Monte Carlo-based Prediction of Electric Vehicle Charging Load and Coupling Mechanisms of Multiple Information Sources

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Abstract- The charging load of electric vehicles at a large scale exhibits spatiotemporal uncertainty and randomness. Its coupling with multiple sources of information, such as the road network, charging infrastructure, distribution network, and market, increases the complexity of charging load forecasting. This paper presents a comprehensive forecasting method that takes into account the coupling factors from multiple sources for electric vehicle ownership and charging load. The research investigates the coupling relationships between electric vehicles and various information sources. Addressing the inadequacy of traditional inventory prediction methods for predicting electric vehicle stock, this study introduces the Box-Cox-Dogit model to compute the maximum market share of electric vehicles. By integrating a time-varying Bass model, a comprehensive electric vehicle inventory prediction model is established, considering multiple factors. The study assesses factors impacting the scalability of electric vehicle charging loads and formulates a prediction function along with its associated parameters. Employing the Monte Carlo method to replicate urban electric vehicle users' travel patterns, the paper forecasts the unstructured charging of three types of electric vehicles in Beijing, designed for various purposes. The cumulative results provide the total charging load of electric vehicles in Beijing. The findings reveal that in 2030, the total charging load of electric vehicles in Beijing accounts for 10.30% of the total grid load. With the large-scale integration of electric vehicles into the grid, the peak charging loads may occur at certain times, potentially impacting some local distribution networks. Hence, Effective control measures are required for electric vehicle charging loads. This study analyzes the impact of various factors on charging load distribution and the electrical grid, thus validating the comprehensiveness and effectiveness of the proposed prediction model.

Keywords Electric vehicles,multi-source information,charging load forecasting,inventory prediction,monte Carlo methods.

Nomenclature

a ， b	the external influence coefficient	*i, j*	Indexes of data centers
a_e	the innovation coefficient for the electric vehicle market	*t*	Indexes of time slots
a_a	represents the innovation coefficient for the conventional vehicle market	*k*	Number of iterations
b_e	represents the imitation coefficient for the electric vehicle market	*x*	represents the year for the predicted vehicle ownership
b_a	represents the imitation coefficient for the conventional vehicle market.	m	the market's maximum potential

d	the mileage of this drive	x_{ik}	a non-positive numerical variable
d_m	the maximum mileage of the vehicle	λ_{ai}	represents the score for the indicators of the innovation coefficient in the conventional vehicle market.
N(t)	the cumulative number of users at time t	λ_k	a transfer factor
'E'	represents the battery capacity of the electric vehicle	λ_{ei}	represents the score for the indicators of the innovation coefficient in the electric vehicle market.
P	the maximum market share of electric vehicles	λ_1 , λ_2	represent the distribution parameters for the weekdays and non-working days
P_j	selecting the j-th type	β_k	undetermined parameters
'p_i'	represents the charging power of the i-th electric vehicle	$f(x)$	represents the predicted ownership quantity
$P_{i,t_{k-1},k}$	represents the charging power of the i-th electric vehicle at the previous time step and node	ρ_{al}	represents the score for the indicators of the imitation coefficient in the conventional vehicle market.
$P_{i,k}$	represents the charging power of the i-th electric vehicle at node k	ρ_{el}	represents the score for the indicators of the imitation coefficient in the electric vehicle market.
SOC_0	the state of charge when the last charge of the battery is completed	'η_i'	represents the charging efficiency of the i-th electric vehicle
SOC_1	the state of charge when the battery starts charging;		
'T'	represents the charging time of the electric vehicle	*Abbreviations*	
V	the automotive market	EV	electric vehicle
V_i	utility term		
V '	the maximum size of the electric vehicle market		

1. Introduction

Due to the intensifying resource scarcity [1], traditional gasoline-powered vehicles are facing challenges in achieving energy efficiency and emission reduction goals [2]. In recent years, the new energy industry [3] has entered a new phase of accelerated development, with electric vehicles receiving significant support and promotion from governments and businesses worldwide [4-7].

Meanwhile, electric vehicles, as a new type of power load, exhibit strong volatility and uncertainty. When extensively integrated into distribution networks, especially small and medium-sized networks with relatively weak stability, they unavoidably impact their operations [8-10]. This impact can range from increased network losses and resource waste to threats to grid operational safety and accidents. Reference [11] indicates that without the implementation of control measures, electric vehicle charging can lead to issues such as an increased peak-to-valley ratio, a reduction in voltage levels, and transformer overloading. Reference [12] demonstrates that implementing an orderly charging strategy for electric vehicles can improve the node voltage levels in the distribution network while reducing network losses. Therefore, to effectively address the adverse effects of large-scale integration of electric vehicle charging loads into distribution networks, accurate prediction of electric vehicle stock and the associated charging load is necessary.

Regarding the prediction of electric vehicle stock, a widely used approach is based on the Bass model [13-15]. Reference [16] proposed a modified Bass diffusion model. This literature analyzed the strengths of the Bass diffusion model while improving the model in the context of automobile scrappage and technological competition in internal combustion engine vehicles. Reference [17] used a generalized bass dispersion model to model external variables such as charging infrastructure, further improving the practicality of this study. Reference [18] introduced an agent-based simulation model that amalgamates individual agent behavior and generates cumulative adoption figures through the Bass diffusion model. This approach allows for the utilization of different parameters and extends previous research on efforts to enhance electric vehicle adoption rates in Brazil. Reference [19] has developed a disaggregated Bass Diffusion agent-based model capable of simulating how the adoption rate of a P2PCS would change according to the characteristics of the population and the effectiveness of

policies subsidizing and supporting the service. In summary, there is a wide variety of electric vehicle inventory prediction models available at present, but further research is required to consider the maximum potential parameters for temporal variation.

In terms of charging load prediction for electric vehicles, early studies [20, 21] mostly analyzed the power battery models of electric vehicles. However, due to the wide variety of power batteries and the lack of unified production standards by global vehicle manufacturers, the prediction difficulty is substantial. In recent years, with the rapid development of electric vehicles and the increasing availability of travel data, it has become possible to predict the spatial and temporal distribution of charging loads. Reference [22] proposed a novel method based on stochastic user equilibrium for predicting the accurate spatial–temporal distribution of EV charging load synchronized with traffic states. Reference [23] presents a systematic methodology for future electric vehicle load forecasting, which employs probabilistic models to describe EV charging profiles and forecast models to predict EV ownership. However, this approach gives relatively less consideration to the coupling factors that affect electric vehicle charging load. Reference [24] proposes an electric vehicle charging load prediction method that considers vehicle types. It uses the Monte Carlo algorithm to construct probability distribution models for travel patterns and charging characteristics, enabling the prediction of load demand when electric vehicles are connected to the grid. Although the aforementioned references have established probabilistic statistical models for load forecasting, they do not delve deeply into the coupling factors of electric vehicle charging load. Electric vehicle charging load is complex due to its mobility, close relationship with the traffic road network and the power grid, and susceptibility to various factors such as weather, charging facilities, and travel patterns. Hence, there is room for more precise and comprehensive analysis.

