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An orderly charging optimization method for electric vehicles based on user demand response

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Abstract

In order to cope with the challenges brought by the rapid development of electric vehicles to the safe and stable operation of the power grid, this paper proposes an optimization method of orderly charging of electric vehicles based on user demand response. Firstly, this paper establishes the EV charging load model, and introduces the model considering user demand response. Secondly, an orderly charging guidance method for electric vehicles based on user demand is designed, aiming to guide users to adjust charging behavior with dynamic electricity price by considering user demand, so as to reduce the load fluctuation of the power grid, reduce the charging cost, and ensure the operation stability of the power grid. Finally, through the improved particle swarm optimization (PSO) algorithm, the simulation results show that the optimized charging strategy can effectively smooth the load curve of the grid, reduce the load pressure during peak hours, reduce the network loss and voltage fluctuations, and effectively control the charging cost of users.

Keywords: Electric Vehicle; Orderly Charging; Demand Response; Electricity Price; Particle Swarm Optimization

1. Introduction

In 2020, The State Council issued the "New Energy Automobile Industry Development Plan (2021-2035)" [1], clearly pointing out that the development of new energy vehicles is a strategic choice to achieve China's automobile industry upgrading and green transformation. With its efficient and clean characteristics, electric vehicles have achieved rapid growth with the support of national policies [2]. However, large-scale EV access to the power grid brings new challenges: the randomness and uncertainty of its load may lead to the phenomenon of "peak-on-peak" during peak hours, exacerbate the fluctuations of the distribution network, expand the peak-valley difference, and lead to problems such as equipment overload and loss increase [3-5].

Existing studies have made remarkable progress in the optimization of EV charging, but there are still some limitations: Literature [6] describes the spatial-temporal distribution of EV through the travel chain model, and introduces prospect theory and logit model to analyze user decision-making, but its TOU tariff division is not closely combined with load characteristics. The dual-layer energy scheduling model constructed in literature [7] proposes a dynamic time-sharing pricing strategy, but there is ambiguity in the user demand response mechanism. Although the literature [8] considers both disordered charging and ordered charging modes, and establishes a mathematical model that takes into account vehicle owner responsiveness, it does not deeply analyze the impact of scheduling process on the power grid. The economic scheduling strategy proposed in literature [9] based on LSTM network considers the demand of electric vehicles, but ignores the influence of user behavior factors. In literature [10], battery loss constraints were introduced into the charging station scheduling model, but the consideration of users' wishes was still insufficient. The charging mode proposed in literature [11] innovatively sets a penalty factor, but its objective function only focuses on minimizing

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the user's charging cost. The research of literature [12] is limited to considering the interests of power grid or users separately, and lacks an overall analysis of the interests of the two. Although the economic benefits of charging behavior were considered in literature [13], a complete optimization framework was not established. Literature [14] realizes peak cutting and valley filling through unified scheduling time, but there is still room for improvement in enhancing user engagement. At present, relevant researches have made progress mainly in the aspects of electricity price guidance and compensation mechanism, but the consideration of user willingness and response degree is still insufficient. Therefore, this study proposes an optimization method of orderly charging based on user demand response, which guides users to adjust charging behavior through dynamic electricity price mechanism, aiming to achieve multiple goals of minimizing load fluctuation, reducing charging cost and improving grid efficiency.

2. Electric vehicle charging load model

2.1. Electric vehicle user travel rule model

The family electric car is usually used as a means of commuting during the morning and evening rush hours and is idle the rest of the time. This paper takes household electric vehicles as the research object and selects the 2017 National Household Vehicle Survey data of the United States (NHTS2017) as the basic data. The time of electric vehicles connecting to the grid and leaving the grid meet the normal distribution, and its probability density function is as follows:

$$f(t_a)=\begin{cases}\dfrac{1}{\sigma_a\sqrt{2\pi}}\exp\left[-\dfrac{(t_a-\mu_a)^2}{2\sigma_a{}^2}\right],\mu_a-12\le t_a\le 24\\ \dfrac{1}{\sigma_a\sqrt{2\pi}}\exp\left[-\dfrac{(t_a+24-\mu_a)^2}{2\sigma_a{}^2}\right],0\le t_a\le \mu_a-12\end{cases} \quad \text{............(1)}$$

