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Forecasting method of electric vehicle charging load based on virtual prediction parameter estimation strategy

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Abstract: In order to deal with the threat of the randomness of large-scale electric vehicle (EV) loads to the safe and economic operation of the distribution network effectively, a forecasting method of EV loads based upon virtual prediction parameter estimation strategy is proposed. Firstly, an in-depth analysis is conducted to thoroughly examine the applicability and target audience of various existing power user load forecasting methods. This initial phase provided a solid foundation for the introduction of the new methods. Secondly, utilizing the Monte Carlo simulation method, a charging load forecasting approach that considers both spatial and temporal distribution is developed. This method effectively captures the diversity of EV charging behaviors by leveraging virtual parameter estimation, integrating insights from historical data into future load predictions, thereby enhancing forecasting accuracy. Finally, to validate the effectiveness of this groundbreaking approach, comprehensive testing was conducted on the MATLAB R2017a simulation platform. This verification phase not only serves to demonstrate the method's accuracy, but also underscores its practicality and reliability in real-world applications.

Key words: distribution network, electrical vehicles, forecasting method, Monte Carlo simulation

1. Introduction

For an extended duration, the developmental challenges within the global electric power industry have garnered widespread attention. Concurrently, efforts to explore and implement reforms within the electric power sector have been deepening. During the 1990s, numerous countries became acutely aware of the significant hindrance posed by the vertically integrated electric power system to the industry's development. Therefore, it has become imperative for the electric power market to undergo reform, as such reforms are essential to facilitate the advancement of the electric power industry. In this context, load forecasting is poised to assume a pivotal role.

Inaccurate load prediction will not only affect the selection of transformer capacity, grid structure, voltage grade and traverse section, but also affect the rationality of the entire network layout. Thus, it will lead to the unreasonable use of power grid investment funds, which is detrimental to the normal development of the distribution network. Therefore, load forecasting should be paid more attention to in the process of compiling rural power grid development planning.

For the last 20 to 30 years, many domestic and overseas experts and scholars have done miles of study on the theory and methods of load forecasting, and have made lots of achievements. In terms of methods, forecasting methods' development roughly gone through four periods:

1. The stage of traditional statistical forecasting methods of historical data represented by linear regression method and moving average method;
2. The time series prediction method stage proposed by Box-Jenkins;
3. The Grey model and combined prediction;
4. The intelligent prediction method stage of learning algorithms based on a neural network and support vector machine, and optimization algorithms based on the particle swarm optimization algorithm and genetic algorithm.

In Reference [1], a data-driven approach is proposed for short-term load forecasting of electric vehicle charging. This approach combines model-driven methods to obtain accurate prediction results and charging behavior information, aiming to enhance the reliability and safety of charging station load. This study proposes an academically rigorous method for spatial-temporal EV charging load forecasting, considering coordination among multiple charging behaviors [2]. It enables effective analysis of their impact on EV charging load distribution. The method integrates vehicle mobility, energy consumption, and charging load determination models, providing a foundation for managing charging facilities and guiding charging behaviors. Implications include enhancing transportation and distribution network planning and operation. Reference [3] presents a deep learning model with a multi-scale structure and a residual network for accurate time series forecasting. Outperforms Informer, Informer+, and ARIMA, improve prediction with reduced errors and provide valuable reference for effective time series prediction. In Reference [4], cluster-based transfer learning reduces training time by 85.6% without accuracy losses. DWR optimizer avoids overfitting and negative learning evaluated on 1 000 distribution nodes with real-world data. Reference [5] presents how to overcome the limitations of existing methods in handling non-stationary multivariate data, utilize the attention mechanism to capture interrelationships and accommodate long input sequences, and validate on real datasets, outperforming dominant models. Experimental assessment shows the effectiveness of the attention mechanism at different time steps. In Reference [6], RQMC sampling with a Sobol' sequence accelerates convergence. The RQMC-PF estimator reduces particles needed for precise state estimates. APF adapts particle count based on estimated covariance. The test results confirm the method's efficiency and precision in estimating unbalanced distribution systems.

With the popularity of EVs, the randomness of charging and discharging of a large number of EVs has brought a great threat to the safety and economic operation of the distribution network.

Therefore, it is very meaningful to accurately predict the load of EVs. There are many factors affecting the charging load of EVs, and at present, there are many researches on State of Charge (SOC), charging time, charging power, charging mode, Time of Use Price (TOU), etc. Therefore, the charging load model must be established to master the charging characteristics better.