Addressing the shortcomings of the aforementioned research, this paper begins by conducting an in-depth examination of the interaction mechanisms among electric vehicles, charging infrastructure, road networks, and the power grid. It highlights the significance of integrating and interacting multiple sources of information in the prediction of electric vehicle charging loads and system optimization. This research lays the theoretical foundation for charging load prediction; Conventional methods for predicting ownership levels are not directly applicable to forecasting electric vehicle ownership. To tackle this issue, the Box-Cox Dogit model is introduced to calculate the maximum market share of electric vehicles. Combined with the Bass model that accounts for temporal variations, a comprehensive model for predicting electric vehicle ownership, considering multiple factors, is established. Furthermore, based on the comprehensive model, the future electric vehicle ownership in Beijing is predicted. By considering the historical proportions of conventional vehicles used for various purposes, the electric vehicle ownership for different purposes in Beijing is estimated. Finally, by incorporating the Monte Carlo simulation method along with the factors influencing electric vehicle charging load, driving data, and parameters, a scalable approach for predicting electric vehicle charging load is established. Using the predicted future ownership data for electric vehicles in Beijing, the load forecast is conducted for electric vehicles in different usage scenarios, achieving an integrated prediction of electric vehicle charging load that takes into account multiple sources of information fusion. A comparison between traditional and modern electric vehicle charging load forecasting methods is depicted in Fig.1. The comprehensive prediction of electric vehicle ownership and charging load was achieved by incorporating the fusion of multiple information sources. This article has validated the comprehensiveness and effectiveness of the proposed method, to some extent, making it more aligned with real-world scenarios.

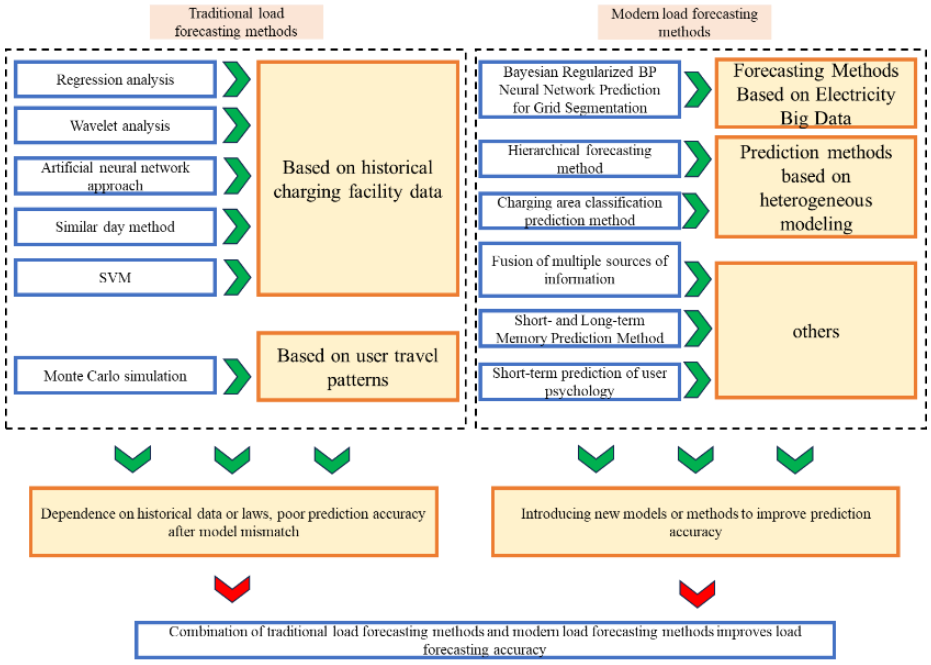


Fig. 1. Comparison of traditional and modern EV charging load forecasting methods.

2. Mechanisms of Multi-Source Information Coupling

2.1. Multi-Source Information System and Integration

The multi-source information exchange system, as shown in Fig.2, mainly includes four information source entities: road network, public charging stations, electric vehicles, and distribution network. The direct or indirect multi-source information exchange among the entities drives the operation of the system and achieves spatiotemporal prediction of charging load in the region.

Road network information mainly includes road node locations, functional area distribution, road topology, traffic congestion, real-time vehicle speed, etc. Traffic congestion not only reflects the traffic volume and speed of each road section but also to some extent affects users' path selection. As the carrier of electric vehicle driving and charging behavior, the transportation network significantly influences the spatiotemporal distribution of electric vehicle charging load. Traffic congestion not only reflects the traffic volume and vehicle speeds on various road segments but also, to some extent, affects users' choice of routes. In urban areas, utilizing a traffic network model for charging load spatiotemporal prediction results in predictions that closely align with the real-world scenario.

Electric vehicle information mainly includes the travel characteristics, charging characteristics, battery parameters, and driving parameters of vehicles. The travel characteristics of vehicles include travel time, destination, path selection, etc. Electric vehicles serve as both a mode of transportation and a mobile power source, and their driving and charging behaviors have an impact on the operation of both the transportation network and the distribution network. On one hand, the random driving patterns of a large number of electric vehicles can lead to congestion on specific routes within the transportation network. On the other hand, the demand for fast charging of electric vehicles can increase the load on the distribution network, which may be detrimental to its safety and economic operation. Additionally, when electric vehicles require charging during their journeys, most users tend to choose nearby charging facilities. However, the uncertainty in their choice of charging routes and the disorderly nature of charging behaviors can lead to an uneven utilization of charging infrastructure. This, in turn, not only affects the quality of electrical energy in the regional distribution network but also results in traffic congestion around charging stations and a decrease in profitability for some charging service providers.

Public charging station information mainly includes charging price, charging power, number of charging piles, charging station location, operation information, and charging load distribution characteristics. The operation information includes real-time charging price, real-time number of charging piles in use, and number of queued vehicles. When electric vehicles head to charging stations for recharging, they may encounter waiting lines. The length of these queues will impact the access time for charging load to varying degrees. Consequently, the distribution of electric vehicle charging load is not only closely coupled with the transportation network and distribution network but is also influenced by the interactive dynamics of the charging stations.