$$f(t_1)=\begin{cases}\dfrac{1}{\sigma_1\sqrt{2\pi}}\exp\left[-\dfrac{(t_1-\mu_1)^2}{2\sigma_1{}^2}\right],0\le t_1\le \mu_1+12\\ \dfrac{1}{\sigma_1\sqrt{2\pi}}\exp\left[-\dfrac{(t_1-24-\mu_a)^2}{2\sigma_a{}^2}\right],\mu_1+12\le t_1\le 24\end{cases} \quad \text{..........(2)}$$

Where t_a and t_1 respectively refers to the time of electric vehicles connecting to the power grid and leaving the power grid, σ_a , μ_a , σ_1 , μ_1 they represent the corresponding standard deviation of normal distribution and mathematical expectation, where the value is $\sigma_a=2.4$, $\mu_a=17.23$, $\sigma_1=2.2$, $\mu_1=8.61$ The overall probability distribution of electric vehicle users' travel characteristics is shown in Figure 1.

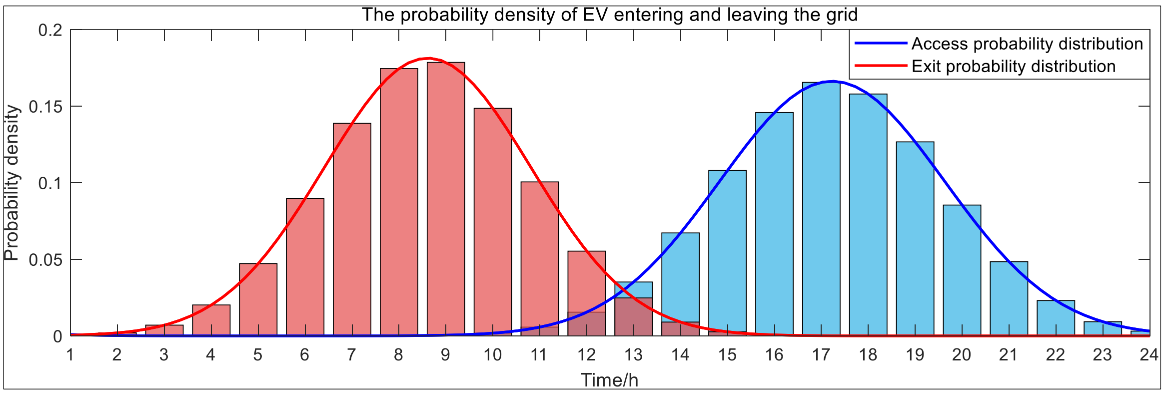

Figure 1 Probability distribution of user travel characteristics

The probability distribution density function of the average daily mileage driven by EV users satisfies the lognormal distribution.

$$f_d(s) = \left\{ \frac{1}{s\sigma_d\sqrt{2\pi}} \exp\left[-\frac{(\ln s - \mu_d)^2}{2\sigma_d^{\ 2}} \right] \right. \qquad \text{................(3)}$$

Where, s is the daily mileage of the electric vehicle, μ_d and σ_d is the expectation and standard deviation respectively, whose values are $\mu_d = 3.32$ and $\sigma_d = 0.86$. Its probability density is shown in Figure 2.

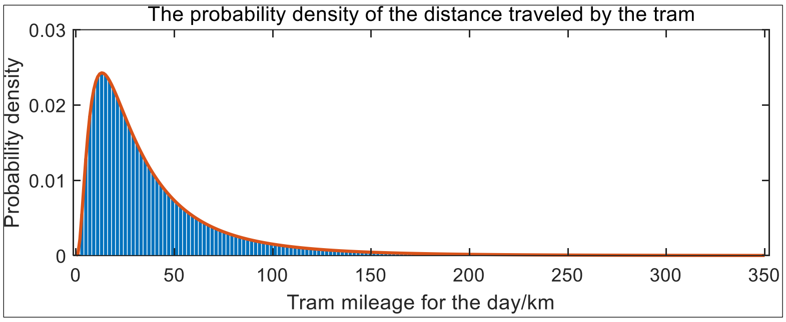

Figure 2 Probability density of daily mileage

2.2. Electric vehicle user travel rule model

As an important reference for the remaining driving distance of electric vehicle users, the State of Charge (SOC) of the battery is the ratio of the current battery power to the total battery capacity, and the SOC change expression is as follows:

