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Regional Electric Vehicle Charging Load Forecasting and Analysis of Its Impact on the Peak-Valley Difference of the Power Grid

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Abstract:

In recent years, the number of electric vehicles has continued to grow simultaneously, and a large number of charging facilities cover the daily driving range of users, which has brought a considerable charging load to the power grid. Therefore, predicting the charging load of electric vehicles is of great significance to the stable operation of the power grid and reasonable dispatch. Based on the Logistic curve, the paper predicts the growth trend of vehicle ownership. According to the time and space characteristics of electric vehicle charging in smart communities, considering the influence of seasons and other factors, the Monte Carlo method is used to simulate the charging load of electric vehicles. Finally, the fast charging characteristics of electric vehicles are analyzed. The results show that: the number of electric vehicles in various countries conforms to the S-shaped growth curve; the grid-connected charging of electric vehicles will cause significant changes in the grid load; the expansion of the rapid charging rate will cause the increase in the peak-to-valley rate and the overall load, but it will affect the overall load Smaller.

Keywords: *Electric vehicle, Charging load forecast, Fast charging, Monte carlo simulation method*

I. INTRODUCTION

Since the 21st century, the proportion of electric energy in the national energy structure has been significantly increased. The "New Energy Automobile Industry Development Plan (2021-2035)" issued by the State Council pointed out that it adheres to the strategic orientation of pure electric drive and strives to achieve new goals within 15 years. The core technology of energy vehicles has developed to an advanced level in the industry. In order to achieve the goal of carbon peak and carbon neutrality, large-scale electric vehicles need to be connected to the grid from the supply side and the structure side to reduce carbon emissions in the transportation sector, alleviate the shortage of traditional energy supply and environmental pollution. Therefore, the problem of electric vehicle (EV) charging load forecasting is of great significance to urban distribution network planning economics and operability.

Many scholars at home and abroad have achieved specific results in the related research on electric vehicle charging load forecasting. Literature [1] uses the Monte Carlo method to consider the initial

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charging time, daily mileage, battery parameters, charging efficiency and other influencing factors, and analyzes the impact of the grid-connected charging of large-scale EVs in cities. Literature [2] uses the autoregressive model algorithm (ARA) of time series analysis and the back propagation neural network algorithm (BPA) to predict the short-term load of an electric vehicle charging station in a specific city in China, and compares the prediction accuracy of the two algorithms. Literature [3] predicts traffic flow (TF) based on convolutional neural network (CNN), and generates a prediction interval (PI) for TF, and calculates the EV arrival rate based on historical data and a hybrid model. Finally, a new probabilistic queuing model that considers charging service limitations and driver behavior characteristics is used to predict the EV charging power. The Q-learning technology proposed in [4] improves the prediction results of traditional artificial intelligence technologies such as recurrent neural networks and artificial neural networks. Literature [5] considered the characteristics of the time and space transfer of the charging load in urban functional areas, It proposed a data-driven method for EV charging demand forecasting model, which effectively predicted the spatiotemporal distribution characteristics and load transfers of different data types and different functional areas. trend. Literature [6] uses the kernel estimation method to fit the probability density of three parameters: charging start time, charging duration, and charging start capacity, and verifies the correlation between time parameters and charging behavior, and uses multiple copula functions to charge different types of charges. The correlation between behavioral time and energy parameters is modeled. Literature [7] uses the Bass model to predict EVs' medium and long-term holdings, uses Monte Carlo simulation to obtain the EV daily charging probability curve, and simulates the EV charging load based on the holdings information and the daily charging probability curve. Literature [7] proposed a new method for EV charging prediction based on long and short-term memory networks. This method does not require any charging information from other EV users, and can independently predict the charging duration of the next day within a specific range. Literature [9] aimed at the time-space transfer and charging decision-making problems of household EVs and electric taxis under complex road networks and proposed a time-space prediction model of EV charging load considering the urban traffic road network and user psychology. Literature [10] analyzed the driving characteristics of different types of vehicles, generated corresponding charging load models based on Monte Carlo simulation, and studied the peak-to-valley ratio of the load under different penetration rates. Literature [11] proposed a new data-driven EV charging load modeling method, which simulated the EV charging demand under different power market conditions by identifying the parameters of different EV load models. Literature [12] proposed an EV charging load prediction method based on random forest algorithm (RF) and load data of a single charging station. Literature [13] designed a method to fill in missing data, which significantly improves the accuracy of EV load forecasting when the data has high missing features. Literature [14] proposed an EV charging load curve simulation method that considers weather, traffic, and the distribution of charging time and space characteristics. The Monte Carlo method is used to simulate the EV charging load in various scenarios. Literature [15] proposed a probabilistic electric vehicle load forecasting method suitable for different geographic regions, using a layered method to decompose the problem into sub-problems in low-level regions, and using gradient enhancement regression tree, quantile regression forest and quantile Standard probability models such as number regression neural network, combined with principal component analysis to reduce the dimensionality of the sub-problems, and based on the

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integrated method of penalized linear quantile regression models to predict the aggregate load of high-level geographic areas. Literature [16] proposed a load forecasting method for electric vehicle stations based on the combination of multivariate residual corrected gray scale model (EMGM) and long short-term memory network. Literature [17] evaluated the performance of the multivariate multi-step charging load prediction method based on the long and short-term memory network and commercial charging data.

The charging load of electric vehicles is affected by environmental temperature, users' electricity consumption habits, travel volume during holidays, road congestion, and travel purpose. There are uncertainties in the three aspects of time, space, and temperature. How to accurately describe this uncertainty is the key and difficult point for researchers to overcome the problem of electric vehicle charging load.

Based on the above research, this paper chooses the least-absolute method to fit the historical car ownership curve, and gives the forecast results of car ownership in the next few years. A log-normal distribution model of daily driving mileage is adopted combined with factors such as the driving characteristics of electric vehicles and the investment of fast charging facilities. Taking a simulated smart community as an example, according to the temporal and spatial characteristics of EV charging, the influence of electric vehicle charging on the community distribution network is analyzed based on the Monte Carlo algorithm. Finally, the characteristics of fast charging are analyzed. Based on the car ownership and the penetration rate of electric vehicles in each city, the influence of fast charging power on the peak load and peak-to-valley difference of the grid is studied.

