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Research on electric vehicle charging load prediction and charging mode optimization

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Abstract: To reduce the influence of the disorderly charging of electric vehicles (EVs) on the grid load, the EV charging load and charging mode are studied in this paper. First, the distribution of EV charging capacity and state of charge (SOC) feature quantity are analyzed, and their probability density function is solved. It is verified that both EV charging capacity and SOC obey the skew-normal distribution. Second, considering the space-time distribution characteristics of the EV charging load, a method for charging load prediction based on a wavelet neural network is proposed, and compared with the traditional BP neural network, the prediction results show that the error of the wavelet neural network is smaller, and the effectiveness of the wavelet neural network prediction is verified. The optimization objective function with the lowest user costs is established, and the constraint conditions are determined, so the orderly charging behavior is simulated by the Monte Carlo method. Finally, the influence of charging mode optimization on power grid operation is analyzed, and the result shows that the effectiveness of the charging optimization model is verified.

Key words: charging load, electric vehicles, Monte Carlo, wavelet neural network

1. Introduction

With the shortage of energy and increasing environmental pollution problems [1], electric vehicles (EVs) with zero emission, low noise pollution and other good environmental and social benefits have been widely studied. The rational planning and construction of charging infrastructure is an important guarantee for the large-scale promotion of EVs. However, the number of charging facilities in China is insufficient, and the blind construction of urban infrastructure leads to the waste of land and capital, as well as the irregular fluctuation of the power grid [2]. Recently, research on charging stations has made great achievements. In [3], in view of the impact of large-scale EV access to the distribution network, a multi-objective scheduling method for large-scale EV access to the distribution network was proposed to ensure the economic operation of the system and reduce the load of distribution network. In [4], the kernel estimation method was used to fit the probability density of the charging characteristic quantity, which was used as the basis for power load prediction and orderly charging management. In [5], cooperative and noncooperative pricing mechanisms and corresponding charging strategies were proposed for different charging behaviors to guide EV charging behaviors and effectively reduce peak-valley differences in charging load. In [6], the interactive dispatching model between EVs and the power grid was proposed, and the user costs were optimized via particle swarm optimization. In [7], a pricing strategy for the time-of-day tariff was proposed, and a price elasticity model of EV demand considering state of charge (SOC) was established, which reduced the volatility of regional electricity load and the loss of the distribution network. In [8], Monte Carlo was used to simulate the charging loads of private cars, taxis and buses, and the influence of different types of EVs on the peak-valley characteristics of grid load was analyzed. In [9], genetic particle swarm optimization was used to optimize the proportion of charging equipment, reduce the investment in charging station equipment, and meet the user' charging demand at the same time. In [10], a two-tier optimization model for EVs based on electricity price guidance was established, and the genetic algorithm was used to solve the model, which increased the economy and stability of the grid system operation. In [6], [9] and [10], a genetic algorithm was used to study the charging problem of EVs, but the stability of the genetic algorithm was slightly poor, while the neural network learning ability was stronger, and the accuracy was higher.

In recent years, due to the impact of large-scale EVs connected to the power grid, it has increasingly become a people concern problem. In this case, the orderly charging strategy is proposed. In [11], the objective function for peak shaving, valley filling and flattening of the power grid load were proposed, and an optimal planning scheme based on EV charging and discharging is established. The hybrid algorithm of particle swarm and Monte Carlo simulation were used to solve the model. While considering the grid peak-valley difference, the users' benefits and charging stations' revenue were ignored in the paper. In [12], a pricing strategy based on the vehicle-to-grid (V2G) concept was proposed, and load conditions, maximum power limits and user load prices were all considered in the strategy system. During the pricing process, the user's profit was maximized, but there were some problems such as power grid stability, and it was not covered in the paper. In [13] and [14], the orderly charging strategy of the charging price interactive decision between charging users and EVs was constructed. However, these papers failed to consider the impact of the peak-valley difference on the operation of the power grid. Therefore, the safe operation of the power grid wasn't guaranteed. The orderly charging strategy was based on the premise of the time-of-use electricity price, considering factors such as users' benefits, charging station revenue, and grid peak-valley differences [15]. In [11–14], the research on the single direction of orderly charging in these papers does not consider factors such as users' benefits, charging station revenue, and grid peak-valley differences at the same time.