$$S_t = S_0 - \frac{d_t}{D_{\max}} \qquad \text{.........(4)}$$

Where, S_t and S_0 are the state values of SOC at time t and initial time respectively, d_t is the total mileage of the current moment, then $D_{\max}$ is the maximum mileage of the EV. After arriving at the charging station, the charging time is selected by the EV user, and the charging time of the user is

$$T(i) = \frac{E_c \Delta S(i)}{P_c \eta} \qquad \text{.....................(5)}$$

In the formula, $T(i)$ is the charging time for the user, E_c is the battery capacity, $\Delta S(i)$ is the SOC change of car i , P_c and η are the charging power and charging efficiency for charging pile.

3. Demand response model considering user psychology

The charging behavior of electric vehicles is affected by many factors, such as driving time, electricity, electricity price and weather, and presents dynamic changes. The traditional model sets the responsivity as a fixed value, ignoring its correlation with state of charge (SOC). Therefore, this study introduces the price elasticity coefficient matrix to quantify the sensitivity of charging price fluctuation to user demand, and its expression is as follows:

$$e_{ij} = \frac{\partial Q_i}{\partial V_j} \times \frac{V_j}{Q_i} \qquad \text{...............(6)}$$

Where, e_{ij} represents the element in the price elasticity coefficient matrix, Q_i represents the demand for charging quantity; V_j represents the electricity price; $\frac{\partial Q_i}{\partial V_j}$ is the partial derivative of quantity demanded Q_i with respect to price V_j , and it is the sensitivity of price change to quantity demanded.

Considering the current time-of-use electricity price, a more detailed division of time periods is made on this basis, and the current three peak, valley and flat periods are expanded into 24 time periods with hourly intervals, and each time period represents the same time, so as to obtain a more detailed electricity price elasticity coefficient matrix M as follows:

$$M=\begin{cases} m_{ij}=e_{ij}-0.65, i=j \\ m_{ij}=\dfrac{e_{ij}-0.5}{|i-j|}, |i-j|\le 8(i\ne j) \\ m_{ij}=e_{ij}-0.3, i-j>8 \end{cases} \text{..............(7)}$$

Where, m_{ij} is the elasticity coefficient of stage time-of-use electricity price. i, j represent different time periods.

There are differences in the response behavior of users to electricity prices, which can be divided into adjustable and non-adjustable categories. Adjustable users only adjust the charging period if the electricity price changes above a specific threshold. Based on the Weber-Fechner law, this response has a nonlinear character, that is, the sensitivity of the user to changes in electricity prices is valid within a certain range. In addition, the charging behavior of electric vehicles is not only affected by the current electricity price, but also takes into account the price fluctuations of multiple periods in the future. Therefore, this paper introduces parameters such as multi-interval price difference, maximum response value and period weighting, and constructs a response model that is closer to the reality. When the user participates in the demand response, the charging difference between the charging period from i to j is

$$\Delta V_{ij}=V_j-V_i \qquad \text{.........(8)}$$

Here V_i and V_j are the electricity prices for the i and j hours, respectively, and ΔV_{ij} is the difference in electricity prices. Consider the impact of user psychology, the transition probability t_{ij} of charging time from the i to the j hour is

$$t_{ij}=\begin{cases} 0, \Delta V_{ij}\le v_1 \\ \dfrac{|m_{ij}|\dfrac{\Delta V_{ij}}{V_i}}{\sum_{k=1}^{24}|m_{jk}|\times\dfrac{\Delta V_{ik}}{V_i}}, v_1\le\Delta V_{ij}\le v_2 \\ t_{\max}, \Delta V_{ij}\ge v_2 \end{cases} \text{.............(9)}$$

Where, v_1 is the dead zone threshold, generally 0.1/kWh; v_2 is the saturation region threshold, generally 1/kWh; $t_{\max}$ is the maximum transfer probability, which is generally 0.9.

