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Spatial-temporal Distribution Prediction of Electric Vehicle Charging Load Considering Vehicle-road-station-network Integration

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ABSTRACT

Aiming at the problem of inaccurate prediction of spatial-temporal distribution of electric vehicle charging load due to insufficient consideration of vehicle-road-station-network interaction, a prediction model of spatial-temporal distribution of electric vehicle charging load based on gravitation model was proposed. Firstly, considering road network traffic flow and ambient temperature, the relationship between external environment and energy consumption of electric vehicles is analyzed. Secondly, considering the influence of external environmental factors such as temperature on user travel, a travel chain model based on travel intention modification is established. Finally, the selection model of EV charging station based on gravitation model is established. The simulation results show that the proposed model can take into account the interaction of EV, road network, charging station and power grid, and accurately calculate the spatio-temporal distribution of EV charging load, and analyze the characteristics of EV charging demand load in multi-regions.

KEYWORDS

Electric Vehicle; Charging Load; Prediction Model of Spatial-temporal Distribution.

1. INTRODUCTION

Under the guidance of the goal of "carbon neutrality and carbon peak", the rapid development of electric vehicles (EVs) powered by clean energy is of great significance for China to achieve the "30·60" dual-carbon goal, promote environmental sustainable development and build an environmentally friendly ecosystem[1]. However, large-scale unordered EV access will bring adverse effects on the power system, power quality decrease[2], and the difficulty of grid operation optimization control[3], which puts higher and higher requirements on the planning of charging stations. Existing studies often solve these problems through orderly charging control, which is based on accurate prediction of spatiotemporal distribution of EV charging demand.

At present, the research on the spatio-temporal distribution of EV charging load is mainly carried out from the EV operation law[4], combined with the travel chain[5]. On the other hand, most current studies directly take EV retention in a region as travel volume[6]. However, external factors such as weather type and ambient temperature will affect users' travel intention, and there is a certain deviation between the actual EV quantity and EV retention.

At the same time, although there are studies on various potential factors affecting EV charging behavior[7], there are few studies on the spatio-temporal distribution of stateof charge (SOC) caused by the change of EV driving trajectory due to the different location of charging stations in a region.

In addition, some scholars have studied the influence of travel path and charging location[8] on the spatial distribution of EV charging load, but most studies have not considered the changes of EV charging state caused by large-scale users' selection of charging stations at different locations.

In view of the shortcomings of the above studies, this paper considers the influence of factors such as intra-regional road congestion and ambient temperature on EV energy consumption and users' travel intention, and establishes the unit mileage energy consumption model and travel chain correction model of EV and road network integration. Further, considering the influence of multiple charging stations on the user's driving path selection and the mutual influence of large-scale EV charging station selection, based on the traditional gravitation model, a charging station selection model based on the integration of EV and charging station is established. Finally, based on the start-destination (OD) matrix and quasi-dynamic traffic flow model, the travel behavior and charging choice of EV in the road network are simulated, and the spatio-temporal distribution prediction of EV charging load is realized under the multi-information fusion of vehicle-road-station-network.

2. INFLUENCE OF EXTERNAL ENVIRONMENT ON EV ENERGY CONSUMPTION

EV unit mileage energy consumption is the basis for calculating the spatio-temporal distribution of EV load under the multi-party integration of vehicle-road-station-network, and ambient temperature and traffic congestion have the greatest impact on EV unit mileage power consumption.

2.1. Influence of Temperature on EV Energy Consumption

2.1.1. Impact of Temperature on Batteries

Different ambient temperatures will affect the charging and discharging efficiency of EV. The study on the power battery system in literature[9] found that within a certain temperature range, the energy efficiency of the power battery system increases with the increase of the ambient temperature. Temperature and EV charging and discharging efficiency curves can be obtained from experimental data in the literature, and the relationship equation obtained by curve fitting is as follows.

$$\eta = -1.567\times10^{-5}T^2 + 2.012\times10^{-3}T + 0.8891 \tag{1}$$

Where: T is the ambient temperature; η is the charging and discharging efficiency of EV batteries.

2.2. EV Energy Consumption Per Unit Mileage Calculation

Based on the above relationship between unit energy consumption and driving speed, considering the influence of battery charging and discharging efficiency and temperature energy consumption coefficient when the air conditioner is turned on on unit mileage energy consumption, the unit mileage energy consumption when the EV air conditioner is turned on is shown in Formula (2).

$$e(t,x,T) = \frac{K_{\text{temp}}}{\eta} e_h(t, V(t,x)) \tag{2}$$

Where: $e(t,x,T)$ is the EV unit mileage energy consumption at position x at time t and the ambient temperature is T.

3. TRAVEL CHAIN CORRECTION TAKING INTO ACCOUNT THE USER'S TRAVEL INTENTION

The existing literature is often based on the traditional travel chain, and does not take into account the impact of users' subjective wishes on the travel chain. Based on the theory of human comfort, this chapter realizes the correction of the traditional travel chain.