In order to improve the accuracy of EV load prediction, a charging load prediction method based on a wavelet neural network is proposed in this paper. Compared with the traditional BP neural network, the prediction error of the wavelet neural network is relatively smaller, and the prediction accuracy is higher, which verifies the effectiveness of the prediction model in this paper. In [16] and [17], a smart charging strategy was proposed to increase the charging revenue of charging stations. Comparing this paper and the literature [13,14,16,17], based on the time-of-use electricity price, an optimization model with the lowest charging cost as an objective function is proposed in this paper, and the Monte Carlo algorithm is used to simulate orderly charging at charging stations. The simulation results show that the revenue of the charging station is increased, user costs are reduced, and peak-valley differences are lowered, which creates favorable conditions for improving the safe operation of the power grid. This paper can provide the basis for further research on the EVs optimization.

2. Analysis of charging station data characteristics

In [18], according to the content of "Henan Province Interim Measures on the Operation and Management of EV Charging Infrastructure Construction" in the 13th Five-Year Plan for Henan Province, the construction proportion of charging piles in public parking should not be less than 10% in 2020. The first type of public charging pile is fast charging, and the second type is slow charging. The paper takes a large charging station in Zhengzhou as an example, which has a total of 52 EV charging piles. The charging station charges new energy vehicles such as electric private cars, electric logistics vehicles and electric taxis in the mode of combined quick charging, and there are thousands of EVs in the area with average daily traffic. The charging load data of this charging station in November 2019 are shown in Table 1.

Table 1. Daily load data of charging station

Date	Maximum load (kW)	Minimum load (kW)	Peak-valley differences (kW)	Average load (kW)
20191101	1666.51	0	1666.51	371.42
20191102	1198.9	0	1198.9	326.49
20191103	1088.75	36.77	1051.98	302.1
20191104	1645.39	0	1645.39	336.41
...	...	...	...	...
20191127	1041.82	0	1041.82	374.2
20191128	877.21	53.4	823.81	356.89
20191129	796.66	52.07	744.59	362.26
20191130	826.78	0	826.78	339.07

The charging vehicles at the charging station are mainly social vehicles, and the factors that affect the load of EVs are EV charging capacity, SOC, charging start time, charging power, EV charging and other charging and discharging characteristic parameters, in which the charging capacity and SOC are the two most important factors. By analyzing mathematical statistics on the original data in the appendix, the probability density histogram of the EV charging capacity of the charging station is shown in Fig. 1.

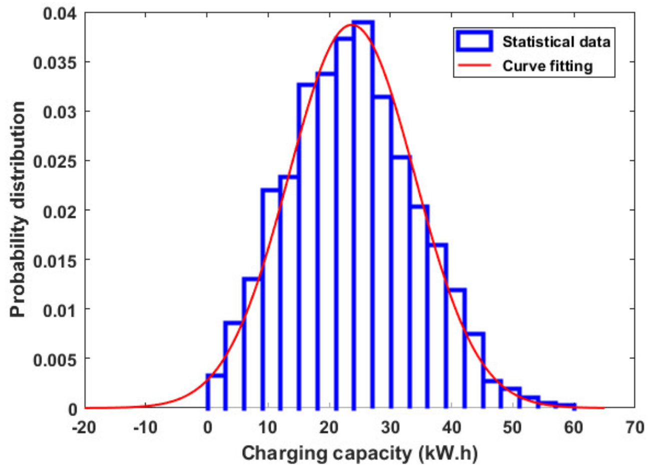


Fig. 1. Probability distribution of EV charging capacity

The histogram of the probability density of EV SOC is shown in Fig. 2.

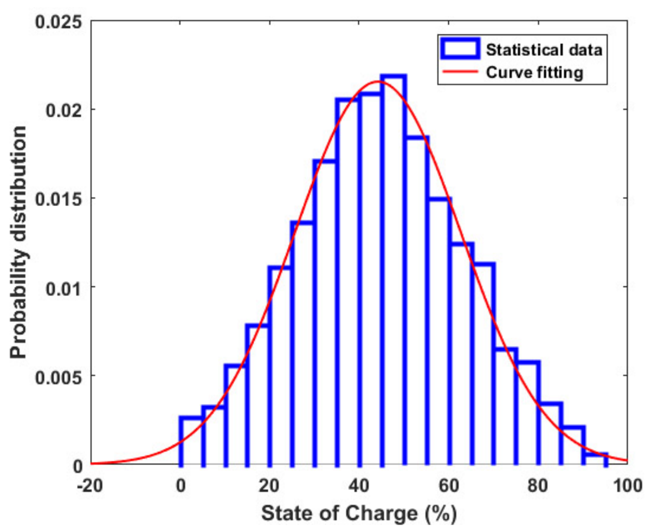


Fig. 2. Probability distribution of EV SOC

The K–S [19] hypothesis test is used for the probability distribution of charging capacity and SOC. In the test, H_0 represents that both the charging capacity and SOC obey a normal distribution, and H_1 represents that charging capacity and SOC disobey a normal distribution.