In Reference [7], optimal weather station selection improves short-term forecasting and reduces computational cost through complexity reduction. The incremental search algorithm identifies the optimal number and locations tested on the Spanish power grid with real data, reducing forecasting errors. The algorithm was deployed by the Spanish transmission system operator for hourly forecasts. In Reference [8], AI methods (RF, DNN, LSTM) were evaluated for short-term PV power forecasting. The statistical approach uses weather and PV output data from Berlin, Germany. RF and DNN models generate accurate forecasts, handle sudden changes in PV output. It brings the benefits of wider adoption of RES, reduces disruptions, improves planning and operational costs in grid management. In Reference [9], a two-stage method enhances PV power forecasting and improves speed and accuracy. It uses MIC weighted grey correlation for sample extraction and employs TCN, BiGRU with Skip connection, and the attention mechanism for power forecasting. Tested on station data, it demonstrated effectiveness and improved metrics. In Reference [10], hybrid deep learning models improve power system load forecasting. ExpWMA handles missing values. GESD detects abnormal values. BiLSTM is used for short-term, random forecasts and the Pearson correlation for mid-term. The optimized parameters yield 2.36% MAPE, outperforming benchmarks. In Reference [11], a Hybrid ResNet-LSTM model improves short-term load forecasting and reconstructs data for ResNet feature extraction. LSTM utilizes extracted features for accurate forecasting. Its superiority and feasibility have been shown through practical examples. It shows higher prediction accuracy compared to other models. In Reference [12], TF is first predicted using a deep-learning-based convolutional neural network (CNN), and different forecast uncertainties are evaluated to formulate the TF prediction intervals. In Reference [13], the charging load prediction of EVs in universities and shopping malls is proposed based on Monte Carlo simulation, and a fair charging strategy based on SOC is proposed. It can be seen that Monte Carlo algorithm simulation is currently one of the most suitable methods for predicting the charging power of electric vehicles, by reviewing a large number of references [14, 15].

In an effort to deal with this threat of stochastic load of large-scare EVs effectively to the safety and economic operation of the distribution network, this paper proposes a load forecasting method for EVs based on a virtual prediction parameter estimation strategy. Firstly, analyzes the applicable scope and object of load forecasting methods of various existing power user. Secondly, based on the Monte Carlo simulation method, proposes a charging load forecasting method for EVs considering the spatial and temporal distribution. Finally, the method is verified on MATLAB.

2. Load forecasting method for power users

Forecasting methods for load and electricity consumption are commonly applicable to power selling companies' jurisdictions and various industries' large users. These methods, based on historical data, can be divided into two categories: one predicts the future based on historical electricity consumption or load, which is simple and reliable; the other forecasts future consumption and load based on predicted values of factors significantly impacting electricity consumption or load, requiring diverse data types and comprehensive user-provided data, enabling a comprehensive analysis of multiple influencing factors.

2.1. Consumption method

1. ***Scope of application***
   This method is typically suitable for forecasting the electricity consumption of typical large users, which is represented by their annual electricity usage. While the single consumption method offers significant advantages in predicting the power consumption of such users, it may not be directly applicable for forecasting power consumption within the jurisdiction of an electricity selling company.
2. ***Mathematical model***
   Using planned product quantity (or output value) and electricity consumption for forecasting annual electricity usage is well-suited for specific industrial and agricultural loads characterized by a single consumption index, especially in the context of near and mid-term load prediction. In this method, it considers the broader socioeconomic development goals, the industrial and agricultural production indices for the planning period, as well as electricity consumption and electricity consumption per 100 million yuan for various product categories in each department. It computes the individual consumption rates for each product and output value, while also factoring in industrial restructuring, loss reduction, and energy efficiency requirements to identify relevant trends. Finally, it employs product output indices and economic indicators from development plans formulated by various national economic departments and applies Eq. (1) for predictive calculations.

   $$A_h = \sum_{i=1}^{n} Q_i U_i, \tag{1}$$

   where: A_h is the electricity consumption of an industry during the forecast period; U_i is the electricity consumption of output (or output value) of various products; Q_i is the output (or output value) of various products.
3. ***The interface data***
   Taking the annual electricity consumption forecast as an example, the input data is the electricity consumption and output of each product to produce a single product for k products produced over the past five years. The output data is the electricity consumption of each of the k products in the year to be predicted. If you need to forecast quarterly/monthly electricity consumption, just change the input data into the quarterly/monthly electricity consumption to be predicted in the last 5 years. A similar generalization can be made for load forecasting.

2.2. Analogy method

The analogy method is an approach to predicting unknown or new phenomena by comparing and analyzing them based on the consistent development principles of similar or analogous entities. Its fundamental principle involves selecting an appropriate analogy object, typically similar industry power consumption and load conditions in economically more developed regions, and comparing the relationship between industrial economy and electricity consumption between two areas. When using the analogy method, it is essential to ensure that the two entities being compared share similar key characteristics, and any differences that may affect the prediction results may require adjustments.

2.3. Maximum load utilization hours method

According to the survey, the user obtains the area percentage of various types of planned land $S(t)$, $t = 1, 2, \ldots, 13$, and obtain the maximum load utilization hours $T_{\max}(i)$ of various types of land by the experience, $i = 1, 2, \ldots, 13$. Taking into consideration factors such as energy consumption, resource utilization, and other relevant metrics, these load utilization hours serve as indicators of the maximum capacity or efficiency at which each type of land can be utilized. The maximum load utilization hours $T_{\max}(j)$ of each township is:

$$T_{\max}(j) = \sum_{i=1}^{13} \sum_{t=1}^{13} [S(t) \cdot T_{\max}(i)], \tag{2}$$

where $j = 1, 2, \ldots,$ m and m is the number of townships in a prefecture.