3.1. Traditional EV Travel Chain Model

EV is mainly divided into private cars, buses and taxis. This paper mainly studies the spatiotemporal distribution of the charging state of private cars. The main travel behaviors of electric private cars and the proportion of each activity trip[10] are set out in Table 1. Travel destinations can be divided into five types: family, company, shopping mall, leisure place and other places, respectively abbreviated as H, W, SE, SR, O.

Table 1. Traditional electric private car travel chain

Type	ID	Trip chain	Account for/%
Working day	C_1	H→W→H	52.8
	C_2	H→W→SR/SE/O→H	24.1
	C_3	H→W→H→SR/SE/O→H	23.1
Day off	C_4	H→SR/SE/O→H(AM)	44.6
	C_5	H→SR/SE/O→H(PM)	55.4

Each travel chain can be decomposed into multiple "travel segments", and the start time t of each travel segment follows the normal distribution shown in equation (3).

$$f\left(t_{\mathrm{s}}\right)=\frac{1}{\sigma\sqrt{2\pi}}\mathrm{e}^{-\frac{\left(t_{\mathrm{s}}-\mu\right)^{2}}{2\sigma^{2}}} \tag{3}$$

Where: μ and σ are the mean and variance of the corresponding start time of different travel chains respectively.

4. ESTABLISHMENT OF EV CHARGING STATION SELECTION MODEL BASED ON GRAVITATION MODEL

4.1. The Law of Gravitation

The gravitational model is often used to describe the law of interaction between two objects in space. Since EV's selection of charging stations is affected by various factors and has a large subjective randomness, it can be likened to the interaction between users and charging stations [11]. At present, gravitation model has been applied to many fields to describe the interaction of physical quantities in space. The traditional gravitation model is shown in equation (4).

Where: F_{12} is the gravitational attraction between celestial bodies; k is the gravitational coefficient; M' is the mass of the central object; m is the mass of the planet; r is the distance between the central body and the planet.

$$F_{12}=\frac{kM^{'}m}{r^{2}} \tag{4}$$

4.2. Calculation of Charging Station Distance Measurement Considering Multiple Paths

Current logistics studies describe the comprehensive distance between two points in space through transportation distance and time. Referring to the idea of calculating comprehensive distance in logistics, this paper selects the length of multiple main routes between two places and the driving time of this route as indicators to determine the comprehensive distance between two places, as shown in equation (5).

$$R_{ij} = \sum_{k=1}^{s} \omega_{ik} \left(d_{ijk} t_{ijk} \right)^{\frac{1}{2}} \tag{5}$$

Where: R_{ij} is the comprehensive distance between EV i and charging station j; s is the number of main routes between the two places; w_{ik} is the weight of the k path adopted by the i EV, which can be determined by the ratio of the driving times of vehicles on this path to the driving times of all paths in the road network. d_{ijk} is the distance from EV i to charging station j by using path k; The time taken by t_{ijk} for the i EV to take the k path to the charging station j is equal to the time taken by EV to choose the k path $t_{road,k}$, namely

$$t_{ijk} = t_{road,k} \tag{6}$$

5. ESTABLISHMENT OF EV CHARGING LOAD CALCULATION MODEL

5.1. OD Matrix

In the field of traffic, OD matrix is usually used to describe the characteristics and changes of traffic flow, and its form is shown in Formula (7).

$$\mathbf{O}_{A\times B} = \begin{bmatrix} o_{11} & o_{12} & \cdots & o_{1B} \\ O_{21} & o_{22} & \cdots & o_{2B} \\ \vdots & \vdots & & \vdots \\ o_{A1} & o_{A2} & \cdots & o_{AB} \end{bmatrix} \tag{7}$$

Each element in the matrix represents the volume of traffic between two nodes, where the row and column of the element represent the number of the starting and ending points respectively, such as O_{ab} represents the volume of traffic from node a to node b.

The EV travel chain in Section 2.1 is divided into multiple travel segments (for example, travel chain C_1 in Table 2 can be divided into travel segments C_{11} and C_{12}, representing H→W and W→H respectively), and the OD matrix of c_{wv} in the travel segment is defined as O^{wv}. O^{wv} is calculated based on the design traffic of each road. The sum of O^{wv} matrix of multiple travel segments in a day is equal to the total OD matrix in the region, that is

$$\sum_{w=1}^{p} \sum_{v=1}^{q} O^{wv} = O \tag{8}$$

Where: q is the number of travel segments; p is the number of travel chains.

5.2. Quasi-dynamic Traffic Flow Simulation based on OD Matrix

Firstly, the OD matrix of each travel segment is divided into N periods according to the probability density curve of departure time of each travel segment, and then distributed to the road network in sequence. Secondly, each layer is allocated by the shortest path method, and the path resistance function is modified synchronously until the N-layer OD matrix is allocated. Finally, the trip volume correction is carried out considering that OD matrix will enter or exit every period of time. Therefore, the volume of traffic at any time and section of the road network is:

$$q_a^z = x_a^z + q_a^{z-1} - x_a^{z-l} \tag{9}$$

Where: $q^z{}_a$ is the traffic volume of section a during the period; Traffic volume assigned to Road a by $x^z{}_a$; $q^z{}_a$ is the traffic volume of Section a during the z-1 period; $x^z{}_a$ is the volume of traffic exiting Road a during the period.