Distribution network information mainly includes the network structure of the distribution network, load information of power supply nodes, and charging price. In the future development of the power market, the formulation of charging prices will fully consider factors such as the power grid load state, voltage situation, number of electric vehicles at the charging station, and electric vehicle charging demand. The charging behavior of electric vehicles is intricately linked to the load level and structure of the distribution network. For the distribution network system, the charging price plays a crucial role in connecting charging stations, and the distribution network and is one of the important factors for users when making charging station decisions.

Electric vehicles, being a combination of a mode of transportation and a mobile power source, encompass both travel characteristics and charging characteristics. Their travel patterns, routes, and geographical distribution impact the traffic network's road congestion levels. Similarly, factors like battery charge status, driving distance, and charging behavior influence the load levels at charging stations, consequently affecting the safety and economic operation of the regional distribution network. Conversely, urban traffic topologies, road traffic flow information, distribution network operation status, and current flow distribution, as well as the queuing status at charging stations, affect the route choices and charging decisions of electric vehicle users. Given the substantial differences in travel characteristics and charging patterns among various types of electric vehicles, when these vehicles are driven in large quantities, the charging load will exhibit distinct spatiotemporal distribution characteristics.

The integration of multi-source information can be achieved through data exchange protocols and algorithms. Data exchange protocols ensure the orderly and efficient transmission and sharing of data between different information sources. These protocols define data formats, transmission methods, and communication rules to ensure effective data exchange among various information sources. Meanwhile, algorithms play a crucial role in the information integration process. They can process data from various sources and perform data fusion, analysis, and prediction. These algorithms integrate data from multiple sources to generate a more comprehensive information set, which is vital for the efficient operation of the system and the accurate prediction of spatiotemporal charging loads. In summary, the integration of multi-source information can be achieved through the collaborative action of data exchange protocols and algorithms. The integration process is essential for a deeper and more comprehensive understanding of the system's mechanisms and behavior. Such informative integration helps to optimize the management of electric vehicle charging demand, improve the utilization of charging infrastructure, reduce traffic congestion, and enhance the security and efficiency of the electric power distribution network.

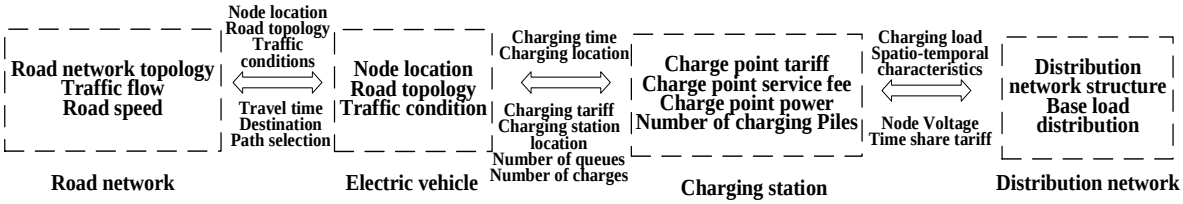


Fig. 2. Multi-information interactive system.

2.2. Mechanisms of Coupling Electric Vehicles, Charging Stations, Roads, And Power Grids

The specific interaction process is as follows: the road network receives vehicle driving positions and parameters, providing real-time feedback to the vehicles regarding traffic flow and road congestion, thereby influencing users' travel time and route selection. On the one hand, electric vehicles accept road network information and change their travel behavior, thereby affecting the operation of the road network. On the other hand, they receive operation and charging price information from the charging stations and provide feedback for charging decisions. Similarly, the public charging stations receive charging information from electric vehicles, provide information feedback to the vehicles, and also receive voltage quality and price information from the distribution network, and provide real-time charging load spatiotemporal characteristics in return. The distribution network receives charging load information from the charging stations and provides voltage and price information feedback to them, prompting the charging stations to adjust their charging prices. Here are specific examples:

- Interaction between the road network and electric vehicles:

In a city, when there is a sudden increase in vehicle density leading to traffic congestion on a major road, the road network can transmit this information to electric vehicles. The electric vehicle's navigation system can provide alternative routes to drivers based on this information to avoid congestion, thereby influencing the drivers' choice of routes.

- Interaction between electric vehicles, road networks, and charging stations:

When an electric vehicle receives information from the road network, such as a traffic congestion alert, it can adjust its driving behavior, such as slowing down or choosing an alternative route to bypass congested road sections, thereby alleviating road network congestion. In addition, electric vehicles can make charging decisions based on real-time information from charging stations, such as charging prices and the availability of charging stations. For example, they may choose a charging station with lower prices or more available charging plugs.

- Interaction between charging stations, electric vehicles, and the distribution network:

Electric vehicles go to charging stations for recharging. If a charging station receives multiple requests from electric vehicles to charge simultaneously, it can provide information to the electric vehicles, informing them whether there is a queue. Electric vehicles can decide whether to wait for charging or go to another charging station, and these decisions are influenced by the feedback from the charging station. Furthermore, charging stations also receive information about voltage quality and electricity prices from the distribution network, hence allowing them to adjust charging prices and load distribution.

2.3. The Real-time Interaction of Multiple Sources of Information and Its Significance

Interaction between electric vehicles and road networks: When the road network provides feedback on traffic conditions. Through feedback from electric vehicles, charging stations can better manage charging demands, reducing waiting times, and enhancing user satisfaction.

Interaction between charging stations and the distribution network: Charging stations not only influence the charging decisions of electric vehicles but also receive information on voltage quality and electricity prices from the distribution network. This information can be used to adjust charging prices and load distribution to meet the load requirements of the distribution network. This helps balance charging demand and the efficiency of power distribution, while improving the charging experience for electric vehicle users.

congestion to electric vehicles, they can adjust their driving behavior based on this information to avoid congested routes, thereby alleviating congestion on the road network. This helps optimize traffic flow, reduce the travel time and energy consumption of electric vehicles, and also mitigates environmental impacts.

Interaction between electric vehicles and charging stations: Electric vehicles receive real-time information from charging stations, such as charging prices and availability. This information influences the charging decisions of electric vehicle users. Users may opt for more cost-effective or better-equipped charging stations, affecting the load distribution of charging stat

In summary, real-time interaction among various sources of information contributes to enhancing the overall efficiency of electric vehicle charging systems, reducing resource wastage, minimizing environmental impacts and improving user satisfaction. Understanding and optimizing these relationships are crucial for achieving smarter, sustainable, and more efficient electric vehicle charging infrastructure.