The maximum load of each township is:

$$P_{\max}(j) = \frac{A(j)}{T_{\max}(j)}, \tag{3}$$

where: $P_{\max}(j)$ is the maximum load of the township; $A(j)$ is the total electricity consumption of the township; $T_{\max}(j)$ is the maximum load utilization hours of the township.

The maximum load utilization hours method is simple and practical in calculating the maximum load of the whole prefecture, but the difficulty lies in determining the maximum load utilization hours of each township when it is used to calculate the maximum load of each township. In this design, after predicting the predicted electricity consumption of each township, the maximum load is obtained by using the maximum load hours method.

2.4. Data mining method

Data mining, also known as knowledge discovery in the database, refers to excavating the hidden, unknown in advance, unusual, and of practical significance information or useful patterns from a large database, and the process of performing with concepts, rules, and the form that people can understand at the same time, and which has application value in the database. Data mining tools can provide good predictions of future trends and behavior to support people's decisions.

3. Load characteristic analysis and its forecasting technology of EV

3.1. Overview of charging loads for EVs

Firstly, large-scale electric vehicles (EVs) can impact distribution network equipment, increasing load levels and potentially causing overloads and equipment damage. This necessitates additional capacity and grid investment for extensive charging stations.

Secondly, the unpredictability of EV users' behavior during driving and charging introduces greater uncertainty in power grid control. Simultaneous charging of numerous EVs can significantly increase peak loads, worsen the grid's peak-to-valley ratio, raise generation costs, reduce grid efficiency, and strain local power supply, overloading distribution facilities. This compounds power grid operation and management challenges.

Thirdly, in the process of charging electric vehicles, the electrical exchange between the grid and the electric vehicles requires rectification and transformation by charging stations or chargers. This process may generate a certain number of harmonics, resulting in some effects on the power supply system, including a decrease in power factor, an increase in three-phase imbalance, and an amplification of node voltage fluctuations, among other issues.

The study on the load prediction of disorderly charging of EVs can provide detailed information and reference significance for the orderly charging of EVs and the feedback of EVs to the power grid as distributed energy source. At the same time, it is of great significance for the study of the load curve, power quality and the voltage loss of load in the distribution network.

3.2. Load characteristics analysis of EVs

There are many factors that affect the charging load of EVs, varying from the type and quantity of cars, the driving characteristics of cars, to the charging and discharging characteristics of power batteries, etc. This paper sums up the charging characteristics of various types of EVs by introducing the travel characteristics of different types of EVs, then analyzes the influence of EV charging loads on the power grid in typical charging mode. The charging loads of EVs is affected by many factors, which are analyzed concretely below:

1. ***Type of EVs***
   Since charging time, daily travelled distance and charging power of EVs are different because of their types, it is important to distinguish EVs' types. According to this "One thousand Vehicles in Ten Cities" project launched by the Ministry of Science and Technology and the Ministry of Finance in Beijing, Shenzhen, Wuhan and other places in January 2009, EVs are mainly promoted in four major areas, including buses, taxis, official cars and private cars. Buses have fixed driving rules and charging locations, while taxis, official cars and private cars operate in relatively flexible ways, and their driving rules and charging locations are randomized, leading to great distinctness in charging behavior of various EVs.
2. ***Initial charging time of EV***
   Affected by the driving rules and user preferences of different types of EVs, the initial charging time of EVs is closely related to the type of EVs.
   a) Buses and taxis
   When considering the prediction of charging times for buses and taxis, there are several key factors to take into account, with one of the most important being commuting time. Commuting time can significantly impact the charging demands of these electric vehicles, as they typically carry a large number of passengers during peak hours. Assume that on and off hours are $t_s t_e$, and the start and end times of lunch break are $t_{r1} t_{r2}$. The EV takes $t_{\max}$ to be fully charged, and the minimum charging time is t_0. The probability distribution function of the initial charging time of buses and taxis is obtained as:
   When $t_0 < t_{r2} - t_{r1}$:

$$f(t) = \begin{cases} \dfrac{1}{t_s - t_e + t_{r2} - t_{r1} - 2t_{\max} + 24} \\ 0 \end{cases} . \tag{4}$$

$$t_{r1} \le x \le t_{r2} - t_{\max}$$

others

When $t_0 \geq t_{r2} - t_{r1}$, the electric vehicle is not fully charged during the noon non-commuting time:

$$f(t) = \begin{cases} \dfrac{1}{t_s - t_e - t_{\max} + 24} & 0 \le t \le t_s - t_{\max} \ \text{or} \ t_e \le t \le 24 \\ 0 & \text{others} \end{cases}. \tag{5}$$

Taking into account the charging capacity acquired at noon, further trip planning can be done to ensure that electric vehicles have sufficient charging levels before they are put into service, thereby optimising the overall travel experience.

b) Official and private cars

Different from buses and taxis, the initial charging time of official cars and private cars is more random, which is the return time of the last trip of a day. According to the central limit law, its initial charging time approximately follows a normal distribution:

$$f(t; \mu_t, \sigma_t) = \frac{1}{\sqrt{2\pi}\sigma_t} \exp\left(-\frac{\left(x - \mu_t^2\right)}{2\sigma_t^2}\right), \tag{6}$$

where μ_t, σ_t are determined by the different types of EV charging modes.

