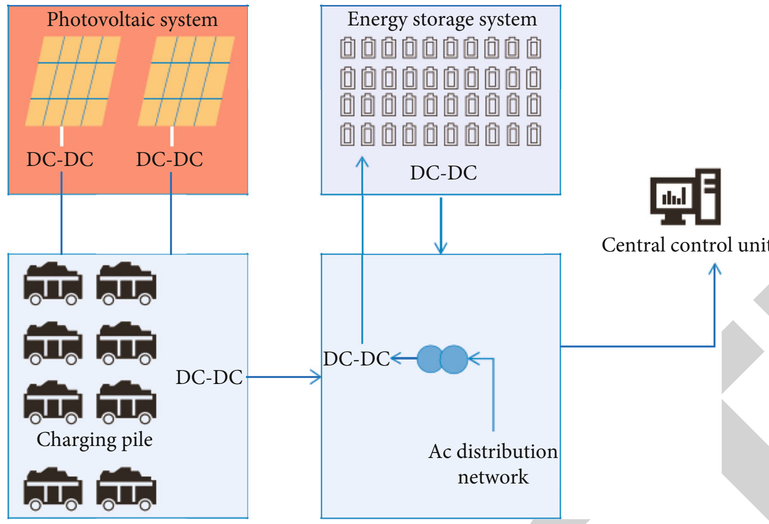

Figure 1: System structure diagram of electric vehicle charging station with photovoltaic power generation.

requirements on the charging time; and (3) the end time of charging and the amount of charging are the constraints; that is, the user wants to make the electric quantity reach the set value within a certain time. The IoV system recommends to the user the earliest starting time of charging and the estimated SOC value of the battery at the end of charging based on the obtained real-time charging status of EVs, including those currently charging and EVs that have been charged by appointment. If the user agrees to the charging scheme, the Internet of Vehicles app uploads the user's charging settings to the charging pile, which will charge the user on time. If the user does not agree with the charging scheme, the user will be charged according to the starting and ending time of the charging set by the user.

3.2. Probability Distribution and Correction Method. By introducing the probability of users responding to push and the probability of choosing different charging modes, the probability of users responding to push and choosing one of the charging modes after receiving APP push is quantified. According to the user response data obtained by the Internet of Vehicles system, the selection frequency of charging mode and the response push frequency of the user in the history were counted. The moving average method is adopted to obtain the current charging mode adopted by daily users and the probability estimate of response push [8, 9]. The formula is shown as

$$P_{k,Ti} = \sum_{f=T-N_n}^{T-1} \frac{P_{kr,fi}}{N_a P_{m,Ti}} = \sum_{f=T-N_n}^{T-1} \frac{P_{mr,fi}}{N_a i} \in [1, 2, \cdots, N_T], \quad (1)$$

$$P_{mr,fi} = \frac{x_{m,fi}}{x_{R,fi}} P_{kr,fi} = \frac{x_{k,fi}}{x_{R,fi} i} \in [1, 2, \cdots, N_T], \quad (2)$$

$$P_{R,Tij} = \sum_{f=T-N_a}^{T-1} \frac{P_{Rr,fij}}{N_a i} \in [1, 2, \cdots, N_T] j \in [S_a, S_b], \quad (3)$$

$$P_{Rr,fij} = \frac{x_{R,fKj}}{n_{fKj}} i \in \left[t_{fKm}, t_{fKn}\right], \quad (4)$$

$$P_{R,TKj} = \sum_{i=t_{TKm}}^{t_{TKn}} \frac{P_{R,Tij}}{N_{PTKj}} \in [S_a, S_b], \quad (5)$$

$$N_{PTK} = \frac{t_{TKn} - t_{TKm}}{a}, \quad (6)$$

where $P_{k,Ti}$, $P_{m,Ti}$ are the probability of quick charging and regular charging for users at the time of T day i; $P_{kr,fi}$, $P_{mr,fi}$ are the frequency of quick charging and regular charging by users at the time of day f and i; $x_{m,fi}$, $x_{k,fi}$ are, respectively, the number of users who received regular charging and quick charging at the time of day I on day f ; $x_{R,fi}$ is the actual response quantity of users at the time of T day i; $P_{R,Tij}$ is the user response probability of EV battery SOC in the interval at the time of T day i; $P_{Rr,fij}$ is the user response frequency of EV battery SOC in the interval J at the time of day f, i; $x_{R,fKj}$ is the user's actual response of EV battery SOC in interval J during the K push period on day f; n_{fKj} represents the actual push volume of EV battery SOC by users in the interval J during the K push period on the factory day; t_{fKm}, t_{fKn} are the start and end time of the K push period on day f; a is the time step; N_a is the item value of the moving average; N_{ptk} denotes the number of time intervals included in the K push period on day T; N_T is the total number of segments of the current day time; and S_a and S_b represent the lower and upper limits of the push range of SOC.