If the test result of the K–S hypothesis is greater than 0.05, then the null hypothesis H_0 will be accepted; otherwise, the null hypothesis H_0 will be rejected. Skewness is a measure of the skewness of the probability density curve at the average. In [20], the skewness is calculated as shown in Equation (1):

$$P = \frac{\sqrt{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{\left[\sum_{i=1}^{n}(x_i - \overline{x})^2\right]^{\frac{3}{2}}}, \tag{1}$$

where: n is the sample size, x_i is the value of the sample i, and $\overline{x}$ is the average of the samples. Kurtosis means that the probability density curve is high or low at the average value, and it is also a characteristic quantity used to measure the slowness and steepness of the value distribution. In [20], the kurtosis is calculated as shown in Equation (2):

$$F = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right]^{2}}, \tag{2}$$

where: n is the sample size, x_i is the value of sample i, and $\overline{x}$ is the average of the samples. According to the equation of skewness and kurtosis to calculate the original data, the hypothesis test results are shown in Table 2.

Table 2. Characteristic value of the hypothesis test

Characteristic	**Kurtosis coefficient *F***	**Skewness coefficient *P***	**K–S**
Charging capacity	–0.271	0.225	0.071
SOC	–0.424	0.061	0.082

It can be seen from Table 2 that the probability density of both EV charging capacity and SOC obey a skew-normal distribution. For further analysis, the logarithmic normal distribution is used to represent the skew-normal distribution. EV charging capacity is approximately subject to $N_1(\mu_1, \sigma_1)$. In [21], its probability density function is shown in Equation (3):

$$f_1(x_1;\sigma_1) = \frac{1}{x_1\sigma_1\sqrt{2\pi}}\exp\left(-\frac{|\ln x_1 - \mu_1|^2}{2\sigma_1^2}\right), \tag{3}$$

where μ_1 and σ_1 are the mean and standard deviation of EV charging capacity, respectively. They represent the degree of dispersion of EV charging capacity.

When the EV arrives at the charging station, the SOC of the EV is approximately subject to $N_2(\mu_2, \sigma_2)$. Its probability density function is shown in Equation (4):

$$f_2(x_2;\sigma_2) = \frac{1}{x_2\sigma_2\sqrt{2\pi}}\exp\left(-\frac{|\ln x_2 - \mu_2|^2}{2\sigma_2^2}\right), \tag{4}$$

where μ_2 and σ_2 are the mean and standard deviation of SOC, respectively. They represent the degree of dispersion of EV SOC.

The EV charging capacity and SOC obey the skewed-normal distribution. According to the EV charging capacity and SOC data in this charging station, the probability distribution of EV characteristic quantity can be obtained by Equations (3) and (4), as shown in Table 3. It shows that the charging capacity of most EVs in the charging station is between 13.35 kW· h and 33.99 kW· h, and SOC of most EVs before charging is between 25.65% and 62.69%.

Table 3. Probability distribution of characteristic quantity of EV

Charge characteristic	**Charging capacity (kW· h)**	**SOC (%)**
Skewed normal distribution	$N_1(23.67, 10.32^2)$	$N_2(44.17, 18.52^2)$

3. Electric vehicle charging load prediction

3.1. The factors affecting electric vehicle charging load

In addition to the main factors affecting the EV charging load, the EV load is also affected by the EV charging mode, the charging time and the EV scale. The charging time is mainly determined by three factors, including the charging start time, SOC and the output power of the charging piles. Among them, the location of the load peak is determined by the charging start time and charging time. Private cars are mainly used for commuting, and they are usually charged in underground garages and company charging stations at noon or at night. The charging station mainly serves private cars, logistics vehicles, taxis and other social vehicles, so EVs are mainly charged from 0:00 to 3:00, from 11:00 to 13:00 and from 20:00 to 21:00, and daily mileage is approximately 300~350 km. Considering the weather, holidays, road conditions and other factors, EVs are charged once a day on average.