3. ***EV charging power***

Figure 1 shows the variation of the charging power of the EV with time. According to Fig. 1, the charging power gradually increases in the beginning process, while gradually decreases afterwards.

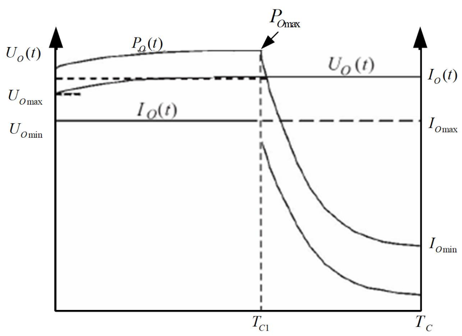

Fig. 1. Variation of charging power of EV with time

a) Effect of battery types

There are mainly three kinds of power batteries used in EVs: lead-acid battery, nickel metal hydride battery and lithium battery. The charging characteristics of various batteries vary. The advantages of the lithium battery compared with the former two are very prominent: large specific energy, high single working voltage, high charge and discharge efficiency, long service time, low pollution and so on, the lithium battery is the first choice of the EV power battery. Therefore, according to the existing situation of EVs and the future development trend, this paper assumes that all EVs in the forecast range adopt lithium batteries.

b) Effect of charging ratio

The charge ratio refers to the charge current value of the battery, which is numerically equal to the multiple of the rated capacity, usually denoted by C. The reason for the different charging times is the various demands of charging time of users. For conventional charging, the charging ratio is generally 0.2 C, and for fast charging, that is generally 1.25 C. The difference of the charging ratio will affect the peak charging power and charging duration.

$$\begin{array}{c} P_{0\,\max} \propto A \\ T_C \propto (1/A) \end{array}. \tag{7}$$

In order to simplify the analysis, the constant current stage is regarded as a linear function and the constant voltage stage as an exponential function. The function model of power and time is obtained as shown in Eq. (8).

$$p_o(t) = \begin{cases} I_{o\,\max} U_o(t), & 0 \le t \le T_{c1} \\ U_{o\,\max} I_o(t), & T_{c1} \le t \le T_c \end{cases}. \tag{8}$$

Assume $U_{o\,\min} = kU_{o\,\min}$, Eq. (8) can be transformed into:

$$p_o(t) = \begin{cases} U_{o\,\max} I_{o\,\max} \left((1-k)\dfrac{t}{T_{c1}} + k \right), & 0 \le t \le T_{c1} \\ U_{o\,\max} I_{o\,\max} e^{-a(t-T_{c1})}, & T_{c1} \le t \le T_c \end{cases}. \tag{9}$$

Accumulate the charging power of all EVs charged at the time t, the charging load curve at the time t can be obtained.

4. ***Analyze of charging mode***

Various charging modes will cause diverse influence on the charging mode of electric vehicles. It can be divided into three modes: conventional charging, quick charging, battery pack replacement. According to the degree of interaction between EVs and the power grid, their charging modes can be divided into distributed plug-in charging mode, centralized charging mode and intelligent charging mode.

a) Distributed plug and charge mode

This situation is mainly aimed at a large number of low-voltage (380 V/220 V) distributed charging points, mainly concentrated in residential buildings and parking lots of many office areas. In this mode, the charging time and location of EVs are completely discretionary by users, while the operation characteristics of the power grid are basically not considered. Meanwhile, affected by the infrastructure, the ordinary charging method is mainly adopted, charging current of which is generally between 0.2 C and 0.5 C (0.2 C means $1/0.2 = 5$ h charge full under ideal conditions, other charging times are the same). It takes approximately 5–8 hours to fully charge the battery.

b) Centralized charging mode

Centralized charging mainly refers to centralized charging in a specific time. Fast charging refers to the situation where the charging current of a battery is several times higher than the normal charging current, which can increase the SOC of the battery quickly. For instance, charging with a current of 2 C can increase the SOC of the battery from 0 to about 80% in 0.5 h.

c) Intelligent charging mode

According to whether power is sent back to the grid, it can fall into unidirectional charging mode and bidirectional charging and discharging mode (V2G). V2G is an EV connection to the grid as the distributed load and energy storage devices. It can release electric power stored in the power battery to the grid, which can send electricity back into the grid to support the grid in the peak period of time or power grid failure in emergencies so as to provide positive support for optimizing power grid operation and security.

3.3. EV load forecasting methods

The EV charging load is influenced by various elements. This paper proposed a load forecasting technique for EVs based on Monte Carlo simulation, which considers spatial and temporal distribution.