The model provides an effective method for predicting the charging behavior of users, and can directly calculate the change in the demand of users as they move from one time period to another due to differences in electricity prices.

4. An orderly charging guidance method for electric vehicles based on user demand response

4.1. Objective function

In this paper, a dynamic electricity price optimization model based on user demand response is constructed. The model aims to stabilize load fluctuation and optimize charging cost. By adjusting charge and discharge price and power, load variance is adopted to quantify the stability of power grid, and economic benefit, environmental benefit and user satisfaction are coordinated to achieve the optimal management of charge and discharge strategy.

Considering the magnitude of load fluctuation of the power grid, load variance is selected as the evaluation index. The greater the load variance, the greater the load fluctuation of the power grid; otherwise, the smaller the load fluctuation of the power grid and the smoother the operation, so the objective function is

$$F_1 = \frac{\sum_{t=1}^{24}\left(P_l^t + P_{EV}^t - P_{ave}\right)^2}{24\sum_{t=1}^{24}\left(P_l^t + P_{EV0}^t - P_{ave0}\right)^2} \quad \text{…………..(10)}$$

$$P_{ave} = \sum_{t=1}^{24}\left(P_l^t + P_{EV}^t\right)/24 \quad \text{………..(11)}$$

$$P_{ave0} = \sum_{t=1}^{24}\left(P_l^t + P_{EV0}^t\right)/24 \quad \text{……………..(12)}$$

Where, P_l^t represents the fixed load power at the time of charging; P_{EV0}^t refers to the charging power of electric vehicles before dispatch; P_{EV}^t refers to the charging power of electric vehicles after scheduling; P_{ave0} refers to the daily average power of the grid before dispatching; P_{ave} indicates the average daily power of the grid after dispatching.

2) In addition, considering the user's participation in charge and discharge scheduling, the maximum proportion of user charging cost savings is targeted.

$$F_2 = \frac{\sum_{t=1}^{24} P_{EV0}^t C_0(t) - \sum_{t=1}^{24} P_{EV}^t C(t)}{\sum_{t=1}^{24} P_{EV0}^t C_0(t)} \quad \text{…………(13)}$$

Where, $C_0(t)$ and $C(t)$ respectively represent the charging electricity price during the t period before and after scheduling.

Considering the correlation between the above two objective functions, the total objective function obtained by multi-objective optimization is

$$\begin{cases} \min F = \lambda_1 F_1 + \lambda_2 F_2 \\ \lambda_1 + \lambda_2 = 1 \end{cases} \quad \text{……….(14)}$$

In the formula, λ_1 and λ_2 represent the corresponding weights of F_1 and F_2 of the above single objectives. Different coefficients can be taken for different application environments and optimization focuses. Here we choose $\lambda_1 = \lambda_2 = 1/2$

4.2. Constraint condition

1) Battery capacity constraints

Battery capacity limits for electric vehicles are designed to prevent safety problems caused by overcharging or over discharging, and to protect the health status of the battery and extend its service life.

$$S_{oc,\min} \le S_t \le S_{oc,\max} \quad \text{…………(15)}$$

Where, $S_{oc,\max}$、 $S_{oc,\min}$ are the upper and lower limits of the remaining battery capacity respectively.

2) Power grid capacity constraints

The capacity constraint of the grid is to prevent the overload of the grid due to high charging demand in a specific time period or area.

$$\sum P_{EV}^{t} \le P_{grid\max} \quad \text{..............(16)}$$

Where, $P_{grid\max}$ refers to the maximum transmission capacity of the power grid, indicating the maximum charging power that the power grid can support in a specific period of time.