Simulation analysis was based on the load data of the charging station in November 2019 as an example. Daily load data consist of a measurement point every 15 min, and there are 96 measurement values in a day, in which a wavelet neural network is used to predict the EV load at the charging station.

3.2. Electric vehicle charging load prediction model

The EV charging load has many influencing factors, so the charging load prediction model is nonlinear and complicated. A wavelet neural network is an effective prediction algorithm and belongs to the basis function neural network. The wavelet neural network is based on the combination of wavelet transform and a neural network, which has higher convergence speed and stability from the internal mechanism compared with the traditional BP neural network. In [22], a wavelet neural network has strong nonlinear fitting ability and high recognition ability. The three-layer topology of the wavelet neural network is shown in Fig. 3.

Put the charging load data into different input layer neurons. The m-th input value of the i-th neuron in the neural network is x_{im}, w_{ij} represents the weight between the input layer and the

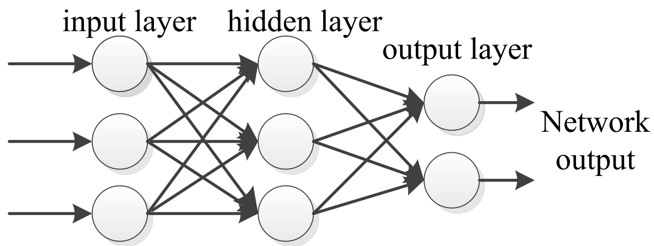


Fig. 3. Topological structure of wavelet neural network

hidden layer, and w_{jk} represents the weight between the hidden layer and the output layer. The output value of the hidden layer is shown in Equation (5).

$$S(j) = s_j \left[\frac{\sum_{i=1}^{I} w_{ij} x_i - b_j}{a_j} \right]. \tag{5}$$

Equation (5) shows that the j-th node output value of the hidden layer is $S(j)$, and the number of input neurons is I. The translation factor and expansion factor are a_j and b_j, respectively. x_i represents the input i-th charging station load data. The hidden layer neurons satisfy the conditions shown in Equation (6).

$$y = \cos(1.75x)\, \mathrm{e}^{-\frac{x^2}{2}}. \tag{6}$$

The output prediction value of the k-th neuron in the output layer is shown in Equation (7):

$$y_I = \sum_{j=1}^{H} w_{jk} S(i), \quad I = 1, 2, \ldots n, \tag{7}$$

where H is the number of hidden layer neurons.

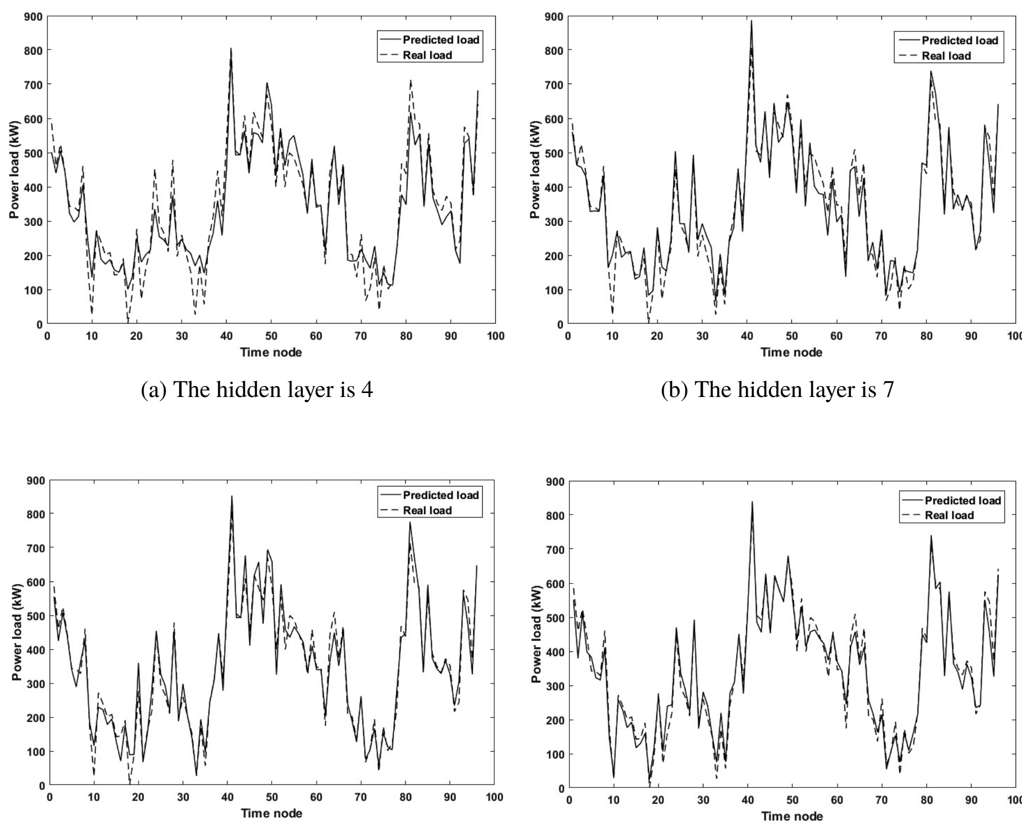
The load data are normalized and used as the input of the neural network, and the processed data have the characteristics of small fluctuation and easy manipulation. There are L nodes in the input layer and M nodes in the output layer. According to the literature [23], the node H of the hidden layer is shown in Equation (8):