1. ***Monte Carlo simulation method***

Monte Carlo connects the problem with a certain probability model and implements random sampling or statistical simulation by computers. According to the traffic behavior database of the national resident travel survey, based on the Monte Carlo principle, a mathematical model with random probability characteristics is established to predict the charging time, location and load demand of cars in the future by simulating the traffic habits of users (including the travel habits and charging habits).

a) Fundamentals of prediction

EV charging load in a region is whole charging power of EVs in the region. In order to obtain accurate load prediction data, Monte Carlo has been applied to imitate four types of EV's loads respectively. The total EV load P can be obtained by superposition, and the calculation method is:

$$P = \sum_{t=1}^{1440} \left(\sum_{n=1}^{N_b} P_{bt}^n + \sum_{n=1}^{N_t} P_{tt}^n + \sum_{n=1}^{N_o} P_{ot}^n + \sum_{n=1}^{N_c} P_{ct}^n \right), \tag{10}$$

where: N_b, N_t, N_o, N_c are the number of electric buses, taxis, official and private cars; $P_{bt}^n, P_{tt}^n, P_{ot}^n, P_{ct}^n$ are the charging power of the n-th electric bus, taxi, official and private car at that moment. To calculate power over a day in minutes, consider a continuous period of time (from $t = 1$ minute to $t = 1440$ minutes, covering the entire day). In each minute, the instantaneous power at that moment is recorded, and these power values are then added together to obtain the total power consumption over the course of the day.

b) Monte Carlo simulation

According to the above model and principle, the relevant load prediction model can be established according to the specific charging mode of different EV types, and Monte Carlo may be applied to simulate the model.

2. ***EV load forecasting considering spatial and temporal distribution based on Monte Carlo simulation method***

   First, predict the total EV ownership in the area to be predicted in the future, and divide this area into different regions. According to the different types of land-using situation and parking characteristics of each region, an improved parking generation rate model can be adopted to calculate the parking demand of each region, and gain the parking demand's spatial and temporal scatter in the predicted area. Then, according to the driving characteristics of EVs in the area to be predicted, set up their charging demand's model, then use the Monte Carlo method to simulate the behavior of driving, parking and charging of EVs in each area as well as obtain the temporal distribution of EV charging load in each area. The set of the temporal distribution of EV charging load in each region is also that of total EV charging load in the area to be predicted. EV charging load's prediction considering spatial-temporal distribution is showed in Fig. 2.

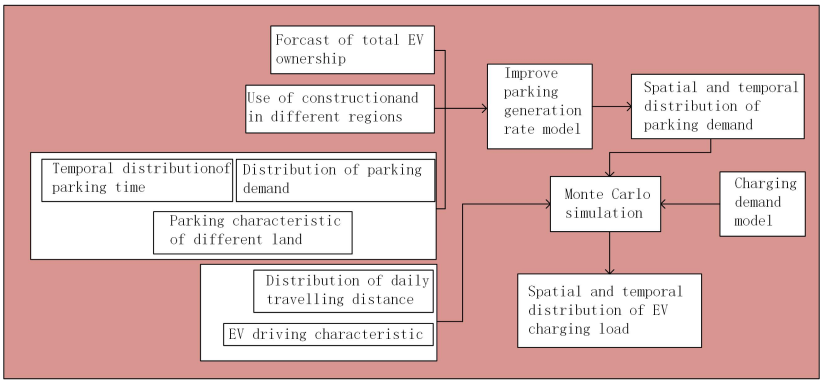

Fig. 2. EV charging load's prediction

Based on data related to the distribution of daily travel distances for electric vehicles, regional land use patterns, parking-to-electricity generation rates, and distribution characteristics, a Monte Carlo simulation is utilized to extract information regarding daily travel distances, behavioral models, parking, driving patterns, and parking times for electric vehicles in different regions and on different types of land. This information is crucial for more accurately predicting the distribution of electric vehicle loads and demand. Key aspects of this analysis process include:

a) Distribution of daily electric vehicle travel distances

   By collecting substantial real-world data on the actual travel distances of electric vehicles, it becomes possible to identify the distribution of daily travel distances for electric vehicles in different regions. This includes information on starting points, destinations, and intermediate stopping points for each vehicle.

b) Regional land use patterns

   Understanding the land use and characteristics of different regions, including commercial areas, residential areas, industrial zones, etc., helps predict the parking and charging demands of electric vehicles in various types of areas.

c) Parking-to-electricity generation rates
Based on the distribution and types of parking facilities, it is possible to estimate the amount of electricity that electric vehicles can generate while parked, thereby meeting some of their charging needs.

d) Distribution characteristics
Taking into account the distribution of the number and types of electric vehicles in different regions, such as private vehicles, shared cars, taxis, etc., helps understand the charging needs and driving behaviors of different user groups.

After utilizing Monte Carlo simulations to extract this information, a more comprehensive forecast of electric vehicle load demands can be obtained. This includes predictions of charging needs, parking requirements, potential charging infrastructure demands, and more for different regions.

4. Case study

4.1. Analysis of examples

Configure simulation parameters in accordance with actual operational scenarios based on practical runtime conditions. Use the method proposed in this paper to predict the charging load of private EVs on weekdays in city S in 2020, then compare and analyze the charging load of each district in the city further, subsequent simulation analyses are conducted on this foundation.