3. Prediction of Electric Vehicle Ownership Considering Multiple Factors

3.1. Box-Cox Dogit Model

If there are J types of branches for selection, and the ratio between the total quantity of the free-choice portion and the forced-choice portion of each branch is 1：c1：c2：…：cJ, the probability Pj of selecting the j-th type is given by [13]:

$$P_j = \frac{exp(V_j)+c_j \sum_j^{\sum(V_i)} exp}{(1+\sum_j c_i) \sum_j^{\sum(V_i)} exp,} \quad (1)$$

where the utility term *Vi* is:

$$V_i = \beta_0 + \sum_{k=1}^{k} \beta_k \, x_{ik}^{(\lambda_k)}, \quad (2)$$

where β_0 , … , β_k are undetermined parameters, x_{ik} represents individual characteristics and characteristics of branch *i*, and λ_k is a transfer factor.

When x_{ik} is a positive numerical variable,

$$x_{ik}^{(\lambda_k)} = \begin{cases} \left(x_{ik}^{(\lambda_k)} - 1\right)/\lambda_k, & \lambda_k \neq 0 \\ ln\, x_{ik}\,, & \lambda_k = 0 \end{cases} \quad (3)$$

When x_{ik} is a non-positive numerical variable or any other type of variable,

$$x_{ik}^{(\lambda_k)} = x_{ik} \quad (4)$$

3.2. Time-varying Bass model

In the traditional Bass model, it assumes that the diffusion rate of a new product in the market is mainly influenced by two types of propagation pathways: external factors such as mass media, and internal factors such as word-of-mouth communication. The Bass model only takes into account the initial purchase and assumes that each individual purchases only one unit of the product. Consequently, the number of users can be defined as the sales volume of the product. The rate of diffusion (usage rate) at any given time, d*N*/d*t*, satisfies the following relationship:

$$n(t) = \frac{dN(t)}{dt} = a[m - N(t)] + \frac{b}{m} N(t)[m - N(t)] \quad (5)$$

where d*N*(*t*)/d*t* represents the non-cumulative number of users at time t, *N*(*t*) represents the cumulative number of users at time *t*, m is the market's maximum potential, and a and b are the external influence coefficient (also known as the innovation coefficient) and the internal influence factor (also known as the imitation coefficient), respectively.

By integrating *n*(*t*) and assuming that the cumulative number of users *N*(0) = 0 at the initial time, the distribution of the cumulative number of users *N* at the time of arrival *t* can be obtained. This represents the Bass model as follows [14]:

$$N = m\left[\frac{1-e^{-(a+b)t}}{1+\frac{b}{a}e^{-(a+b)t}}\right] \quad (6)$$

The traditional Bass model assumes that the internal and external influence coefficients remain constant throughout the entire lifecycle of the product. However, this assumption does not align with reality. In practice, the diffusion of a product is likely to be influenced by various factors, both objective and subjective, which can lead to changes over time. Assuming that the effect of the influence is linear, the Bass model based on time change can be obtained:

$$N = m\left[\frac{1-e^{\frac{-2(a+b)t}{T+1}}}{1+\frac{b}{a}e^{\frac{-2(a+b)t}{T+1}}}\right] \quad (7)$$

3.3. A Multi-Factor Electric Vehicle Ownership Prediction Model That Takes into Account Multiple Factors

The Box-Cox Dogit model is used to predict the market share of electric vehicles in the future automobile market. It assumes that consumers always choose the option that maximizes their utility when purchasing a car. In the context of car purchase, the two options are buying an electric vehicle or buying a conventional vehicle, and the utility value of each option is determined by the consumer's personal characteristics and the characteristics of the options. The influencing factors for consumers' choices between electric and conventional vehicles are represented as characteristic vectors, and the weights of these factors in influencing consumer purchasing behavior are represented as parameter vectors. Various factors such as driving range, overall failure rate, government support, environmental requirements, vehicle operating costs, and after-sales service level are considered as characteristic vectors, each with its respective parameter vector.

By combining the given characteristic vectors and parameter vectors in Eq.(2), the utility term can be calculated. Using Eq.(1), the maximum market share of electric vehicles in the automotive market can be computed. Based on the overall size of the automotive market *V* and the maximum market share of electric vehicles *P*, the maximum size of the electric vehicle market *V* ' can be calculated by the following formula:

$$V' = VP \quad (8)$$

Analogous to the conventional automotive market, the indicators for the innovation coefficient in the electric vehicle market primarily include the extent of policy influence, economic conditions, and the number of competitors. The indicators for the imitation coefficient in the electric vehicle market mainly include product price, product lifespan, and product usability. The innovation coefficient and imitation coefficient for conventional vehicles can be estimated using the Bass model by fitting historical data of conventional vehicle ownership through nonlinear least squares estimation. Then through Eq. (9) and Eq.(10), the innovation coefficient and imitation coefficient of the electric vehicle market are as follows:

$$a_e = a_a \times \frac{\lambda_{ai}}{\lambda_{ei}}, (i = 1,2,3) \quad (9)$$

a_e represents the innovation coefficient for the electric vehicle market.

a_a represents the innovation coefficient for the conventional vehicle market.

λ_{ai} represents the score for the indicators of the innovation coefficient in the conventional vehicle market.

λ_{ei} represents the score for the indicators of the innovation coefficient in the electric vehicle market

$$b_e = b_a \times \frac{\rho_{al}}{\rho_{el}}, (l = 1,2,3) \quad (10)$$

Where:

be represents the imitation coefficient for the electric vehicle market.

b_a represents the imitation coefficient for the conventional vehicle market.

ρ_{al} represents the score for the indicators of the imitation coefficient in the conventional vehicle market.

ρ_{el} represents the score for the indicators of the imitation coefficient in the electric vehicle market.

Finally, according to the obtained innovation coefficient and imitation coefficient of the electric vehicle market and the largest scale of the electric vehicle market, the growth of electric vehicle ownership can be obtained through Eq.(7). The schematic diagram of the multi-factor electric vehicle ownership prediction model is shown in Fig.3.

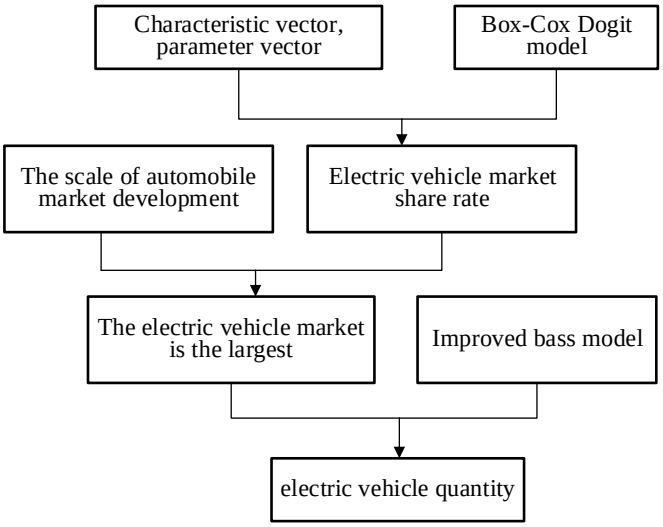


Fig. 3. Block diagram of electric vehicle ownership prediction model considering multiple factors.