$$\begin{cases} H \le L - 1 \\ H > \log_2 L \\ H < \sqrt{L + M} + a \end{cases}, \tag{8}$$

where $0 < a \le 10$, if the number of input neurons is too high, the training efficiency is low and even the training effect is not good, so this paper preliminarily sets the input layer to $L = 15$. According to Equation (8), the number of hidden layer nodes can be determined between 4 and 14. The prediction results output a group of daily load data, so the number of output layer nodes is $M = 1$.

3.3. Instance analysis

To verify the effectiveness of the wavelet neural network in predicting EV load, 2880 load data points of the charging stations in this month are selected. Among them, the data of the first 21 days are used as the wavelet training value. The BP neural network [24] model is added for comparison. The sample data are predicted by Equations (5) to (7) for the wavelet neural network, the prediction samples are reversely normalized, and the data on the 22nd day are tested. The comparison between the prediction data obtained by this method and the real data is shown in Fig. 4. It shows the prediction load and real load output results when the number of input and output layers is the same, but the number of hidden layers is different. In the case of the same sample data, the BP neural network is used for prediction, and it is verified that the prediction effect is best when the hidden layer is 14. The comparison between the prediction data obtained by this method and the real data is shown in Fig. 5.



(a) The hidden layer is 4

(b) The hidden layer is 7

(c) The hidden layer is 11

(d) The hidden layer is 14

Fig. 4. Comparison of wavelet neural network prediction value and real value

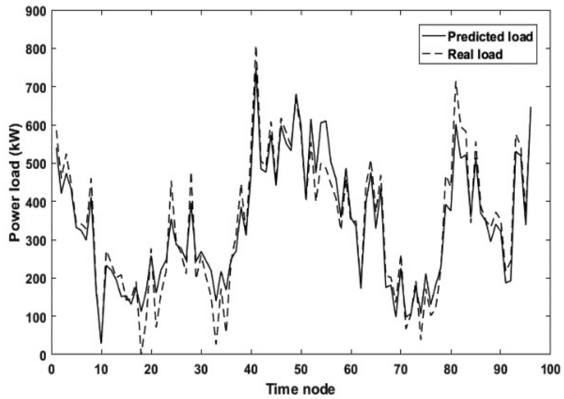


Fig. 5. Comparison BP of neural network prediction value and real value

3.4. Accuracy verification of prediction model

The accuracy of the prediction data is verified to evaluate the authenticity, reliability and consistency of the prediction results. Three error analysis indicators, namely, the mean absolute error (MAE), mean square percentage error (MSPE), and coefficient of determination (R^2), are used to judge and analyze the prediction results.

The mean absolute error, mean square percentage error and coefficient of determination of the model evaluation index are defined as follows [25]:

$$\mathrm{MAE} = \frac{1}{96}\sum_{i=1}^{96}\left|y_i' - y_i\right|, \tag{9}$$

$$\mathrm{MSPE} = \frac{1}{2}\sqrt{\sum_{i=1}^{96}\left(\frac{y_i' - y_i}{y_i'}\right)^2}, \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{96}\left(y_i' - y_i\right)^2}{\sum_{i=1}^{96}\left(y_i - y\right)^2}. \tag{11}$$

where: y_i represents the original load data of the charging station; y_i' represents the corresponding prediction load data; y represents the mean value of the original load data. The error analysis results are shown in Table 4.