1. ***Parking demand***
   Calculate the land area of various types of land in the city in 2020 according to Overall Urban Planning of City S (2010-2020). Referring to Technical Guidelines for Determining Floor Area Ratio in Preparing Legal Plans of City S (Trial) and Standards and Guidelines of Urban Planning of City S (2012), estimate the average floor area ratio and average berth construction standards of all types of land in City S. Calculate the total berth construction demand of all types of land in City S by replacing the generation ratio of parking demand with the berth construction standard. The results are shown in Table 1.
2. ***EV ownership***
   At present, EVs sold in the market are offered mainly in two types: small cars with a power consumption of about 10 kW·h per 100 km and a battery capacity of about 18 kW·h; ordinary cars with a power consumption of about 21 kW·h per 100 km, and a battery capacity of about 30 kW·h.
   According to the EV demonstration and promotion plan of City S, it is assumed that there were 240 000 private EVs in City S in 2020. Among them, the percentage of small cars is 30%, and that of ordinary cars is 70%.
3. ***Settings of prediction parameters***
   It is assumed that the distribution of daily driving mileage of private cars on weekdays, parking demand in residential areas (residential land), and parking demand in industrial and commercial areas (other types of land) in City S in 2020 met the requirements.

Taking 02:00 as the starting time of the simulation, and assuming that most cars start to travel around 07:00, the parking time of all cars parked at 02:00 is initialized to conform to the normal distribution.

Table 1. Planning construction land and berth demand of City S in 2020

Type of construction land	**Land area/km^2**	**Average floor area ratio**	**Allocation standards (per·m^2)**	**Total planned berths/ thousand**
Residential land	22 000	1.50	0.0090	2 970.00
Commercial service facility land	5 200	2.40	0.0150	1 872.00
Educational and research	3 000	0.63	0.0100	189.0
Healthcare	900	0.56	0.0100	50.4
Culture and entertainment	550	1.00	0.0080	44.0
Sports facilities	700	1.00	0.0080	56.0
Industry	22 000	1.50	0.0045	1 485.0
Storage	1 600	1.50	0.0050	120.0

In the industrial and commercial area, 95% of the parked cars are commuter cars from 07:00 to 10:00 in the morning, and 70% of the commuter cars park until getting off work in the afternoon, with the average parking time of 8 h; 30% of them park until midnoon, with the average parking time of 4 h; 50% of parked cars are commuter cars in 11:00–15:00 which park until getting off work in the afternoon with the average parking time of 4 h; and the average parking time of non-commuter cars of every time frame is 1.5 h.

The cars parked in the industrial and commercial area from 20:00 to 24:00 at night are considered as the last parking of the day in a certain proportion (from 10% to 100% linearly with time), while the cars parked after 24:00 are considered as the last parking.

The average parking time of residential area in daytime is 2 h, and the parked cars in residential area from 17:00–22:00 are considered as the last parking of the day in a certain proportion (from 10% to 100% linearly with time), while the cars parked after 22:00 are considered as the last parking.

It is assumed that EV starts with a fully charged battery each day. The alert value of the remaining SOC for fast charging is 20%. The remaining SOC threshold selected for charging when parking at different destinations is adjustable during the simulation.

Based on the charging needs of different vehicle types and specific regional power facilities, EVs can be charged by AC (DC) charging interfaces, and the parameters of different interfaces are shown in Table 2.

Table 2. Parameters of different charging interfaces for EVs

Charging interfaces	**Nominal voltage/V**	**Nominal current/A**
AC	250/440	16/32
DC	750	125/250

Suppose that the commuter cars are charged by AC charging interfaces with a nominal voltage of 250 V in residential areas; non-commuter cars are charged by AC charging interfaces with a nominal voltage of 440 V in industrial and commercial districts; and cars are charged by DC charging interfaces in quick charging station.

4.2. Effect of driving behavior on charging load

Through the utilization of the Monte Carlo simulation method, an analysis was conducted on the impact of electric vehicle driving behavior on charging loads. The figure below was generated on the MATLAB R2017a simulation platform, illustrating the relationship between the energy levels and time of electric vehicles under different State of Charge (SOC) threshold selections. Figures 3 to 6 provide crucial insights into the dynamic variations of charging loads for electric vehicles. By investigating the relationship between energy levels and time under various SOC threshold conditions, a more profound understanding of the patterns and trends in the charging demands of electric vehicles can be achieved. This analytical methodology contributes to ensuring the secure and efficient operation of electric vehicle charging networks to meet the ever-growing demands for electric vehicles.