4. Monte Carlo-Based Model for Electric Vehicle Load Forecasting

4.1. Analysis of Electric Vehicle Charging Load Characteristics

Based on transportation statistics and the current development status of Beijing [25], this study focuses on three types of electric vehicles in the city: electric buses, electric taxis, and private electric cars. Different types of electric vehicles may adopt different charging methods in different regions or locations. The factors influencing electric vehicle owners' choice of charging mode primarily include charging prices, charging speed, charging station availability, parking duration, economic benefits, and driving range among others. The importance of these factors may vary depending on the type of electric vehicle and the usage scenario. The following part will primarily discuss the role of charging prices, charging speed, and charging station availability in the decision-making process of electric vehicle owners when choosing a charging mode:

- Charging Prices: Charging prices are a significant factor in an electric vehicle owner's choice of charging mode. Fast charging is typically more expensive than regular charging, so electric vehicle owners may weigh the cost when selecting a charging method. In the case of private electric vehicles, if they can accept cheaper regular charging and have sufficient parking time, they may opt for regular charging. However, in some commercial areas, electric vehicle owners may prefer fast charging because it requires shorter stops, and the relatively lower-cost regular charging may not be suitable for brief stays.

- Charging Speed: Charging speed is also a deciding factor. Electric vehicle owners aim to complete charging quickly, especially for taxi drivers whose profits are directly related to the number of service trips. Therefore, electric taxis typically choose fast charging to accommodate more customers. However, electric buses, due to their larger battery capacity and longer driving ranges, may require more time for charging. During daytime operation, when they cannot stay for extended periods, they might use regular charging during breaks, while they can take advantage of longer charging times during non-operational hours.

- Charging Station Availability: The availability of charging stations also influences the choices of electric vehicle owners. Electric vehicle owners need to ensure that the chosen charging method has available charging facilities in their area. If the number of fast charging stations is limited, or regular charging facilities are more accessible, electric vehicle owners may be influenced by charging station availability when deciding which method to use.

For private electric cars, when parked at workplaces or residential areas where the vehicles stay for relatively longer periods, there is ample time for charging, and they typically use the regular charging mode. However, in public areas such as commercial districts and social gathering places where the vehicles stay for shorter durations, fast charging mode is usually employed to minimize the charging time.

Electric taxis, aiming to maximize economic benefits during their operational hours, generally opt for fast charging to save time and serve more customers for increased profits. Therefore, electric taxis exclusively use the fast-charging mode for charging.

Electric buses, with longer driving distances and larger battery capacities, require more time for charging. During daytime operational hours when buses cannot stay for extended periods, they rely on regular charging during rest breaks. In non-operational periods, they utilize regular charging as well. Hence, electric buses exclusively use the regular charging mode for charging.

4.2. Vehicle Travel Time-Space Modeling Analysis

4.2.1 Departure time for travel

The commencement time of electric vehicle journeys is influenced by various factors, including the type of electric vehicle, battery capacity, users' personal travel habits, travel season, and holidays. According to the "2021 Annual Development Report of Beijing City" published on the official website of the Beijing Transportation Development Research Institute, statistical data provides information on the time distribution of different types of vehicles reaching their destinations in Beijing.

For private cars in Beijing, the peak period for commuting to work is between 07:00 and 08:30, with the peak arrival time occurring between 08:00 and 09:00. The peak period for private cars leaving work is between 17:30 and 18:30, with the peak arrival time falling between 18:00 and 19:00. By integrating the statistical distribution of arrival times for private cars commuting to and from work in Beijing, it can be reasonably assumed, in a general context, that the initial charging time for private cars follows a normal random distribution. The probability density function of the normal random distribution is given by:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{11}$$

By fitting the data to a normal distribution and making assumptions, converting a day into 1440 minutes, it can be inferred that the initial charging time for private cars approximately follows a normal random distribution $N(1150,100^2)$. Due to the lack of specific statistical constraints on the initial charging time for non-working days and the relatively dispersed arrival times of users in residential areas on non-working days, the variance of the normal random distribution for the initial charging time of private cars on non-working days is larger compared to working days. However, the mean value of the initial charging time does not vary significantly. Hence, this paper assumes that the initial charging time for private vehicles on non-working days follows an approximately normal random distribution with parameters $N(1150, 150^2)$.

Taxis have a high daily mileage and usually require multiple charges to meet operational requirements. This study focuses on short-term load forecasting. Considering that taxis need to charge twice a day, the day is divided into two periods to consider the initial charging time. It is assumed that the peak charging periods are at 7:00 in the morning and 19:00 in the evening. For the time period from 00:00 to 14:00, the initial charging time follows a normal random distribution $N(420,100^2)$. For the time period from 14:00 to 24:00, the initial charging time follows a normal random distribution $N(1140,100^2)$.

The charging time for electric buses is not fixed, and the starting time for charging can occur at any time during the day, following a uniform distribution.

Furthermore, weather conditions, traffic situations, and special events can also impact the starting time of electric vehicle journeys. Adverse weather conditions such as heavy snow, heavy rain, or extreme temperatures may delay the beginning of electric vehicle journeys. In unfavorable weather conditions, users may choose to postpone their trips or opt not to use electric vehicles. Traffic congestion or road closures can lead users to alter their travel plans, which may either delay or expedite the commencement of their journeys. Special events, such as holidays or major sporting events, might prompt people to begin their journeys earlier or later. Taking all these factors into account, the starting time of electric vehicle journeys is a complex and dynamic process in real-life situations. The statistical models assumed in this study, such as normal distributions and uniform distributions, are simplifications used to estimate the starting times of electric vehicle journeys.

4.2.2. Daily travel distance

The mileage of private cars is influenced by multiple factors, with the most significant impact observed on working days and holidays. The daily mileage of private cars can be approximated to follow an exponential distribution, and the probability density function of the exponential distribution is represented by Eq.(12):

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & x \geq 0 \end{cases} \tag{12}$$

The symbol λ represents the distribution parameter in the equation, where $1/\lambda$ represents the mathematical expectation, which corresponds to the daily mileage of electric private cars.