II. PREDICTION OF VEHICLE OWNERSHIP BASED ON THE LEAST ABSOLUTE METHOD

Studying the growth trend of car ownership is of great significance to exploring the technology of EV access to the grid (V2G). The increase in overall ownership is conducive to the formation of group characteristics of EVs and the stability of energy storage characteristics, which can promote their use in various auxiliary services of the power grid. Application and development.

Because the unique shape of the S curve fits well with the growth pattern of population, holdings, population, etc., the Logistic curve fitting method is used to predict the growth pattern of EV holdings. At the same time, this paper uses the least-one method to improve the traditional least-squares method, which is more sensitive to data offset.

2.1 Least Absolute Multiplication

Mathematicians Laplace and Boskovic first proposed LAD (Least Absolute Multiplication). LAD is based on the principle of zero error and pursues the principle of absolute deviation and minimum. Compared with the least square method, it has the advantages of robustness, intuitiveness, and generality.

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Therefore, this article uses LAD to improve curve fitting. Suppose the set of all real-valued continuous functions on a closed interval is Φ, and the fitting function $f(x) \in \Phi$ is first-order derivable in this interval. On this basis, given k sets of discrete data (x_i, y_i), $i = 1, 2, \cdots k$, where $b = (b_1, b_2, \cdots, b_n)^T$, and $n \le k$, then:

$$\sum_{i=1}^{k} \left| y_i - f(x_i, b) \right| = \min \tag{1}$$

LAD can better identify abnormal data points and discard them in regression problems, reducing their interference to the fitting results. Therefore, the comparative analysis with the results obtained by the least square method can play a perfect supplementary role.

2.1.1 LAD solution process in curve fitting

If there is $b = b^* \in R_n$, make the objective function:

$$Q = Q\left(b^*\right) = \sum_{i=1}^{k} \left| y_i - f\left(x_i, b^*\right) \right| = \min \tag{2}$$

holds. Then the fitting function $f\left(x, b^*\right)$ is characterized as: there are at least n points $x_1, x_2, \cdots x_n$, which can make

$$y_i - f\left(x, b^*\right) = 0 \quad i = 1, 2, \cdots, n \tag{3}$$

true, then these n points that meet the condition are zero deviation points.

The absolute value equation has the characteristic of being non-differentiable. To solve the equation, it needs to be divided into two steps:

1) The absolute value equation can be miniaturized, and an approximate solution approaching the limit can be obtained;

2) Using the method of solving equations, determine the solution with the highest accuracy among the approximate solutions as the best solution. In practical engineering applications, the best solution is the exact solution.

Let $b^* = b + \Delta b$ be a specific slight offset of the exact solution. When Δb approaches 0, the following approximate relationship can be obtained:

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$$\left\|y-f\left(x,b^{*}\right)\right\|_{1}=\min_{b+\Delta b\in R_n}\left\|y-f\left(x,b+\Delta b\right)\right\|_{1}\approx\min_{b+\Delta b\in R_n}\left\|y-f\left(x,b\right)-\frac{\partial f\left(x,b\right)}{\partial b}\Delta b\right\|_{1} \tag{4}$$

Using the method of finding the extreme value of the multivariate function in advanced mathematics, combined with the necessary conditions $\frac{\partial Q}{\partial b_1}=\frac{\partial Q}{\partial b_2}=\cdots\frac{\partial Q}{\partial b_n}$, the following equations can be obtained:

$$\begin{cases}\frac{\partial Q}{\partial b_1}=-\sum_{i=1}^{k}\frac{y_i-f\left(x_i\right)}{\left|y_i-f\left(x_i\right)\right|}\cdot\frac{\partial f}{\partial b_1} & \sum_{i=1}^{k}\frac{r_i}{\left|r_i\right|}\cdot\frac{\partial f}{\partial b_1}=0\\ \frac{\partial Q}{\partial b_2}=-\sum_{i=1}^{k}\frac{y_i-f\left(x_i\right)}{\left|y_i-f\left(x_i\right)\right|}\cdot\frac{\partial f}{\partial b_2} & \sum_{i=1}^{k}\frac{r_i}{\left|r_i\right|}\cdot\frac{\partial f}{\partial b_2}=0\\ \vdots & \\ \frac{\partial Q}{\partial b_n}=-\sum_{i=1}^{k}\frac{y_i-f\left(x_i\right)}{\left|y_i-f\left(x_i\right)\right|}\cdot\frac{\partial f}{\partial b_n} & \sum_{i=1}^{k}\frac{r_i}{\left|r_i\right|}\cdot\frac{\partial f}{\partial b_n}=0\end{cases} \tag{5}$$

In the formula $r_i=y_i-f\left(x_i\right)$, $\frac{\partial f}{\partial b_j}=\frac{\partial f\left(x,b\right)}{\partial b_j}$, $j=1,2,\cdots,n$, $r_i\neq 0$.

Carrying out the first-order Taylor expansion of the function $f\left(x,b\right)$ at point $b^{(0)}=\left(b_1^{(0)},b_2^{(0)},\cdots b_n^{(0)}\right)$, we can get:

$$f\left(x,b\right)=f\left(x,b^{(0)}\right)+\sum_{j=1}^{n}\varphi_j\Delta b_j \tag{6}$$

$$r_i=r_i\left(b\right)=y_i-f\left(x_i,b\right)=y_i-f\left(x_i,b^{(0)}\right)-\sum_{j=1}^{n}\varphi_{i,j}\Delta b_j \tag{7}$$

Where each variable satisfies: $\varphi_j=\left.\frac{\partial f\left(x,b\right)}{\partial b_j}\right|_{b=b^{(0)}}$, $\varphi_{i,j}=\frac{\partial f}{\partial b_j}=\left.\frac{\partial f\left(x_i,b\right)}{\partial b_j}\right|_{b=b^{(0)}}$, $j=1,2,\cdots,n$, $1\le i\le k$, $\Delta b=b-b^{(0)}=\left(\Delta b_1,\Delta b_2,\cdots,\Delta b_n\right)^T$, $\Delta b_1=b_1-b_1^{(0)},\Delta b_2=b_2-b_2^{(0)},\cdots,-\Delta b_n=b_n-b_n^{(0)}$, $r_i^{(0)}=y_i-f\left(x_i,b^{(0)}\right)$.