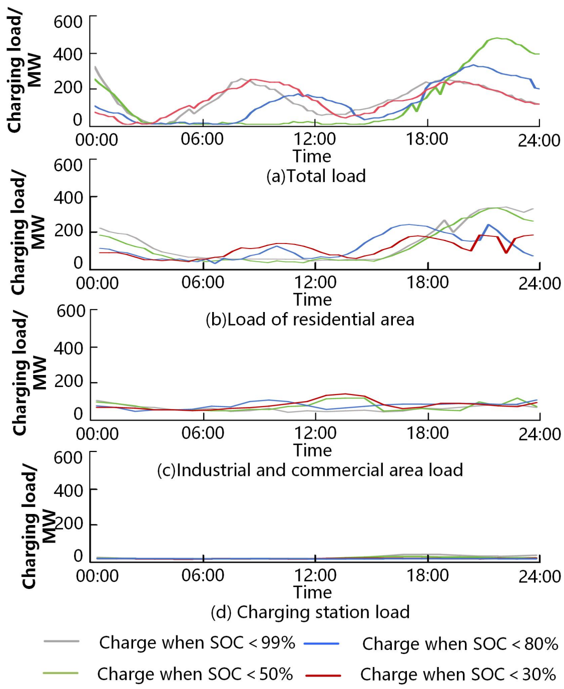

Fig. 3. Charging load under different SOC threshold selection

Assume that 100% of residential areas and industrial and commercial areas are equipped with charging facilities, and the remaining SOC threshold before EV charging is 99%, 80%, 50% and 30%, respectively. Figure 3 shows the charging load curve of private EVs in various places on weekdays. According to Fig. 3, loads of residential regions is generally higher than industrial or commercial regions on weekdays, and both have two load peaks at noon and night; the loads of charging stations is the lowest and are mainly concentrated at night. With the decrease in the SOC threshold of charging selection, the loads of residential areas (industrial and commercial areas) are all transferred from noon to night, which makes the total loads decrease at the noon peak and increase at the evening peak, and the loads of the fast-charging station increase significantly. When the SOC threshold of charging selection is lower than 50%, the noon peak virtually disappears, and the charging loads will be mainly the residential charging loads, as shown in Fig. 3.

4.3. Effect of charging infrastructure construction on charging load

Assume that the parking lots of residential areas and commuter car work units are equipped with charging facilities. There are 30% of cars charge when SOC is lower than 30%, 40% charge when SOC is lower than 30%, and 30% charge depend on demand. Simulation analyses the changing situation of private EV charging load in various places on weekdays under different charging facilities in industrial and commercial public parking lots, as shown in Fig. 4.

According to Fig. 4, an increase in the proportion of charging facilities in public parking lots in industrial and commercial areas will attract some EVs to choose charging in the daytime, reducing the peak charging load at night, as well as the charging load of fast charging stations.

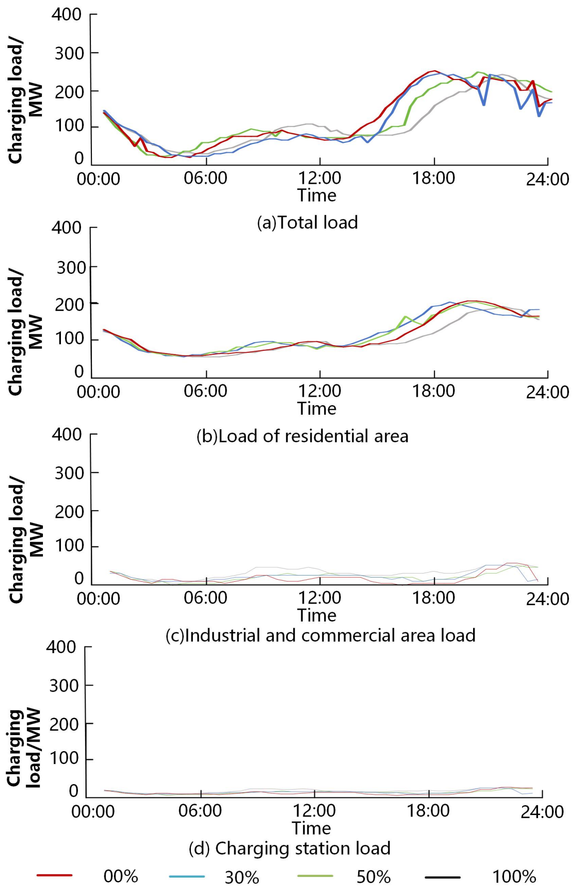

Fig. 4. Charging load of different charging facilities

4.4. Difference of charging load in different areas

The three districts A, B and C of City S have better economic development and are the central regions of City S. According to the statistics of City S in 2012, although the total area of the three districts only accounted for 17.4% of City S, the population accounted for 32.0%, and the GDP accounted for 50.7%. Among these three districts, District A has the largest area and the smallest population density, but owning to its developed industry, it has the highest per capital GDP; District B has the largest population density; District C has the smallest area and flourishing business and trade.