Letλ_1 and $\lambda_2$represent the distribution parameters for the weekdays and non-working days, respectively, with λ_1= 0.020 and λ_2 = 0.018. Therefore, the daily mileage of electric private cars on weekdays and non-working days follows the exponential distributions $X \sim E(0.020)$ and $X \sim E(0.018)$, respectively.

For electric taxis, the daily mileage during the time periods 00:00-14:00 and 14:00-24:00 follows a normal random distribution $N(275, 15^2)$.

Assuming that the daily mileage of electric buses under normal operating conditions follows a uniform distribution [150, 200].

4.2.3. Daily travel distance

Conventional charging and fast charging are the two energy supply modes commonly used for electric private cars.

The average charging power for conventional charging stations targeting electric private cars in the market is typically 6 kW, while fast charging stations have an average charging power of 15 kW. Therefore, this paper considers that the charging power of private cars is 6kW when charging normally, and the charging power of fast charging is 15kW.

Taxis have longer daily mileage and complex travel patterns, making it challenging for electric vehicles with smaller battery capacities to meet the operational requirements. Assuming that the charging power for electric taxis is consistent with the actual average charging power of the BYD e6 electric taxi, which is 32 kW.

In China, electric bus charging stations are available with power ratings of 100 kW and 80 kW, with the majority being 80 kW DC fast charging stations. This paper assumes that the electric bus's charging power is 80 kW.

4.2.4. Modeling the charging load of electric vehicles

According to the previous principles and model studies, assuming that electric vehicles of different uses are in a disordered charging state, with the same energy consumption per kilometer during driving and constant power charging during the charging process, the load values are calculated every minute, with a total of 1440 load calculation nodes. The specific modeling steps are as follows:

- Predict the number of electric vehicles for each use in Beijing and determine the size of the electric vehicle market.
- Based on the parameters obtained from the data analysis, determine the number of simulation iterations, the number of simulated electric vehicles, and the maximum mileage for each type of electric vehicle. Initialize the simulation program parameters and use the Monte Carlo method for MATLAB simulation. Randomly select the date type, electric vehicle starting charging time, and daily mileage.
- Calculate the initial state of charge for electric vehicles[23]:

$$\mathrm{SOC}_1 = \left(\mathrm{SOC}_0 - \frac{d}{d_m}\right) \times 100\% \tag{13}$$

Where , SOC_1 is the state of charge when the battery starts charging; SOC_0 is the state of charge when the last charge of the battery is completed; d is the mileage of this drive; d_m is the maximum mileage of the vehicle.

- Calculate the time required for charging:

$$T = \frac{E}{\eta_i p_i} \tag{14}$$

In the equation, 'p_i' represents the charging power of the i-th electric vehicle, 'η_i' represents the charging efficiency of the i-th electric vehicle, 'E' represents the battery capacity of the electric vehicle, and 'T' represents the charging time of the electric vehicle.

- Calculate the power load at each node

$$P_{i,k} = \sum_k^N P_{i,t_{k-1},k} \tag{15}$$

Where, Pi,k represents the charging power of the i-th electric vehicle at node k, and $P_{i,t_{k-1},k}$represents the charging power of the i-th electric vehicle at the previous time step and node.

5. Analysis of Calculation Cases

5.1. Forecasting the Electric Vehicle Ownership Considering Multiple Factors

Authors may acknowledge to any person, institution or department that supported to any part of study.

The Beijing Municipal Bureau of Statistics released the data on vehicle ownership in Beijing from 2018 to 2022, as shown in Fig. 4.

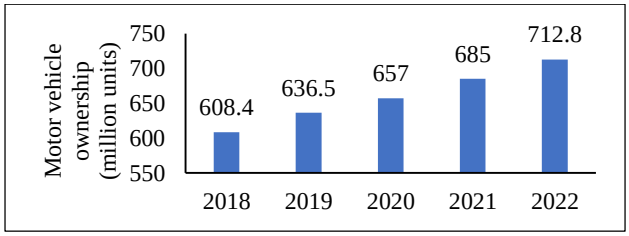


Fig. 4. The number of cars in Beijing by year

By conducting regression analysis on the car ownership data across different years, an approximate fitting formula for the car ownership in Beijing has been derived. This formula, known as the Gaussian formula, is presented below:

$$f(x) = c_1 \, exp\left(-\left(\frac{x-c_2}{c_3}\right)^2\right) \tag{16}$$

Where, x represents the year for the predicted vehicle ownership, $f(x)$ represents the predicted ownership quantity. After fitting the data using the Curve Fitting Toolbox, the linear regression curve provides three parameters: c_1=12370, c_2=2170, c_3=87.68.

Based on the equation above, the projected vehicle ownership in Beijing for the years 2024-2030 is presented in Table 1. The indicators for the Box-Cox Dogit model's feature vector are listed in Table 2. By combining historical statistics and Eq.(1), the maximum market share for electric vehicles is determined to be 0.254. Consequently, the theoretical maximum size of the future electric vehicle market in Beijing can be calculated, as shown in Table 3.

Table 1. Future car ownership in Beijing

Year	Future car ownership (million units)
2024	773.03
2025	802.85
2026	833.61
2027	865.32
2028	898.00
2029	931.67
2030	966.35

Table 2. Box-Cox Dogit model feature vector metrics

Eigenvector	Traditional cars	Electric Vehicles
Comprehensive failure rate	1	0.6
Government Support	0.5	0.7
Maximum range	1	0.6
Environmental demand degree	0.4	0.7
After-sales service level	1	0.6
Vehicle usage cost	0.6	0.7

Table 3. Beijing's future electric vehicle market theoretical maximum retention

Year	Maximum retention (million units)
2024	196.35
2025	203.92
2026	211.74
2027	219.79
2028	228.09
2029	236.64
2030	245.45

Using the nonlinear least squares method in the MATLAB environment, the historical data of conventional vehicle ownership is fitted with the time-varying Bass model. The fitted values for the innovation coefficient a1 and the imitation coefficient b1 in the Bass model for the conventional market are obtained as a1=0.0021 and b1=0.1298.

By conducting statistical analysis, key indicators for scoring the innovation and imitation coefficients in the time-varying Bass model are obtained. The scoring results are presented in Table 4 and Table 5.

Table 4. Innovation coefficient key indicator score

Influencing Factors	Economic conditions	Policy Impact	Number of Competitors
Traditional cars	1	1	1
Electric Vehicles	1.2	1.3	0.8

Table 5. Imitation factor score of key indicators

Influencing Factors	Convenience of use	Service life	Price
Traditional cars	1	1	1
Electric Vehicles	0.8	1	0.8

By using Eq.(9) and Eq.(10), the innovation coefficient a2 and the imitation coefficient b2 in the time-varying Bass model for the electric vehicle market can be determined as a2=0.0019 and b2=0.1498.