3.3. Optimization Algorithm of Theoretical Push Volume. The theoretical value of push volume per hour is obtained by using the optimization algorithm. Considering the probability distribution of different charging modes and charging time of electric vehicles, with orderly charging of electric vehicles as the goal to smooth the fluctuation of the load

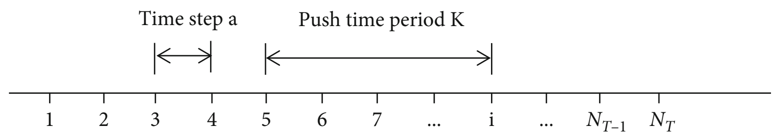

FIGURE 2: Diagram of push time period division.

curve, the optimization model [10–12] is built under the constraint conditions of the total amount of electric vehicles (equation (10)), avoiding charging during peak load periods (equation (11)) and not forming evening peak charging periods (equation (12)).

For the target function, the formula is shown as

$$\min \sum_{i=1}^{N_T} \left(P_{L,Ti} + P_{C,Ti} - P_{av,T}\right)^2 i \in [1, 2, \cdots, N_T]. \tag{7}$$

For constraint conditions, the formula is shown as (8) and (9):

$$\begin{aligned} P_{C,Ti} = {} & x_{Ti} P_{k,Ti} P_{ke} + x_{Ti} P_{m,Ti} P_{me} \\ & + \sum_{j=i-T_m}^{i-1} x_{Ti} P_{me} P_{m,\mathrm{Tj}} P(t_c > i - j) \\ & + \sum_{q=i-T_k}^{i-1} x_{Tq} P_{ke} P_{k,\mathrm{Tq}} P(t_c > i - q) i \in [1, 2, \cdots N_T], \end{aligned} \tag{8}$$

$$P_{\mathrm{av},T} = \frac{\sum_{i=1}^{N_T} \left(P_{L,Ti} + P_{C,Ti}\right)}{N_T}, \tag{9}$$

$$x_{Ti} \geq 0 \sum_{I=1}^{N_T} x_{Ti} \leq N_{\mathrm{EV}} i \in [1, 2, \cdots N_T], \tag{10}$$

$$P_{C,Ti} = 0 i \in T_b, \tag{11}$$

$$P_{C,Ti} + P_{L,Ti} < P_{Lm,T} i \in [1, 2, \cdots N_T] i \notin T_b, \tag{12}$$

$$P_{Lm,T} = \sum_i \frac{P_{L,Ti}}{N_{Lm} i \in T_b}, \tag{13}$$

$$T_m = \frac{t_m}{a T_k} = \frac{t_k}{\mathrm{a} N_{Lm}} = \frac{T_b}{a}, \tag{14}$$

where $P_{L,Ti}, P_{C,Ti}$ are the load power on day T and charging power of electric vehicles at the time of day i, where the charging power of electric vehicles at time i is the sum of the charging power of electric vehicles connected at time i and the charging power of electric vehicles connected and continuously charged until time i. $P_{\mathrm{av},T}$ is the average value of total load after user response on day T; P_{me}, P_{ke} are the charging power of conventional charging and quick charging of electric vehicles; $P_{Lm,T}$ is the average peak load of current daily electricity; N_{Lm} is the segment number of peak time of electricity consumption; $P(tc > i - j)$ is the probability that the charging time of electric vehicle is greater than $I - j$; x_{Ti} is the theoretical value of the number of charging users in response at the time of T day i; t_m, t_k are the time required to charge the battery SOC from the lower limit to the upper limit in the fast charging mode and the conventional charging mode, respectively; N_{EV} is the total number of electric vehicles; and T_b is the peak period of electricity consumption [13–15].

TABLE 1: Probability distribution of EV charging time.