Thus, substituting formula (7) into the formula (5), we can get:

$$\begin{cases}\sum_{i=1}^{k}\frac{1}{\left|r_i\right|}\varphi_{1,i}\left(\varphi_{1,i}\Delta b_1+\cdots+\varphi_{n,j}\Delta b_n\right)\approx\sum_{i=1}^{k}\frac{r_i^{(0)}}{\left|r_i\right|}\varphi_{1,i}\\ \sum_{i=1}^{k}\frac{1}{\left|r_i\right|}\varphi_{2,i}\left(\varphi_{1,i}\Delta b_1+\cdots+\varphi_{n,j}\Delta b_n\right)\approx\sum_{i=1}^{k}\frac{r_i^{(0)}}{\left|r_i\right|}\varphi_{2,i}\\ \vdots\\ \sum_{i=1}^{k}\frac{1}{\left|r_i\right|}\varphi_{n,i}\left(\varphi_{1,i}\Delta b_1+\cdots+\varphi_{n,j}\Delta b_n\right)\approx\sum_{i=1}^{k}\frac{r_i^{(0)}}{\left|r_i\right|}\varphi_{n,i}\\ r_i\neq 0\end{cases} \tag{8}$$

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Define $\sum=\sum_{i=1}^{k}$, $\varphi_j=\varphi_{i,j}$, and set the number of iterations as p, there are:

$$\begin{pmatrix} \sum\frac{\varphi_1\varphi_1}{|r_i|} & \cdots & \sum\frac{\varphi_1\varphi_n}{|r_i|} \\ \sum\frac{\varphi_2\varphi_1}{|r_i|} & \cdots & \sum\frac{\varphi_2\varphi_n}{|r_i|} \\ \vdots & \ddots & \vdots \\ \sum\frac{\varphi_n\varphi_1}{|r_i|} & \cdots & \sum\frac{\varphi_n\varphi_n}{|r_i|} \end{pmatrix} \begin{pmatrix} \Delta b_1 \\ \Delta b_2 \\ \vdots \\ \Delta b_n \end{pmatrix} = \begin{pmatrix} \sum\frac{r_i^{(p)}}{|r_i|}\varphi_1 \\ \sum\frac{r_i^{(p)}}{|r_i|}\varphi_2 \\ \vdots \\ \sum\frac{r_i^{(p)}}{|r_i|}\varphi_n \end{pmatrix} \tag{9}$$

In the formula, $\Delta b_1,\Delta b_2,\cdots\Delta b_n$ are the micro variables in the iterative process, which has:

$$b_1^{(p+1)}=b_1^{(p)}+\Delta b_1,\cdots,b_n^{(p+1)}=b_n^{(p)}+\Delta b_n \tag{10}$$

Among them, $p=0,1,\cdots$, the initial solution $b^{(0)}$ of the iteration can be artificially set or the result obtained by the least square method. It can be known from linear algebra that because $D[x_1,x_2,\cdots x_n,x_{n+1}]\neq 0$, there is only a unique solution. The iteration method can be used to solve $b_j^{(p+1)}$, and the iteration will be stopped when the accuracy requirements are met.

2.1.2 Analysis and prediction results of the saturation value of inventory

The typical expression of the Logistic curve is:

$$y_i=f(x)=\frac{k}{1+c\cdot\exp(-dx_i)} \tag{11}$$

The formula y_i represents the prediction result of the number of electric vehicles in the i-th year, and x represents the time variable related to the i-th year. c and d are constants, and historical data need to be used for fitting and solving, k determines the predictor variable's saturation value. Because (11) is a non-linear expression, in order to facilitate the solution, it is transformed into a linear expression by taking the logarithm of both sides. Let $y_i'=\ln(k/y_i-1)$, $c'=\ln c$, $d'=-d$, $x'=x$, then $y_i'=c'+d'x_i'$. c' and d' become the new parameters to be sought, which can be solved by linear regression.

In order to simplify the model, ignoring the influence of population on the saturation value, y_i is defined as the number of cars per capita.

Figure 1 shows the number of cars per thousand people in various countries in recent years. It can be seen that the number of vehicles in various countries in the figure conforms to the S-shaped curve. Considering the practicality, this paper uses the Logistic curve to fit the growth trend of the number of

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electric vehicles.

The fitting result of the least square method is used as the initial value of LAD, and the fitting result of the parameters c and d is obtained by fitting the curve of China's car ownership.

Least-squares fitting results:

$$y' = -0.1125x' + 6.083 \tag{12}$$

LAD fitting results:

$$\begin{aligned} y' &= -1067x' + 5.7502 \quad k = 0.4 \\ y' &= -1065x' + 5.9739 \quad k = 0.5 \\ y' &= -1064x' + 6.1565 \quad k = 0.6 \end{aligned} \tag{13}$$

Figure 2 shows the curve using LAD, least squares and historical data. LAD and least-squares have achieved good fitting results, but LAD is slightly better than least squares.

Table reflects the average fitting error of k under different values.

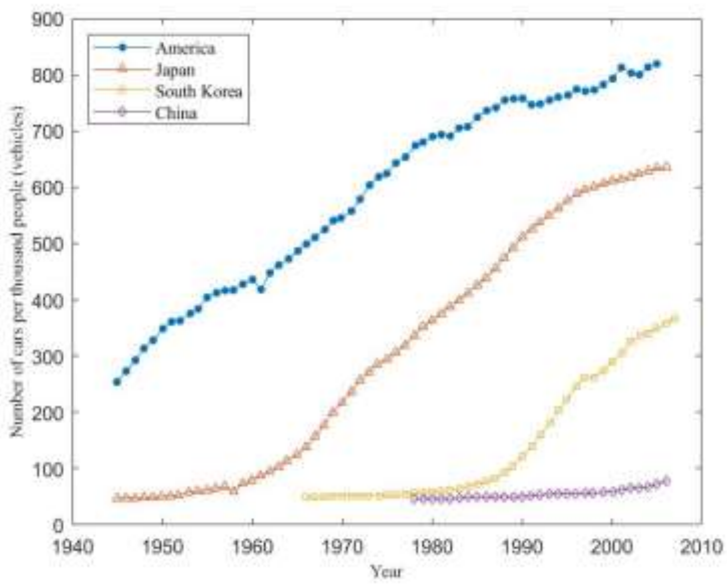

Figure 1 Car ownership per thousand people in a typical country (1945~2007)