Based on the time-varying Bass model for the electric vehicle market, the predicted electric vehicle ownership in Beijing for the years 2024-2030 is presented in Table 6.

Table 6. Future electric vehicle ownership in beijing

Year	Retained volume (million units)
2024	70.11
2025	82.69
2026	97.67
2027	115.26
2028	135.52
2029	158.19
2030	182.58

According to the "2021 Beijing Traffic Development Report" released by the Beijing Municipal Institute of Transportation Research and the available statistical data, the proportion of vehicle ownership by different usage categories in 2021 can be seen in Fig. 5.

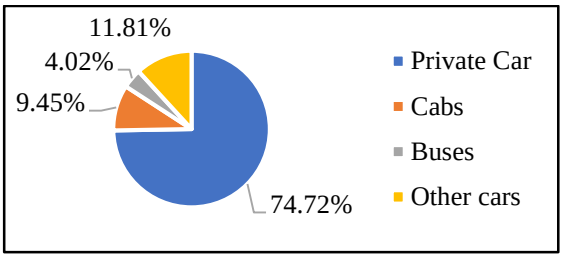


Fig. 5. Percentage of car ownership by use in Beijing in 2021.

Given that the proportion of vehicles in a city is unlikely to undergo significant changes, the article assumes that the proportion of electric private cars, electric taxis, and electric buses in Beijing's future will remain the same as the proportion of vehicle ownership by different usage categories in Beijing in 2021. By performing calculations, the projected electric vehicle ownership for different usages in Beijing from 2024 to 2030 can be obtained, as shown in Table 7.

Table 7. Future electric vehicle ownership in beijing for different purposes

Year	Electric private cars (million units)	Electric cabs (million units)	Electric buses (million units)
2024	52.39	6.59	2.80
2025	61.79	7.77	3.31
2026	72.98	9.18	3.91
2027	86.12	10.83	4.61
2028	101.26	12.74	5.42
2029	118.20	14.87	6.33
2030	136.42	17.16	7.30

5.2. Electric Vehicle Charging Load Prediction Based on Monte Carlo Method

Flowchart for Scalable Electric Vehicle Charging Load Prediction using Monte Carlo Method as depicted in Fig.6.

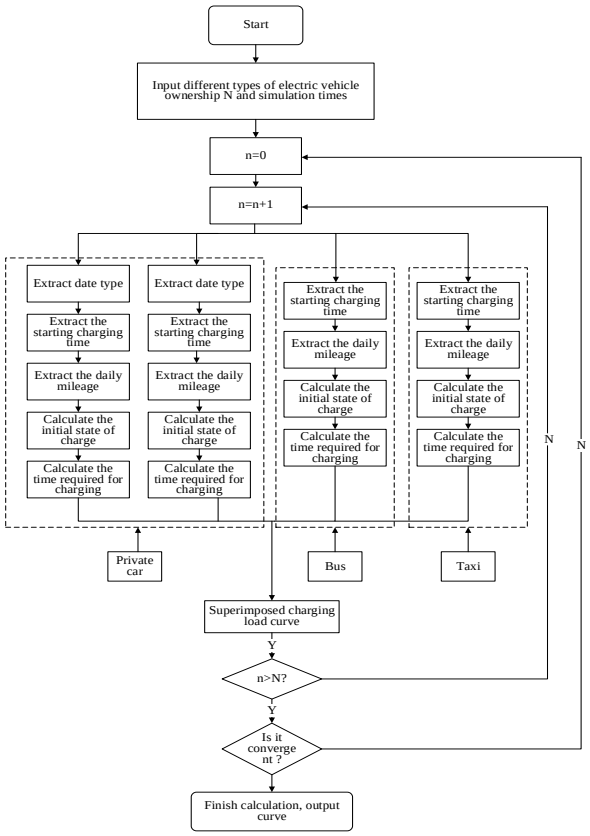


Fig. 6. Flowchart of the calculation of scaled electric vehicle charging load prediction based on Monte Carlo method.

The simulation results are shown in Fig. 7 to Fig. 10.

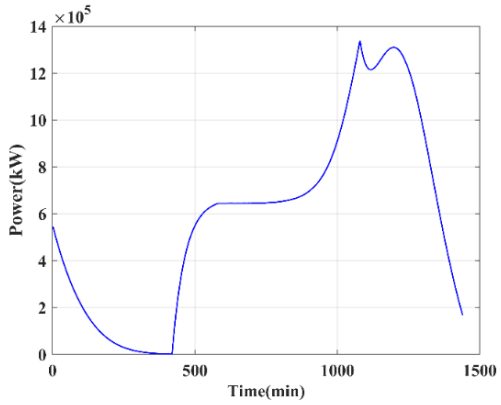


Fig. 7. Electric private vehicle charging load forecast curve in Beijing in 2030.

According to Fig.7, the peak of the electric private car charging load in Beijing in 2030 is approximately 1331 MW, and it occurs around 8 PM. During other times, the charging load remains relatively stable at around 645 MW, which is roughly half of the peak load. In the morning, around 7 AM to 8 AM, when most electric private cars are used for commuting or transportation, there is a valley in the charging load, which is around 8 MW.

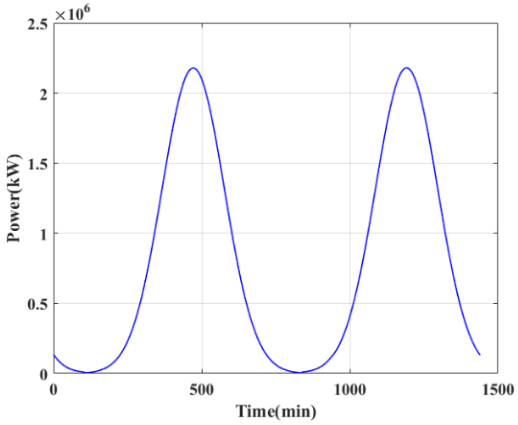


Fig. 8. Electric cab charging load forecast curve in Beijing in 2030.

Based on Fig.8, the charging load of electric taxis in Beijing in 2030 shows two peaks, occurring in the morning at around 8 AM and in the evening at around 8 PM. The peak values are approximately 1090 MW. Additionally, there are two valleys observed at around 1:30 AM and 2 PM, with valley values close to 8.96 MW and 6.77 MW, respectively.