SOC (%)	Charging duration (h)	Probability
0.3-0.4	5-6	0.03
0.4-0.5	4-5	0.18
0.5-0.6	3-4	0.40
0.6-0.7	2-3	0.39

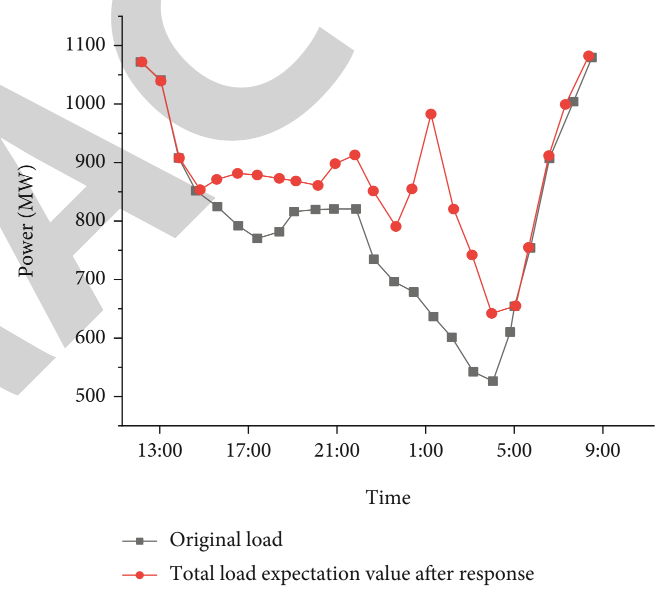

FIGURE 3: Theoretical value of EV charging load.

3.4. Calculation Method of Actual Push Volume. According to the theoretical value of user push quantity in each time interval obtained by the optimization model, the current ET is divided into several push periods (as shown in Figure 2), combined with the probability distribution of user response.

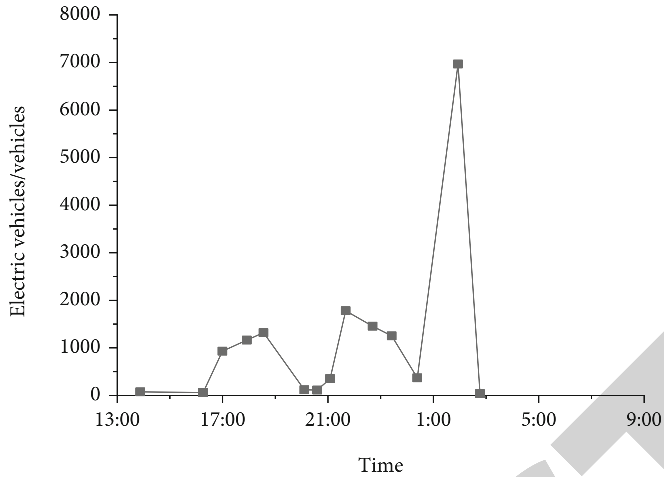

FIGURE 4: Theoretical value of electric vehicle push volume.

$$X_{TK} = \sum_{j=S_a}^{S_b} n_{TKj},$$

$$n_{TKj} = \min \left\{ \begin{array}{c} \dfrac{\left(\sum_{i=t_{TKn}}^{t_{TKn}} x_{Ti} - \sum_{q=S_a}^{j-h_{\mathrm{SOC}}} n_{TKj} P_{R,TKq} \right)}{P_{R,TKj}}, \\ \left(N_{\mathrm{EV}} - \sum_{l=1}^{K-1} X_{Tl} \right) \alpha_j \end{array} \right\} \quad j \in [S_a, S_b]. \tag{15}$$

In the formula, $P_{R,TKj}$ is the user response probability corresponding to the EV battery SOC in the interval j during the K push period on the T day; X_{TK} represents the total amount of push during the K push period on the T day; h_{SOC} represents the block step size of SOC; α_j represents the probability that EV battery SOC is in the interval j; and t_{TKm}, t_{TKn} are the starting and ending times of the K push time period on the T day.

4. Simulation and Results

4.1. Assumption Conditions and Parameter Settings

(1) Parameter setting

There are about 2.34 million private cars in Guangzhou, of which 100,000 are electric vehicles, with a penetration rate of 4.27. The model is BYDE6, with a maximum range of 400 km, fast charging power and regular charging power of 90 kW and 14 kW, respectively, and constant power charging. For quick charging and conventional charging, the time required for charging the battery power from the lower limit to the top limit is 1 h and 6 h, respectively, and the time step is 1 h [16, 17].