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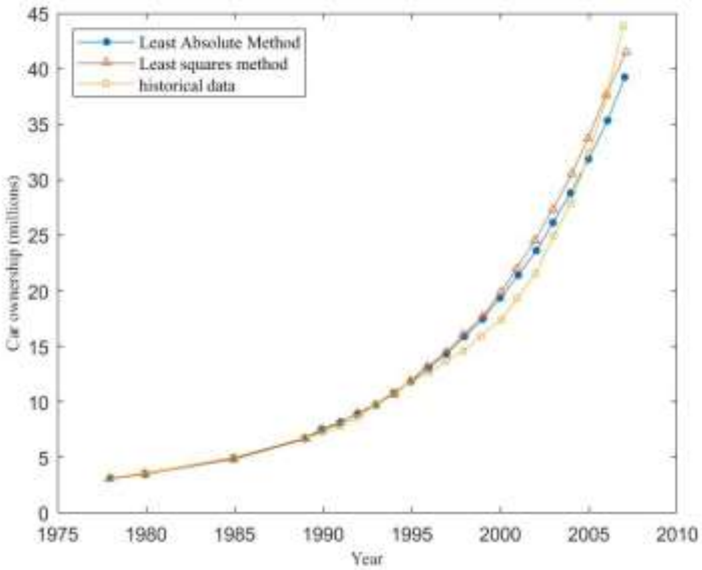

Figure 2 Curve fitting results of China's car ownership

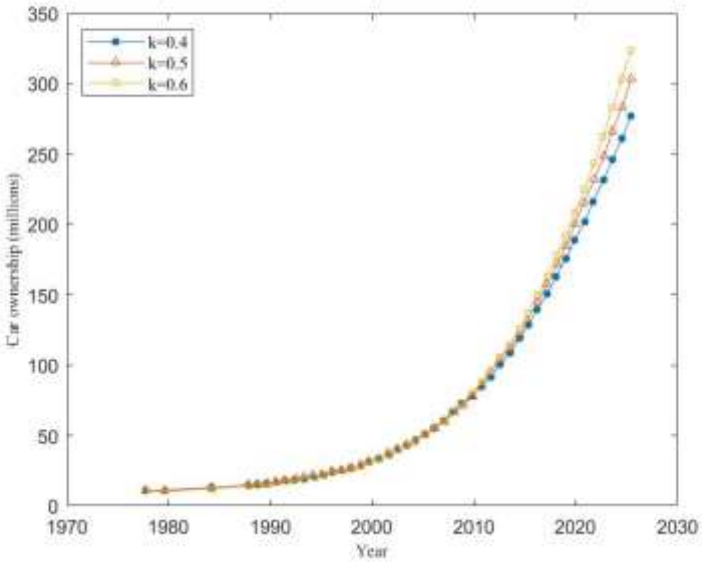

Figure 3 Forecast results of China's car ownership under different conditions

The method proposed in this section predicts the ownership of all cars. The number of electric vehicles will increase with the increase in the overall number of vehicles. Therefore, from the growth trend of overall car ownership, it can be judged that the number of electric cars will increase explosively in the next few years. The relationship between electric vehicles and the total number of vehicles is determined by the penetration rate which is equal to the number of electric vehicles divided by the total number of vehicles.

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Table I. The average error of the least square method and the least square method in curve fitting

	LAD(k=0.4)	LAD(k=0.5)	LAD(k=0.6)	Least squares method (k=0.5)
average error	5.57%	5.56%	5.59%	7.42%

III. ANALYSIS OF CHARGING CHARACTERISTICS OF ELECTRIC VEHICLES IN SMART COMMUNITIES

Suppose there are 100 households in a smart community. Because the smart community has a limited area, each household can be equipped with at most one car, and the number of charging facilities in the community can cover all households. Compared with electric vehicles, fuel vehicles have the advantages of long mileage, stable condition, and short replenishment time. Some families will not purchase electric vehicles as a means of transportation. Based on the above analysis, it is estimated that about 60% of the residents in this smart community will be equipped with an electric car in the future.

Assuming that the maximum mileage of each electric vehicle is 400km, the battery charging capacity of the electric vehicle is 35kWh, and the logarithmic probability distribution of the daily mileage conforms to the normal distribution $N(3.2, 0.88^2)$. If the power of fast charging and conventional charging of an electric vehicle are 45kW and 7kW, respectively, in order to simplify the calculation, without considering the charging characteristics of the battery, the time required to charge the battery when the battery is exhausted fully 48 minutes and 5 hours, respectively.

Lithium-ion battery charging at low temperature will lead to reduced life. Suppose fast charging is used in low low-temperature conditions, in order to reduce the impact on battery life. In that case, car owners often need to charge with conventional power for about 6 minutes before increasing the conventional power to High-power charging, and the charging efficiency of electric vehicles will also be affected by low temperatures. Assuming that the charging efficiency of electric vehicles in summer is 90%, and the fast charging power of 45kW can be used directly when fast charging is selected; the charging efficiency of electric vehicles in winter is 75%, and the charging power of 7kW for 6 minutes must be used when fast charging is selected. Raise it to a fast-charging level of 45kW.

Table II. Charging behavior characteristics of residents in smart communities

User charging time period	Charges per day	Charging length limit(min)	Probability of charging in each period	Logarithmic probability distribution of daily mileage	Starting time distribution
7:30-17:00	1	no	0.2	$N(3.2, 0.88^2)$	$N(9, 0.5^2)$
19:00-7:00	1	no	0.7	$N(3.2, 0.88^2)$	$N(19, 0.5^2)$
19:00-22:00	1	80	0.1	$N(3.2, 0.88^2)$	$N(19.5, 0.5^2)$

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IV. EV CHARGING LOAD FORECASTING METHOD BASED ON MONTE CARLO METHOD

The theoretical basis of the Monte Carlo method is the law of large numbers and the central limit theorem in probability theory. Under constraints, random number sequences are continuously generated to assist the simulation process.

The error of the Monte Carlo method is affected by its variance and mathematical expectation, so whether the setting value of the random variable is excellent or not is related to the size of the Monte Carlo method error. For a particular problem, one should choose the best one among various random variables. After the variance of the random variable is determined, the error can be effectively reduced by increasing the number of Monte Carlo simulations.

4.1 Regional Charging Load Prediction Method for Electric Vehicles

The steps of the electric vehicle charging load calculation method are as follows:

1) Set random variables that conform to various probability models, and then judge the power grid connection and charging behavior of electric vehicles based on factors such as the charging probability, charging length limitation, and seasonal differences in each period, to calculate the electric vehicle's power consumption per minute after being connected to the power grid. Charging power.

2) Superimpose the charging power of electric vehicles connected to the grid every minute to obtain the electric vehicle load forecast curve for 1440 minutes a day.