3) Electricity price constraint

Electricity price constraints ensure that users can economically accept price fluctuations of charging or discharging.

$$V_{\min} \le V_t \le V_{\max} \quad \text{..........(17)}$$

Where, V_t is the charging price at time t ; In order to prevent the extreme electricity price from harming the interests of users, $V_{\min}$ and $V_{\max}$ are set as the lower limit and upper limit of electricity price respectively.

5. Algorithm and example analysis

5.1. Improved particle swarm optimization

Particle swarm optimization (PSO), as an efficient global optimization tool, is widely used in nonlinear optimization problems because of its simple structure, few parameters and strong adaptability. However, the algorithm has limitations when dealing with discrete optimization problems. Therefore, this paper introduces an adaptive weight strategy to improve the performance of the algorithm by dynamically adjusting the inertia factor. The improved inertia factor can be automatically adjusted according to the particle fitness value, and its expression is as follows:

$$\omega_i = \begin{cases} \omega_{\min} - (\omega_{\max} - \omega_{\min}) \cdot \dfrac{f_i - f_{\min}}{f_{ave} - f_{\min}} & f_i \le f_{ave} \\ \omega_{\max} & f_i > f_{ave} \end{cases} \quad \text{..........(18)}$$

Where, $\omega_{\min}$、$\omega_{\max}$ are the maximum and minimum values of the inertia factor; f_{ave}、$f_{\min}$ are the average fitness value and minimum fitness value of the current particle, so the value of inertia weight ω will be dynamically adjusted according to the fitness value of the particle during the iteration process. When ω increases, the global search capability of the algorithm is enhanced. On the contrary, when ω decreases, the local search ability of the algorithm will be improved.

5.2. Example analysis

Based on the typical daily load data of a local power grid in a city, assume that the power grid covers a total of 33 nodes, each node has 10 electric vehicles, the total battery capacity of each electric vehicle is 75 kWh, the maximum power of electric vehicles during charging and discharging is 12 kW, and the upper and lower limits of battery SOC are 0.9 and 0.2 respectively. The power grid buys electricity from the main network at a price of 0.6 yuan /kWh, dividing the day into 1,440 periods of 1 minute each. The initial simulation population is 650 groups. Through 500 cycles of simulation, the average value is taken to simulate the charging behavior of electric vehicles in this environment, and the simulation runs in the environment of Matlab 2021b software.

In the basic scenario of the power grid without electric vehicle load, the change of active power network loss of the system in each time period is shown in Figure 3, the voltage distribution of each time period and each node is shown in Figure 4, and the interval and price of time-of-use electricity price are shown in Table 1.