The MAE and MSPE are used to measure the degree of deviation between the prediction data and the real data. The smaller the deviation value is, the more accurate the prediction will be. R^2 is used to judge the degree of fitting between the prediction and the real load curve. The closer R^2 is to 1, the better the fitting degree will be and the more accurate the prediction result will be. In Table 4, when the number of hidden layers is 14, the MAE is 25.07, the MSPE is 0.88%, and R^2 is 0.97, so the three error values are relatively small, and the prediction effect is significant.

Table 4. Error parameter analysis of prediction model

Prediction model	Number of hidden layers	MAE	MSPE	R^2
Wavelet neural network	4	40.06	1.21‰	0.92
	7	31.38	1.04‰	0.95
	11	28.43	0.98‰	0.96
	14	25.07	0.88‰	0.97
BP neural network	14	32.91	0.92‰	0.94

When the number of hidden layers in the BP neural network is 14, the MAE is 32.91, the MSPE is 0.92‰, and R^2 is 0.94. Compared with the wavelet neural network, the BP neural network has lower prediction accuracy. Therefore, the wavelet neural network algorithm is more suitable for charging station load prediction.

4. Orderly charging strategy

4.1. Determination of orderly charging objective function and constrains

A large number of EVs are randomly connected to the power grid, which causes large load fluctuation. In particular, disorderly charging increases the difficulty of grid dispatch. The objective function is to minimize user charging costs, decrease peak-valley differences, increase station revenue, not exceed the total charging parking spaces of charging stations and keep the total daily charge of the charging station constant, which are constraints. Under the condition that EV charging is not affected, effective economic systems or measures are used to control and guide the orderly charging of EVs. According to the Henan Province grid price list, the power grid charges for charging stations are shown in Table 5.

Table 5. Price standard of industrial segment

Period type	Period	Electricity price (yuan/kW· h)
Trough period	0:00–6:00	0.33
Stable period	12:00–18:00	0.62
	22:00–24:00	
Peak period	6:00–12:00	0.95
	18:00–22:00	

Charging stations have different price standards for users at different time periods. The price standard is 0.88 yuan/kW· h from 0:00 to 18:00, and 1.18 yuan/kW· h from 18:00 to 24:00. Now, it is necessary to optimize the specific charging on the 22nd day of charging at the station. Taking the lowest user charging cost as an optimization model, the objective function is established as shown in Equation (12).

$$Y_1 = \min \sum_{\tau=1}^{96} \sum_{m=1}^{N_\tau} X_\tau P_{\tau\cdot m} t_{\tau\cdot m} \,. \tag{12}$$

In the above equation, the charging station charges users for different periods of time divided into 96-time nodes; Then $1 \leq \tau \leq 72$ (from 0:00 to 18:00) period, and X_τ is 0.88 kW· h. Then $73 \leq \tau \leq 96$ (from 18:00 to 24:00) period, and X_τ is 0.88 kW· h. N_τ represents the EVs entering the charging station in the period τ; X_τ represents the user charging costs of the charging time node τ; $P_{\tau\cdot m}$ is the charging power of the m-th EV in the period τ; $t_{\tau\cdot m}$ is the charging time of the m-th EV in the period τ.

Constraint:

1. The larger the peak-valley difference is, the greater the pressure on the power grid load is caused by the charging station. Therefore, the peak-valley difference should be reduced. The peak-valley difference of the power grid is shown in Equation (13):

$$\min_{1\leq\tau\leq96} [\max(P_\tau) - \min(P_\tau)] \leq \Delta P \,, \tag{13}$$

where: each 15 min represents a time period, and a day can be divided into 96 nodes; P_τ represents the charging load of the charging time node τ; ΔP represents the peak valley difference of the charging station on that day.