3) Due to the high randomness of Monte Carlo random number generation, the same method is used to perform multiple simulations to improve the accuracy of the data of the load forecasting curve and analyze the overall trend of the obtained curve.

4) Combine the simulation results to verify the conjecture and ask questions.

The calculation flow chart is shown in
Figure 4.

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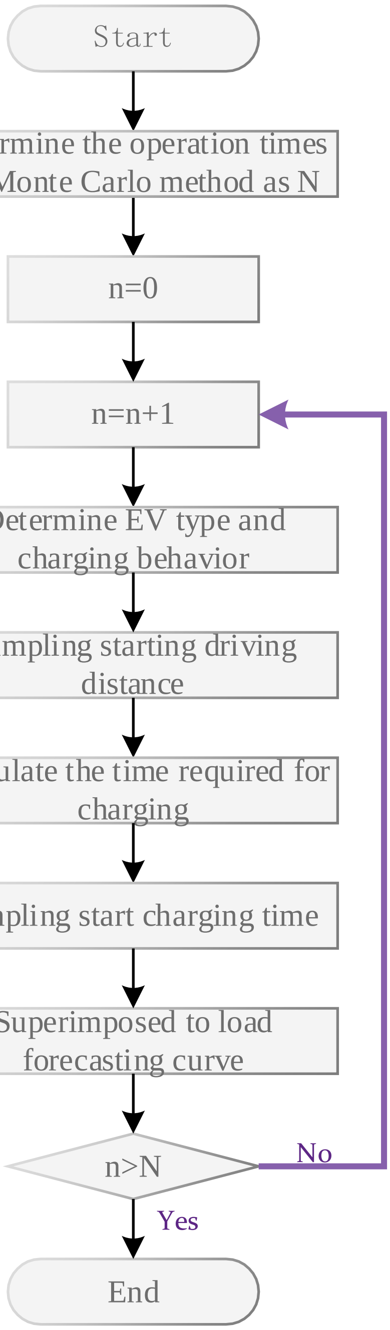

Figure 4 Flowchart of electric vehicle charging load forecast

4.2 Simulation Results of Charging Load Forecasting for Smart Communities

According to the electric vehicle charging load forecasting process, the Monte Carlo method is used to calculate the charging load. Under the boundary condition that the coefficient of variance is less than 0.05%, the number of Monte Carlo simulations is set to 30,000.

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The simulation results are shown in

Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, and Figure 12. The simulation results show that a large number of electric vehicles connected to the grid will bring a significant impact load to the distribution network. In summer, smart community's overall load and peak-valley difference are significantly higher than in winter. In some extreme cases, the initial load can be increased by nearly half. In winter, the grid-connected charging of electric vehicles lasts longer than in summer. This is because the winter temperature is low, which causes the charging efficiency to decrease.

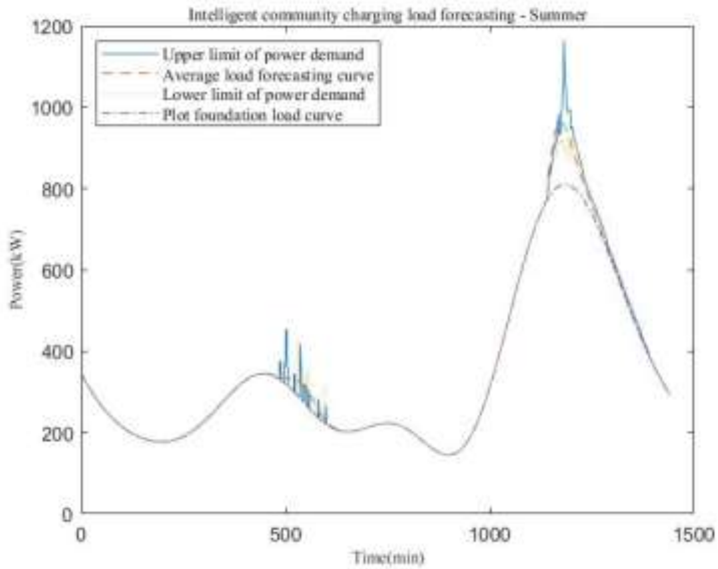

Figure 5 Summer load curve of smart community

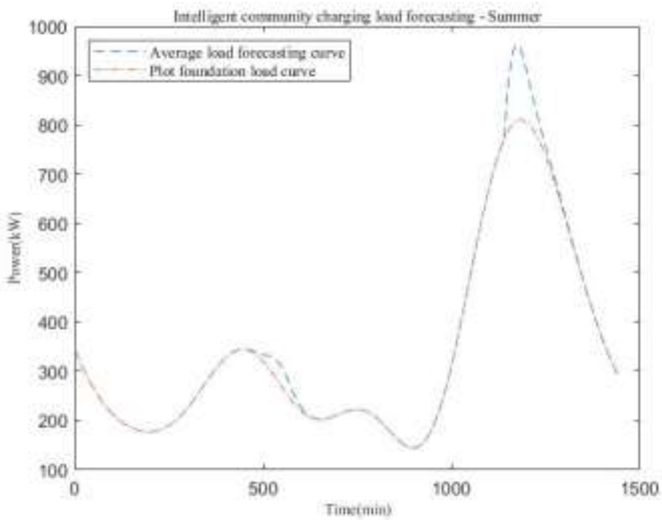

Figure 6 Summer average load forecasting curve of intelligent community

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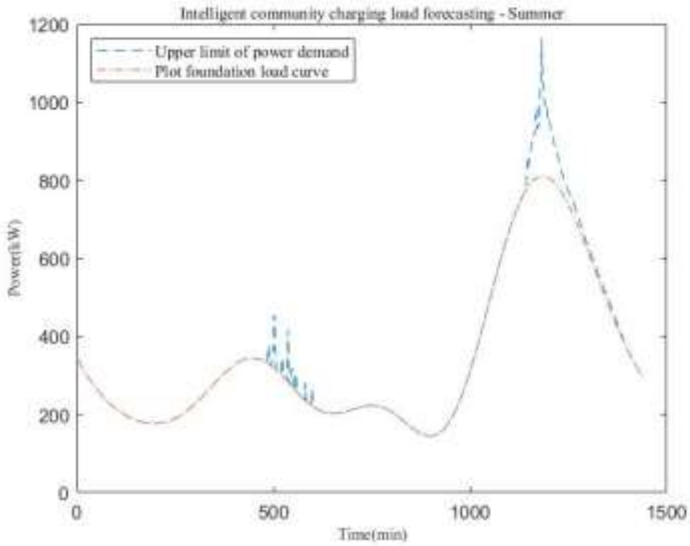