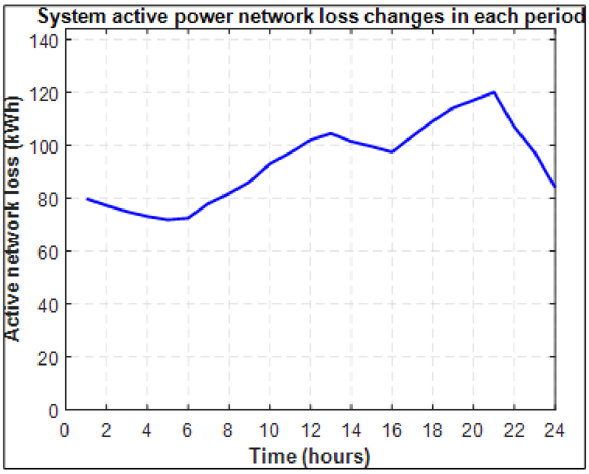

Figure 3 Active power network loss change diagram

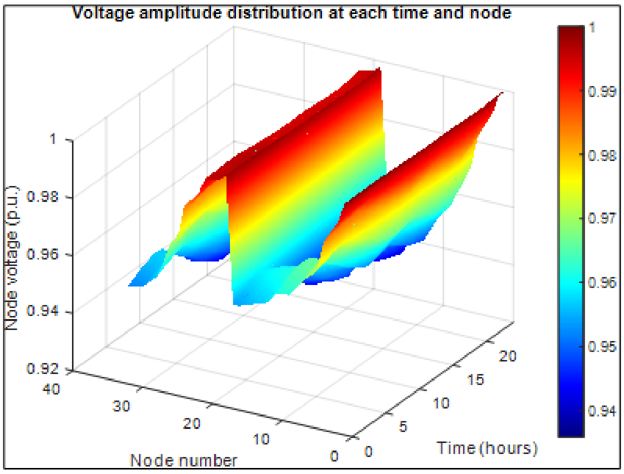

Figure 4 Voltage amplitude distribution diagram of each node

Table 1 Time-of-use electricity price range and price list

Item	Time period	Price/(Yuan/kWh)
Peak period	9:00-11:00;18:00-23:00	0.75
Valley period	1:00-7:00;24:00	0.385
Normal period	8:00; 12:00-17:00	0.55

When electric vehicles are connected to the power grid, their disorderly charging will affect the operation of the power grid to a certain extent. In order to analyze the impact on the power grid in detail, the power flow calculation and indicator analysis can be used to evaluate the operation performance of the power grid when electric vehicles are connected to the power grid without order charging. Figure 5 shows the load demand of disordered charging of electric vehicles under the effect of time-of-use price; Figure 6 shows the charging load diagram of electric vehicles at each time period and each node under disordered charging; Figure 7 shows the change diagram of system active power network loss at each time period under disordered charging of electric vehicles; Figure 8 shows the voltage distribution diagram at each time period and each node under disordered charging of electric vehicles.