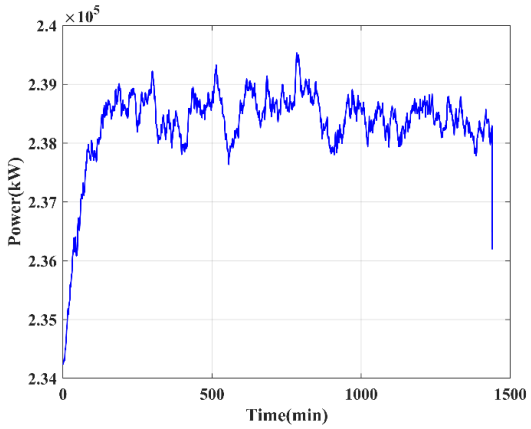


Fig. 9. Electric bus charging load forecast curve in Beijing in 2030.

Based on Fig.9, the peak of the charging load for electric buses in Beijing in 2030 is approximately 261.1 MW. Since buses have the opportunity to charge throughout the day, the charging load remains relatively stable and consistent, maintaining a similar value throughout the day.

Studying and analyzing the charging load curves of electric vehicles for different purposes in Beijing, it can be observed that the overall charging load curve for the city follows a similar trend to that of electric private cars. This is because electric private cars have the largest proportion among all electric vehicles, thus exerting the greatest influence on the total load. On the other hand, the charging start times for electric buses are relatively evenly distributed, resulting in a more evenly distributed charging load curve. The fluctuations in the curve mainly stem from the variations in departure and arrival times at different bus stations. As for electric taxis, their charging load is primarily concentrated around the regular charging time intervals, leading to fluctuations in the charging load curve occurring at these specific time points.

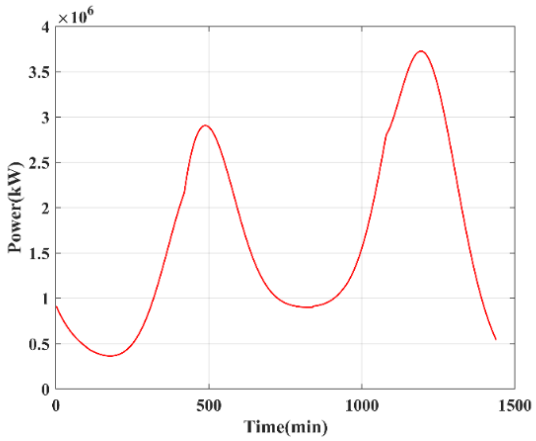


Fig. 10. Electric vehicle charging load forecast curve in Beijing in 2030.

Based on Fig.10, it can be observed that in 2030, the peak of the total charging load for electric vehicles in Beijing occurs around 8:00 PM, reaching approximately 3745 MW. A valley appears around 4:00 AM with a value close to 387 MW. The peak of the total charging load for electric vehicles is primarily influenced by the charging behavior of electric private cars, which return to parking lots for charging during this time period. Additionally, electric taxis also choose this time slot for charging, and the charging load of electric buses further contributes to the overall peak load. The combination of these three types of electric vehicles' charging peaks results in a prominent peak load. The maximum load of the Beijing municipal grid was 24510 MW in 2021, and it increased to 25,640 MW in 2022. A conservative prediction estimates that the maximum load of the Beijing municipal grid will reach 30000 MW in 2030. The peak load percentage of electric vehicle charging in Beijing is shown in Table 8.

Table 8. The proportion of the electric vehicle charging load peak in Beijing in the year 2030

Year	The peak electric vehicle charging load. (MW)	The peak grid load not integrated with electric vehicle charging load (MW)	The peak grid load integrated with electric vehicle charging load. (MW)	The proportion of electric vehicle charging load.
2030	3745	30000	33745	10.30%

In 2030, the total electric vehicle charging load in Beijing accounts for 10.30% of the total electrical grid load. The charging load of electric vehicles is characterized by temporal and spatial uncertainties and randomness. As mentioned earlier, in the intelligent grid system, multiple sources of information interact with each other, and various entities are intertwined. Due to variations in distribution network equipment or materials in different areas of Beijing, the charging load of electric vehicles can have adverse effects on local distribution networks. These effects can include exacerbating peak-to-valley differences in the grid load and significantly altering the distribution of power flow. Furthermore, with the future large-scale integration of electric vehicles, the proportion of the charging load they contribute to the total load will continue to increase, placing a significant additional burden on the power grid. Therefore, effective control measures need to be implemented for managing the charging load of electric vehicles. This can include practices such as demand-side management and time-of-use electricity pricing policies. Encouraging users to shift their charging to off-peak hours, actively participating in demand response programs, and promoting load shaping can help alleviate the operational pressure on the grid and improve grid utilization.

6. Conclusion

The intricate interplay between electric vehicles and various sources of information such as road networks, charging infrastructure, and distribution networks has heightened the complexity of forecasting electric vehicle charging loads. To address the uncertainty in electric vehicle charging loads, this paper proposes a comprehensive forecasting method that takes into account the coupling factors of multiple sources of information for electric vehicle ownership and charging loads. The primary points are as follows:

This paper introduces a multi-source information interaction system, encompassing entities like road networks, public charging stations, electric vehicles, and distribution networks. It delves into the interaction mechanisms and impacts between electric vehicles and various multi-source information entities, underscoring the significance of integrating and interacting multiple sources of information in the context of electric vehicle charging load prediction and system optimization. It provides an in-depth understanding of the coupling mechanisms of multiple sources of information and offers a perspective on enhancing the efficiency and sustainability of electric vehicle charging infrastructure.

In contrast to the traditional Bass model, which exhibits minimal growth in ownership once saturation is approached, this paper introduces a multi-factor electric vehicle development forecasting model. It amalgamates the characteristics of the Box-Cox Dogit model and the time-based Bass model, considering the diverse influencing factors associated with the development of electric vehicles. This results in a multi-factor electric vehicle ownership prediction model that aligns more closely with real-world scenarios, facilitating predictions of electric vehicle ownership for various purposes in Beijing.

Leveraging the factors affecting electric vehicle charging load forecasts and electric vehicle ownership predictions, this paper utilizes Monte Carlo simulation to project the daily charging load curves for private electric cars, electric buses, and electric taxis in Beijing for the year 2030. The summation of the charging load curves for these three vehicle types yields the overall electric vehicle daily load curve, enhancing prediction accuracy compared to previous research and rendering predictions more congruent with actual conditions.

In conclusion, the analysis of the forecast results indicates that the large-scale integration of electric vehicles into Beijing's power grid may have adverse effects on certain local

distribution networks. Therefore, effective control measures such as demand-side management will be necessary in the future. Additionally, future considerations should encompass other influencing factors on electric vehicle charging loads, including weather, holidays, and owner preferences, necessitating further research in subsequent work.

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