Figure 7 The upper limit of the electric vehicle charging load demand in the smart community in summer

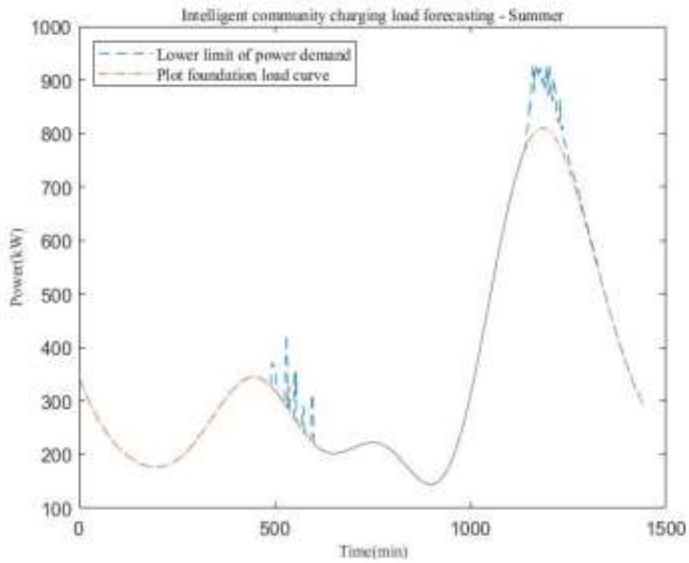

Figure 8 The lower limit of the electric vehicle charging load demand in the smart community in summer

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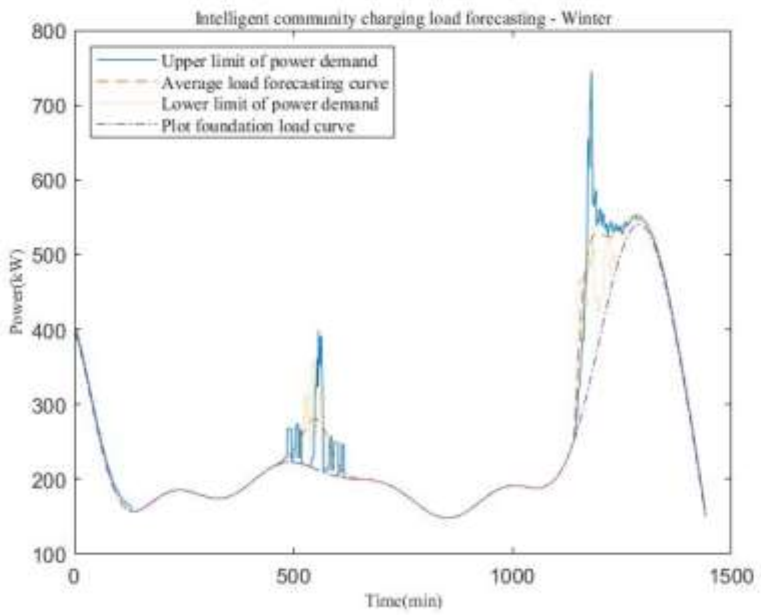

Figure 9 Winter load curve of smart community

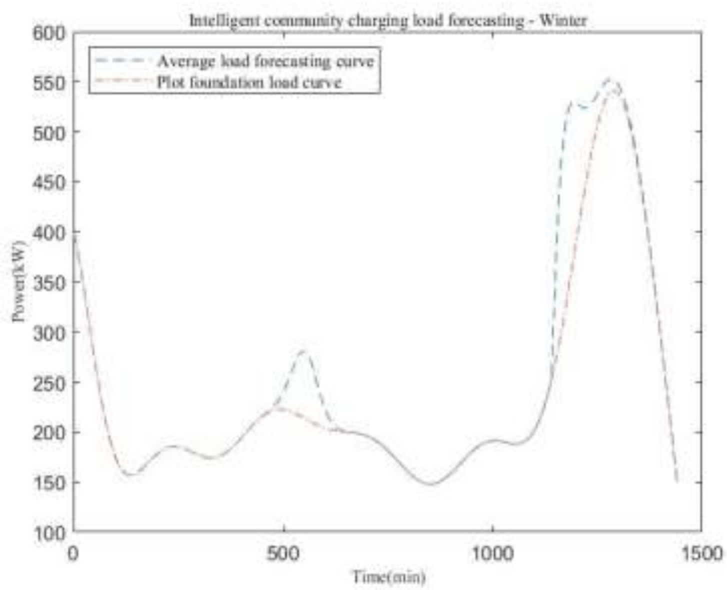

Figure 10 Winter average load forecasting curve of intelligent community

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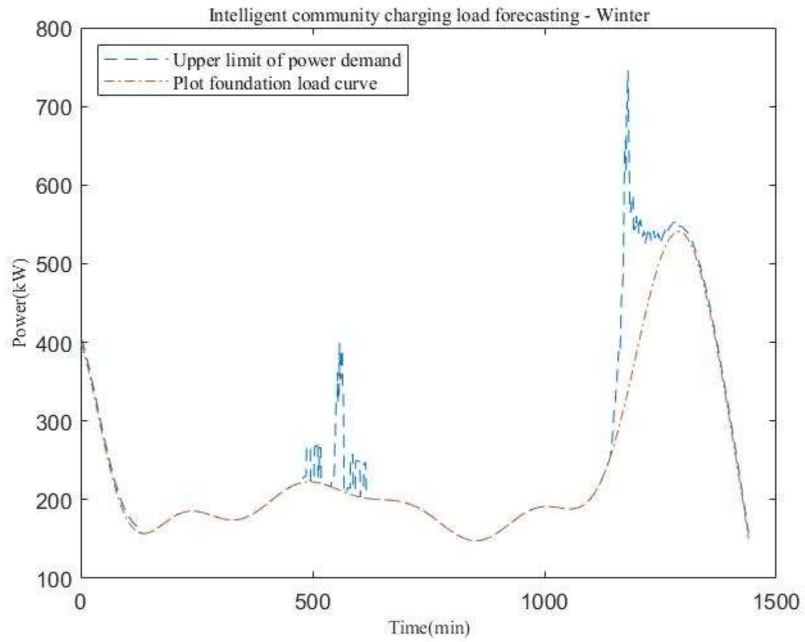