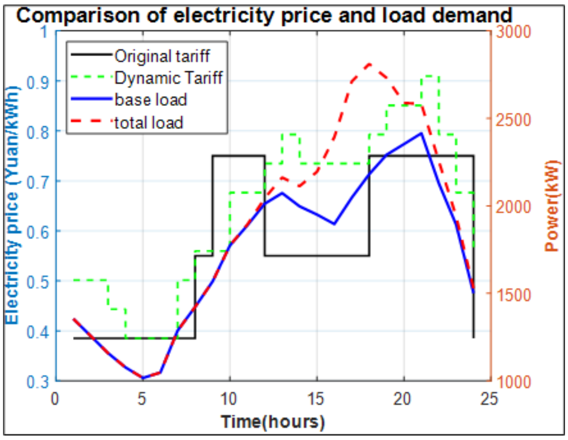

Figure 5 Comparison of electricity price and load under unordered charging

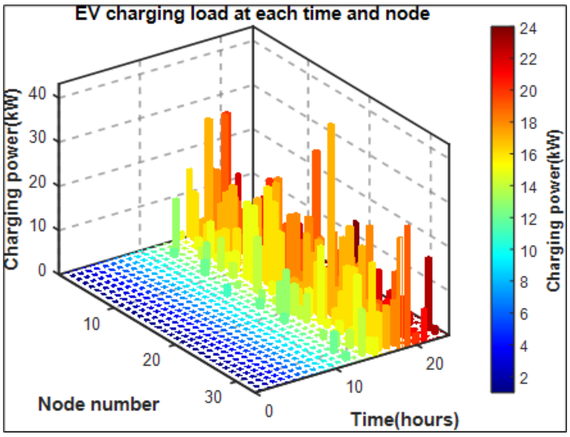

Figure 6 EV charging load diagram under unordered charging

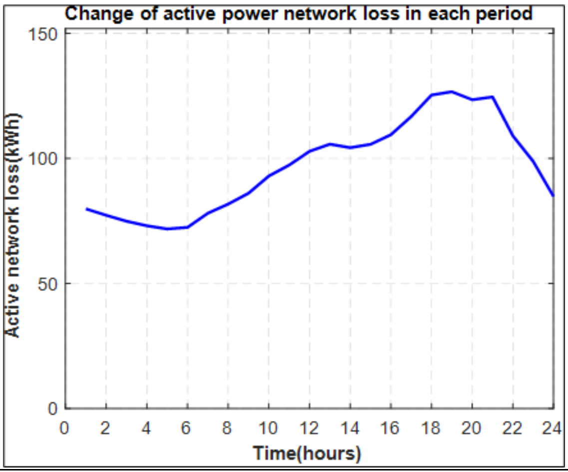

Figure 7 Disordered charging active power network loss change diagram

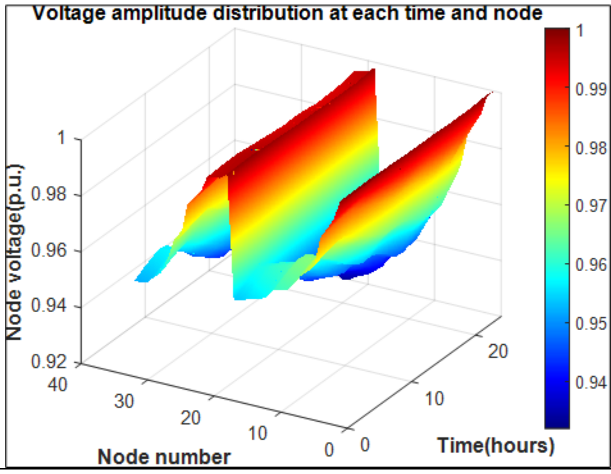

Figure 8 Voltage amplitude distribution of each under unordered charging

The results of the example show that the charging load of the nodes is unevenly distributed in time and space under the unordered charging mode, and the phenomenon of "peak-on-peak" will occur in the peak hours of the grid even if 24-hour dynamic electricity price is used. Figure 7-8 shows that the increase in charging load leads to a significant increase in network loss of the system, especially during peak hours, which not only increases the loss cost in the user's electricity bill, but also may cause the voltage of some nodes to be lower than 0.95p.u. Security threshold, which threatens the stable operation of the power grid.

In contrast, Figure 9-10 shows the optimization effect of orderly charging: Through dynamic electricity price guidance, the load curve flattens out, effectively spreading out the peak pressure. This mode reduces the risk of equipment wear and failure, while reducing user charging costs. The load comparison analysis confirms that the optimized charging plan improves the economy while ensuring the safety of the grid.

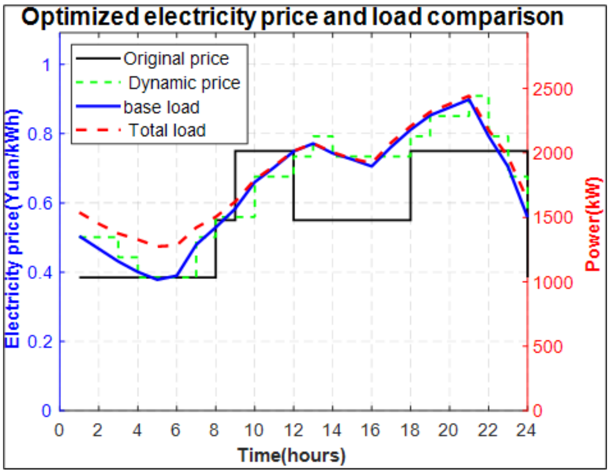

Figure 9 Comparison diagram of electricity price and load demand under orderly charging

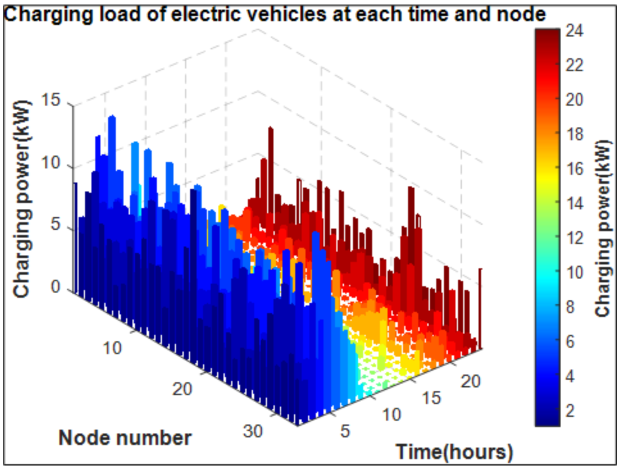

Figure 10 Charging load diagram of electric vehicle under orderly charging

Figure 11-12 shows the system network loss and node voltage distribution during orderly charging. The data show that the voltage of each node is stable within the standard range of (0.95-1.05p.u.), which verifies that the charging optimization does not affect the stability of the grid. The network loss curve shows that the load balancing strategy effectively reduces the energy loss during peak hours, which not only reduces the operating cost of the grid, but also improves the charging efficiency. From the perspective of economic benefits, the reduction of network loss helps to stabilize the user's charging cost, while increasing the amount of charging per unit time.