2. Ensure that user charging costs decrease, while charging station revenue increases. Five time periods of the industrial electricity price are divided into 96 time periods, which are represented by $C_\tau = [C_1, C_2, \ldots, C_{96}]$. If each user charges 1 kW· h, then the charging station gains $(X_\tau - C_\tau)$ yuan revenue. The charging station revenue constraint is shown in Equation (14):

$$\sum_{\tau=1}^{96} \sum_{m=1}^{N_\tau} (X_\tau - C_\tau)\, P_{\tau\cdot m} t_{\tau\cdot m} \geq Y_2 \,, \tag{14}$$

where Y_2 is the daily revenue of the charging station on that day.

3. The number of charged EVs is constrained as shown in Equation (15):

$$\sum_{\tau=1}^{96} P_{\tau\cdot m} = N_{\max} \,, \tag{15}$$

where $N_{\max}$ is the number of EVs with the largest capacity in the charging station.

4. The daily charging station capacity is constrained as shown in Equation (16):

$$\sum_{\tau=1}^{96} \sum_{m=1}^{N_\tau} P_{\tau\cdot m} t_{\tau\cdot m} \approx W_0 \,, \tag{16}$$

where W_0 represents the daily charging capacity of the charging station on that day.

4.2. Determination of simulation algorithm

The load of the charging station used by different social vehicles is very random, and the loaded EV is affected by the charging start time, charging capacity, SOC and other characteristics, which are the premise of orderly charging. Compared with disorderly charging, orderly charging is proposed on the basis of a time-of-day tariff, which is used to guide users to avoid peak electricity consumption and encourage them to use electricity in low periods, and users choose cars to charge within a reasonable period of time according to the price of electricity. In [26], the Monte Carlo algorithm, namely, the random sampling method, can realistically simulate actual physical processes and easily obtain satisfactory results. Solving multidimensional and complex problems with this method is simpler than using other algorithms, and the application is more flexible and convenient.

5. Orderly charge simulation analysis

In this paper, according to the data in Table 1 for the 22nd day of the charging station in Zhengzhou, the charging station has a total of 1300 EV charging records. As the charging station concentrates on charging during peak load times, it increases the charging load difference and the burden on the power grid, so the charging of the 1300 EVs is recorded as disorderly charging. The Monte Carlo algorithm is used to simulate the orderly charging of the charging station.

The simulation steps of the EV orderly charging using the Monte Carlo method are as follows:

1. Iteration times M and load points i ($0 \le I \le 96$) are initialized.
2. Using the probability distribution of charging capacity and SOC, the charging load data of the load points i are simulated.
3. The objective function and constraints are initialized, and the EV charging load is calculated.
4. The charging load is accumulated and the load curve is fitted.
5. To judge whether the fitted load curve converges, the variance coefficient β is used to evaluate the accuracy of load calculation. The variance coefficient [27] is shown in Equation (17):

$$\beta_i = \frac{\sigma_i(L)}{\sqrt{ML_i}}, \tag{17}$$

   where: L_i represents the EVs' load data in the load points i, $\sigma_i(L)$ represents the load standard deviation, M represents the number of simulations; when $\mathrm{Max}(\beta_i) \le 0.05\%$, the simulated curve converges. The flow chart of the Monte Carlo algorithm is shown in Fig. 6.

When performing disorderly charging, EV users usually work at noon. Due to work reasons during the day, the peak power consumption of the power grid is concentrated from 11:00 to 13:00. In the afternoon, it usually drops at 6 o'clock, and the peak power consumption of the grid is concentrated from 20:00 to 21:00. At this time, centralized charging increases the impact on the power system load, the peak-valley difference further increases, and the user charging costs are high, which brings about a burden for the safe operation of the power grid. During the orderly charging simulation, the EV should be adjusted to avoid the peak period of power consumption at night. The EV is charged as low as possible at 0:00 in the morning to reduce the user charging costs and achieve a peak cut at the same time, while other peaks should also be avoided. The simulation results of orderly charging and disorderly charging are shown in Fig. 7.