Figure 11 The upper limit of electric vehicle charging load demand in smart communities in winter

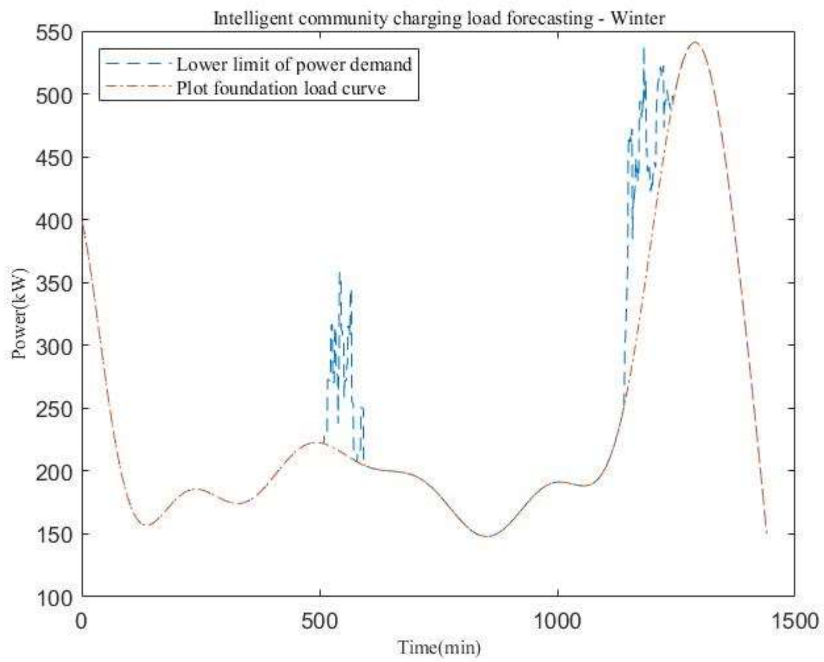

Figure 12 The lower limit of the electric vehicle charging load demand in the smart community in winter

Table III. The load and corresponding time of the maximum charging point of the smart community in summer and winter

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Maximum load point	Best case(kW)	Corresponding time(min)	average value(kW)	Corresponding time(min)	Minimal case(kW)	Corresponding time(min)
summer	1157.66	1180	963.72	1175	947.69	1153
winter	678.66	1229	553.34	1279	545.47	1279

V. ELECTRIC VEHICLE FAST CHARGING LOAD FORECAST

5.1 Analysis of Fast Charging Characteristics

The impact of conventional grid-connected charging of electric vehicles on the overall load of the grid is basically within a tolerable range. However, with the increasing development of the electric vehicle industry, fast charging will inevitably become the primary charging method in the future.

5.1.1 Charging rate and charging time

As of now, there is no clear boundary between regular charging and fast charging. For a unified standard, this article defines that if the charging rate is greater than or equal to 1C, then the charging process is regarded as a fast charging process.

Assuming that the battery capacity of each electric vehicle is 35kWh, regardless of the volatility of the charging power during the battery charging process, under different charging rates, the charging power and the corresponding consumption time of the electric vehicle are shown in Table .

Table IV. The relationship between charging rate, charging power and charging time

Charge rate	1C	3C	5C
Charging power(kW)	35	105	175
Charging time(min)	60	20	12

Assuming that fast-charging stations are widespread and cover the range of users' daily activities, the probability of going to the charging station for electrical energy replenishment during driving will increase, increasing the randomness of charging behavior. When the charging power is greater, the charging time is shorter, resulting in a decrease in the number of vehicles charged simultaneously. Therefore, the research on the characteristics of user charging behavior is significant in the fast charging load of electric vehicles.

5.1.2 Car ownership and number of electric cars

This article analyzes car ownership in the five cities of Hangzhou, Beijing, Ningbo, Lianyungang and Changzhou. Suppose the penetration rate (the ratio of the number of electric vehicles to the total number of vehicles) is defined as 4%, 10%, and 20%, respectively. According to statistical results, as of the end of

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2011, the car ownership in the above cities is shown in Table . The calculated number of electric vehicles under different penetration rates is shown in

Table .

Table V. Statistics of car ownership in each city (as of the end of 2011)

City	Car ownership (ten thousand)	Car ownership per thousand people (ten thousand)	Population per household (person/household)	Average car ownership per household (vehicles/household)
Hangzhou	200	230	2.59	0.60
Beijing	500	226	2.71	0.61
Ningbo	100	130	2.59	0.34
Lianyungang	60	43	3.27	0.14
Changzhou	56	124	1.78	0.22

Table VI. The number of electric vehicles under different penetration rates

Electric vehicle penetration rate		4%	10%	20%
Number of electric vehicles (ten thousand)	**Hangzhou**	8	20	40
	Beijing	20	50	100
	Ningbo	4	10	20
	Lianyungang	2.4	6	12
	Changzhou	2.24	5.6	11.2

5.2 The Impact of Fast Charging on the Grid

5.2.1 Analysis of electricity consumption in each city

With reference to GB/T50293-1999 "Urban Electricity Planning Code", each city's planning level of comprehensive electricity consumption per capita is shown in Table .

Table VII. Analysis of electricity consumption in each city

City	Total power consumption (100 million kWh)	Comprehensive electricity consumption per capita (kWh/person)	Higher level of electricity consumption	Upper-middle power consumption level	Medium electricity consumption	Low electricity consumption
Hangzhou	559	6426	■			
Beijing	850	3841			■	
Ningbo	459	5962		■		
Lianyungang	93	667				■

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Changzhou	288	6372	■			

5.2.2 Fast charging power demand and growth ratio

Electric vehicles have the greatest correlation with their driving characteristics. Ignoring the influence of charging mode and charging power, the following assumptions are made for electric vehicles:

1) Height=1.6 tons.

2) Consumption=10kWh/t·100km.

3) Average annual mileage S=20000 kilometers.

Ignoring the impact of the charging conversion rate, the average annual charging capacity of electric vehicles is 3200kWh. According to the data in Table VIII, under different electric vehicle penetration rates, the electricity demand of each city due to the investment of electric vehicle fast-charging facilities and its ratio relative to the original load demand are shown in Table .