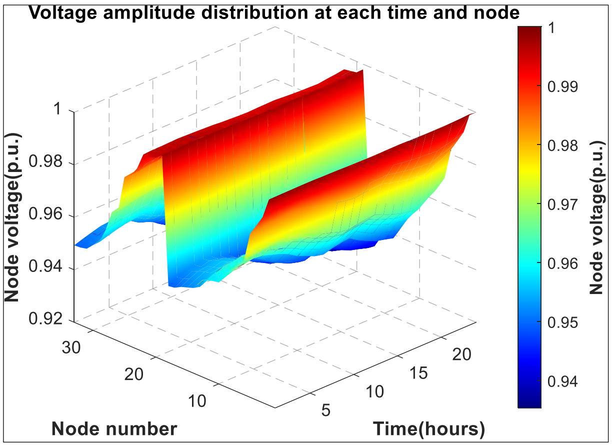

Figure 11 Change diagram of active power network loss under orderly charging

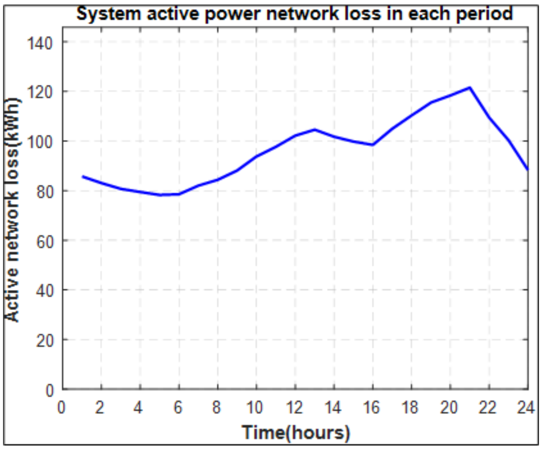

Figure 12 Voltage amplitude distribution of each de under orderly charging

Table 2 Comparison table of different charging strategy indicators

Item	Unordered charging	Ordered charging
Standard deviation of load fluctuation	577.41	362.14
Peak load curve/kW	2810.81	2448.68
Load curve Valley value/kW	1016.62	1260.15
Charging fee/ten thousand yuan	1293.73	995.08

Table 2 compares the strategies of unordered charging and orderly charging, and the results show that orderly charging effectively smooths the load curve of the power grid and reduces load fluctuation. The load peak value decreases and the valley value increases, indicating that orderly charging effectively reduces the peak load and improves the trough load, and improves the economy and stability of the power system. Dynamic electricity price guides users to charge during off-peak hours, reduces charging costs, reduces problems such as power shortage, and optimizes the utilization of power grid resources to improve the overall economy of electric vehicles.

6. Conclusion

Aiming at the impact of EV charging load on the power grid, this paper proposes an EV charging optimization strategy based on demand response. By constructing a charging load model considering user response behavior, the dual influence mechanism of electricity price and SOC on charging behavior is analyzed. A multi-objective optimization model with the aim of peak cutting and valley filling, reducing user cost and improving power grid economy is established. The improved particle swarm optimization algorithm is used to solve the optimization problem, and the reasonable allocation of charging period is realized. The simulation results show that this strategy significantly reduces the load fluctuation of the power grid, especially in the peak hours, effectively alleviates the power supply pressure, and optimizes the charging cost of users. The research shows that the proposed dynamic pricing guidance mechanism can improve the charging economy while ensuring the stable operation of the power grid.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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