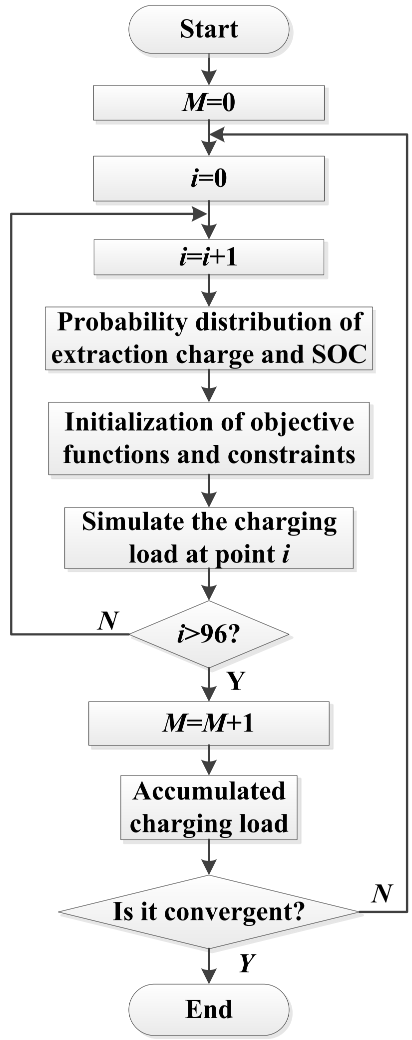


Fig. 6. Monte Carlo algorithm flow chart

Figure 7 shows that the load in the valley area of orderly charging has an upward trend compared with disorderly charging. More EV users charge from 0:00 to 6:00. Compared with the day, the user night charging costs are reduced. At approximately 20:00, some EV users do not charge to avoid the conflict between household electricity and charging station electricity. Table 6 shows the comparison of related parameters between orderly charging and disorderly charging.

In this paper, the orderly charging strategy is proposed on the premise of the time-of-use price. The Monte Carlo algorithm is used to simulate a charging behavior curve, which takes the minimum user cost as the objective function and meets the constraints, that is, the orderly charging load curve. The simulation results in Table 6, show that the charging cost for users is

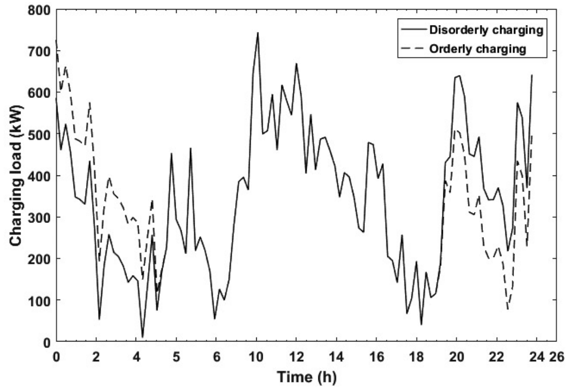


Fig. 7. Simulation results of orderly and disorderly charging loads of EVs

Table 6. Index of profit and peak-valley difference in orderly and disorderly charging

	User costs (yuan)	**Station costs (yuan)**	**Profit (yuan)**	**Peak-valley differences (kW)**	**Peak-valley rate**
Disorderly charging	28111.7	19578.3	8533.4	809.07	1
Orderly charging	27690.6	18647.6	9043	782.47	0.96

reduced, the revenue from charging stations is increased, and the peak-valley difference of orderly charging is reduced. It is beneficial to maintain the stability of the power grid and ensure the coordinated development of EVs and the power grid.

6. Conclusions

The characteristic value of the EV charging load is analyzed in this paper. EV charging capacity and SOC are tested by the K–S method. The results show that the charging capacity and SOC obey the normal distribution. From the analysis of the characteristics of skewness and kurtosis, they are all found to obey the skew-normal distribution.

The EV charging load is affected by the output power of the charging piles and the charging time. When the number of hidden layers in the BP neural network is 14, the MAE is 32.91, MSPE is 0.92%, and R^2 is 0.94. However, when the number of hidden layers in the wavelet neural network is 14, the MAE is 25.07, MSPE is 0.88%, and R^2 is 0.97. So, the error of the wavelet neural network is relatively smaller, and the prediction accuracy and reliability are higher. The research results of the wavelet neural network have certain reference significance for the EV load prediction.

An objective function is established in view of the user charging costs related to constraints of decreasing the peak-valley difference, increasing station's revenue, not exceeding the total parking space of the charging station, and keeping the total daily charge of the charging station constant.

Monte Carlo methods are also used to simulate the behavior of orderly charging. The results show that the peak-valley difference in the grid load and distribution network losses are reduced. When a large number of EVs participate in the time-of-day tariff strategy, the problem of Peak cut is effectively solved. Therefore, the publicity and guidance of EVs for orderly charging is to reduce effective measures for the impact of small EV loads on the operation and regulation of the power system.

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