Table VIII. Electricity demand for electric vehicles in each city and the ratio of electricity growth

Electric vehicle penetration rate	**4%**		**10%**		**20%**	
	Total charge ($10^8 kWh$)	**Growth rate (%)**	**Total charge ($10^8 kWh$)**	**Growth rate (%)**	**Total charge ($10^8 kWh$)**	**Growth rate (%)**
Hangzhou	2.6	0.47	6.4	1.15	12.8	2.29
Beijing	6.4	0.76	16	1.89	32	3.77
Ningbo	1.3	0.26	3.2	0.64	6.4	1.27
Lianyungang	0.8	0.87	2	2.16	3.9	4.20
Changzhou	0.8	0.28	1.8	0.63	3.6	1.25

5.2.3 Load changes under the fast charging scenario

The typical daily load curve characteristics of each city are shown in Table .

In order to quantitatively calculate the impact of fast charging of electric vehicles on the load characteristics of the grid, the following assumptions are made:

1) The user's fast charging behavior characteristics obey the Poisson distribution, that is, within a certain period t, an electric vehicle enters the fast charging station. Among them, $p(X=k)=\left(\exp(-\lambda t)(\lambda t)^k\right)/k!$, λ is the arrival rate of electric vehicles arriving at the charging station and

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λt is the mathematical expectation of charging vehicles.

2) The fast-charging frequency of electric vehicles is 0.714 times/day.

3) The normal distribution of the daily SOC curve of electric vehicles is $N(0.4, 0.1^2)$.

4) Assume that electric vehicles have approximately the same probability of arriving at the charging station simultaneously during the period of 7:00 to 19:00. During the period of 6:00~7:00, 19:00~20:00, it is also assumed that a user arrives at the charging station for fast charging.

Under the above assumptions, the calculated vehicle arrival rate is shown in
Table .

Under 1C, 3C, and 5C charging rates, Monte Carlo simulation can be used to obtain the daily load curve after the grid is superimposed with a fast charging load. The maximum load increase and peak-to-valley difference changes caused are shown in
Table and
Table , respectively.

It can be seen that the impact of electric vehicles on the overall load of the grid mainly depends on the behavior characteristics of electric vehicle owners, the charging rate of charging facilities, and the characteristics of electric vehicle charging and power consumption. In the context of the increasing development of electric vehicles, the investment in fast charging facilities will cause an increase in power consumption, which depends on the inherent driving characteristics of electric vehicles and their energy efficiency parameters. In addition, the investment of fast-charging facilities for electric vehicles will in most cases cause an increase in the maximum daily load (daily peak load) of the grid and an increase in the peak-to-valley difference between the maximum load and the minimum load. For example, under the influence of a penetration rate of 20% and a charging rate of 5C, it is predicted that the maximum electricity load in Hangzhou will increase by 6.28%, and the peak-to-valley rate will increase by 3.52%. However, when the charging rate increases, the charging time becomes shorter, which indicates that the proportion of the number of vehicles charged at the same time in most of the period will decrease. This is also caused when considering the impact of fast charging power on Lianyungang. The reason for the decrease in peak-to-valley rate. Therefore, the impact of increasing the charging power of fast charging facilities on the overall charging load of the grid is within a tolerable range.

Table IX. Typical daily load curve characteristics

City	**Daily maximum load($10^4 kW$)**	**Minimum daily load($10^4 kW$)**	**Peak-to-valley difference rate(%)**
Hangzhou	407.2	242.7	40.4

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Beijing	1239.2	739.8	40.3
Ningbo	548.1	326.8	40.4
Lianyungang	120.7	88.9	26.3
Changzhou	584.9	380.4	35

Table X. Vehicle arrival rate under different penetration rates

	Electric vehicle penetration rate	**4%**	**10%**	**20%**
Arrival rate (vehicles/min)	**Hangzhou**	79	198	397
	Beijing	198	496	992
	Ningbo	40	99	198
	Lianyungang	24	60	119
	Changzhou	22	56	111

Table XI. Maximum load increase caused by fast charging of electric vehicles

Permeability	**4%**			**10%**			**20%**		
Charge rate	**1C**	**3C**	**5C**	**1C**	**3C**	**5C**	**1C**	**3C**	**5C**
Hangzhou	1.16%	1.30%	1.29%	3.02%	3.16%	3.17%	5.87%	6.15%	6.28%
Beijing	0.96%	1.01%	1.03%	2.40%	2.48%	2.59%	4.86%	5.07%	5.17%
Ningbo	0.44%	0.47%	0.48%	1.34%	1.36%	1.41%	2.23%	2.26%	2.38%
Lianyungang	0.33%	0.77%	0.90%	0.87%	2.11%	2.75%	1.6%	3.86%	5.16%
Changzhou	0.24%	0.25%	0.25%	0.60%	0.58%	0.63%	1.14%	1.18%	1.22%

Table XII. Change of peak-to-valley difference caused by fast charging of electric vehicles

Permeability	**4%**			**10%**			**20%**		
Charge rate	**1C**	**3C**	**5C**	**1C**	**3C**	**5C**	**1C**	**3C**	**5C**
Hangzhou	0.70%	0.72%	0.76%	1.70%	1.78%	1.83%	3.38%	3.43%	3.52%
Beijing	0.57%	0.59%	0.61%	1.40%	1.44%	1.51%	2.77%	2.88%	2.93%
Ningbo	0.26%	0.28%	0.29%	0.79%	0.80%	0.83%	1.30%	1.32%	1.39%
Lianyungang	-0.99%	-0.77%	-0.63%	-2.30%	-1.52%	-1.16%	-4.70%	-3.11%	-2.61%
Changzhou	0.15%	0.16%	0.16%	0.39%	0.38%	0.41%	0.75%	0.77%	0.79%

VI. CONCLUSION

This paper mainly studies the electric vehicle charging load forecasting method. Based on the least-sum method and historical inventory data, the logistic curve fitting method is used to predict the future growth trend of the vehicle inventory; Monte Carlo method is the core to charge electric vehicles Load calculation, especially considering the impact of summer and winter charging efficiency and user charging behavior characteristics, based on the probability distribution of charging time and space characteristics, set up the application scenarios of smart communities, and predict and calculate the charging load; considering the driving characteristics, Under the condition of making quantitative assumptions, the impact of the investment of fast charging facilities under different charging rates on the city's maximum load and the peak-valley difference is analyzed, which provides a certain reference for the operation and dispatch of the power grid.

Conditions such as climate, traffic, distribution of charging stations, and battery charging characteristics will also have an indirect impact on the behavior of users and the charging efficiency of electric vehicles. In future research, the probability density distribution model can be established based on the above conditions so that the prediction results are more realistic.

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