(2) Assumptions

With the user charging mode and the initial response behavior probability distribution, considering the efficiency of the user response data and distance from the current day, the response data to estimate the probability of the reference value is low, so the moving average number is 3; it is using the current user response having 3 d data for the current user response probability and charging mode selection probability estimates. The initial SOC of the user follows the normal distribution $N \sim (0.6, 0.1)$. In the case of conventional charging, the SOC of the EV battery reaches the upper limit at the end of charging; then, there is a linear relationship between charging time and SOC, and its probability distribution is shown in Table 1. Push is mainly aimed at users whose SOC value is lower than 0.7. Considering the characteristics and safety of the battery, the push range of the SOC is $(0.3, 0.7)$.

4.2. Determination of Push Volume. The MATLAB nonlinear programming function is used to solve the optimization model of equations (4)–(11). The expected value of push per hour and the theoretical curve of expected charging power are obtained in Figures 3 and 4.

At this time, the load is at a low point in the day. Since private cars are mainly used after work on weekdays, combined with the optimization results, select the current 16:00 and 21:00 to push. According to the probability model, the user response probabilities are 0.6 and 0.56, respectively; therefore, the actual value of push volume in two periods is 11,000 and 44200 vehicles, respectively [18–20].

4.3. User Response. Based on the user's initial SOC probability distribution, by simulating the response behavior of each user at each push moment, the actual charging power curve of the user is obtained as shown in Figure 5.

It can be seen from Figure 4 that the current daily user response is insufficient, and the response is only 56% of the expected value in the trough of electricity consumption between 0 and 7 hours, As can be seen from the results of the calculation examples, the actual response data of users collected by the Internet of Vehicles app is used to correct the probability distribution of users' selection of charging mode and response behavior, the user response was insufficient in

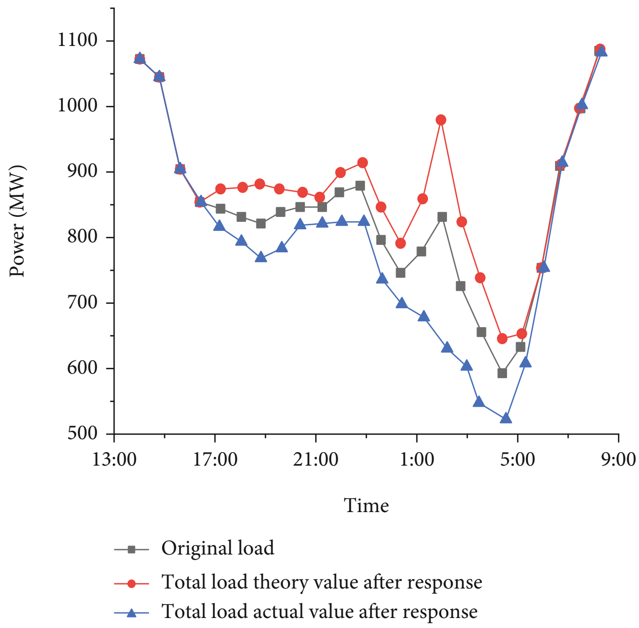

FIGURE 5: Response of electric vehicles.

the first 2 days after the start of the push, and the user response was excessive after the push volume was increased on the third day [21, 22]. After the push volume was modified using correction method, the actual charging response curve of users on the fifth day approached the theoretical curve obtained through the optimization algorithm, basically reaching the expected charging effect. The calculation showed that the variance of the total load curve after charging was reduced from 169.35 to 127.39, a reduction of 24.8% [23, 24].

5. Conclusions

To sum up, in order to reduce the adverse effects of disordered charging of electric vehicles on the distribution network, an orderly charging strategy based on a multiobjective method is proposed, and the scheduling strategy will continuously roll and update the electric vehicle's schedule over time. The simulation results show that the proposed orderly charging strategy can effectively reduce the charging cost of electric vehicle users and the peak-to-valley difference of the distribution network load, play a good role in peak-valley filling, and improve the convergence accuracy of the algorithm, which is an optimal solution to the problem. The follow-up work can optimize the long-term operation of the system, further determine the daily circulating electricity value, and select the best daily scheduling scheme. The wireless charging technology of electric vehicles has the advantages of convenience and speed, but it is still in the research and development and exploration stage, and there is still a lot of work to be done in terms of practical application. In addition, according to the actual situation of the current energy shortage, it is still too early for electric vehicles to realize the industrialization of high-power wireless charging technology, but as a flexible charging method in the future, it is necessary to carry out preliminary exploration. With the continuous improvement of this technology, combined with the construction of China's smart grid, its application in the intelligent charging and swapping service network of electric vehicles will greatly promote the large-scale application of electric vehicles.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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