Assume that the land area ratio, parking demand generation ratio of Districts A, B and C are all equal to the average value of City S in 2020, the predicted EV charging load in various type of places in each district on weekdays are shown in Fig. 5. Charging load per hectare in different areas is shown in Fig. 6. It can be seen that in weekdays, charging load in various type of places of

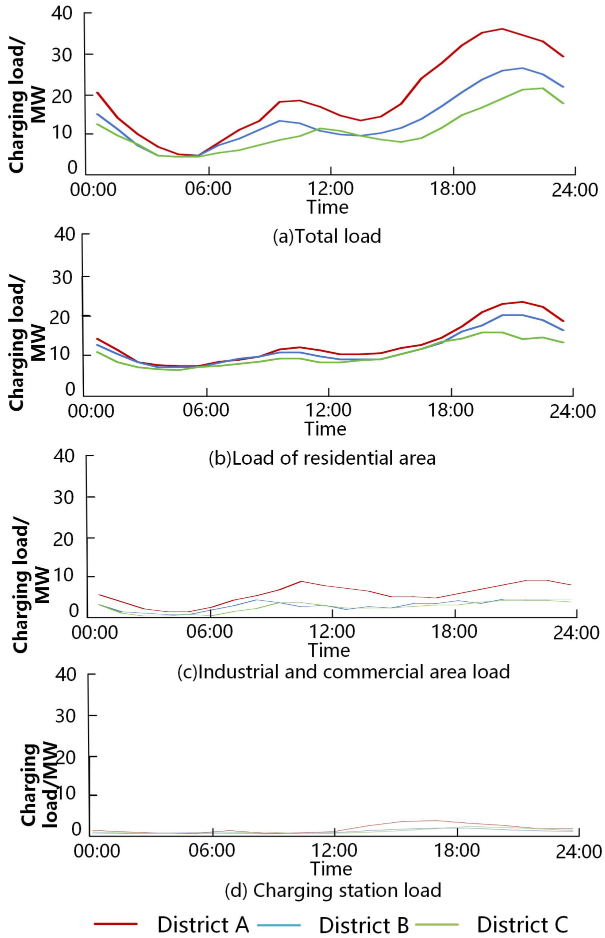

Fig. 5. Overall charging loads of different regions

District A is higher than that of District B and C, while the load of residential areas of District B is higher than that of District C, and the industrial and commercial region's loads in District B is similar to District C. According to charging load per hectare, the total charging load of the three districts A, B and C is obviously higher than that of other districts; and the load of residential areas of region B exceeds regions A and C, but the industrial and commercial region's load in District B is slightly lower than District C.

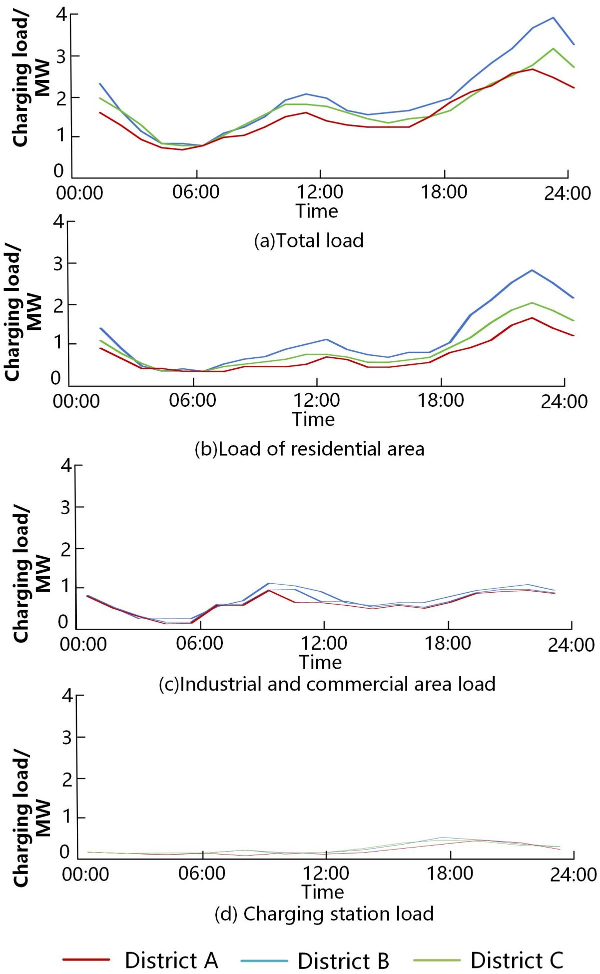

Fig. 6. Charging load per hectare in different areas

Observations reveal that on weekdays, the charging loads of private electric vehicles (EVs) in District A are consistently higher than those in Districts B and C. This suggests that EV users in District A engage in more frequent charging activities. Conversely, in District B, the residential area exhibits higher charging loads compared to District C, indicating a higher prevalence of EV ownership among residents in District B. Interestingly, the charging loads in the industrial and commercial regions of District B closely resemble those in District C, possibly due to the relatively stable charging demands of industrial and commercial users.

Furthermore, it becomes evident that the combined charging loads of Districts A, B, and C are significantly higher than those of other districts. This may be attributed to a higher concentration of EVs and denser charging infrastructure in these areas. Additionally, in District B, the charging load within residential areas surpasses that of Districts A and C, reflecting a greater demand for EV charging within residential zones in District B.

5. Conclusions

Aiming at the developing trend of the increasing popularity of EVs and charging them through the distribution network on a large scale, a forecasting method of EV charging loads is put forward built on virtual prediction parameter estimation, including the EV load characteristic analysis and EV charging power prediction method based on Monte Carlo. Finally, the effectiveness of the method proposed is verified by an example analysis.

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