Thus, the road impedance and traffic flow conditions at any time in a day can be obtained, and the traffic situation can be simulated in a day.

5.3. EV Charging Load Calculation

The initial charging state of EV is obtained through Monte Carlo sampling, and combined with the energy consumption per unit mileage $e_i(t,x,T)$, the charging state of EV i is equal to the remaining EV power at the beginning of the travel segment minus the driving power consumption, as shown in equation (10).

$$E_i = E_i^{'} - Le_i(t,x,T) \tag{10}$$

Where: E_i is the current remaining electricity of the i EV; E_i' is the initial remaining electricity of EV i; L is the length of the road.

Taking the current position of EV as the initial point, if E_i cannot meet the driving to the next destination, the charging demand is triggered, and its judgment condition is shown in Formula (11).

$$E_i \leqslant L^{'} e_i(t,x,T) \tag{11}$$

Where: L' is the distance from the current location of the vehicle to the next destination.

6. ANALYSIS OF NUMERICAL EXAMPLES

6.1. Parameter Settings

This paper takes the planning area shown in Figure 1 as an example for simulation test. The area is 18.8km×9.7km in size and contains 19 zones, 17 nodes and 33 roads. Among them, different dashed line colors correspond to different types of areas, brown indicates industrial areas, yellow indicates residential areas, blue indicates commercial areas, green indicates green areas, and red indicates unplanned areas. Different road colors indicate different road grades.

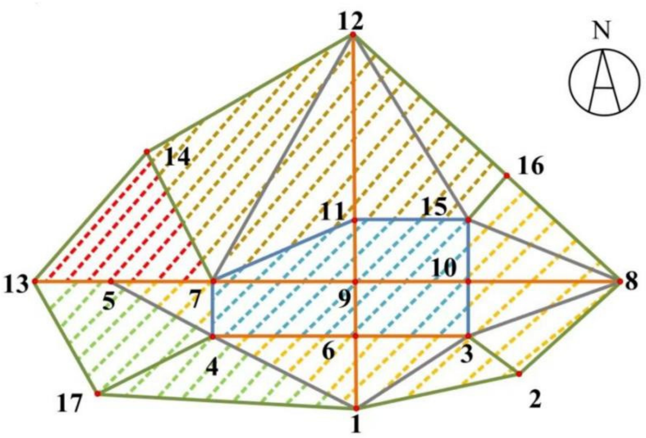


Fig 1. Network structure

In order to fully consider the influence of the interaction of multiple EVs in the regional road network on the selection of charging stations, this paper temporarily does not consider charging through private charging piles, but only considers charging by users at charging stations. Assuming that charging devices in the region are concentrated in nodes 2, 7 and 15, the number of available charging piles is 105, 120 and 150.

6.2. Analysis of Travel Chain Correction Results

According to the previous, you can get PMV, PPD and satisfaction. Thus, the user travel chain correction results are obtained during normal temperature weeks. Only the travel chain correction results of some periods are listed here, as shown in Table 2.

As can be seen from Table 2, before and after the revision of the workday travel chain, the proportion of C_2 travel chain decreases, while the proportion of C_1 and C_3 travel chain increases. Before and after the rest day travel chain correction, the actual number of trips decreased compared with that before the correction. To sum up, the revised travel chain takes into account the subjective wishes of users, and makes up for the inaccuracy of load prediction caused by the traditional travel chain directly taking EV ownership as the number of EV trips.

Table 2. Correction results of travel chain for part of the week at normal temperature

Trip chain	Travel chain ratio(08:00-12:00)/%					Trip chain	Travel chain ratio (08:00-18:00)/%	
	Monday	Tuesday	Wednesday	Thursday	Friday		Saturday	Sunday
C_1	55.97	54.69	55.97	55.97	56.84	C_4	42.41	37.64
C_2	20.34	22.03	20.34	20.34	18.97	C_5	52.69	43.60
C_3	23.69	23.08	23.69	23.69	24.19			

6.3. Simulation Analysis of Charging Station Selection based on Gravitation Model

In order to verify the effectiveness of the gravity-based charging station selection model proposed in this paper and analyze the interaction between EV users when choosing charging stations, the following two simulation scenarios are set up for analysis:

Simulation scenario 1: Considering the attraction of the charging station, but ignoring the interaction between multiple EVs, users only consider the scale and facilities of the charging station, comprehensive distance and their own charging state to select the charging station.

Simulation scenario 2: Considering the attractiveness of charging stations and the interaction of multiple EV choices, users can obtain global information through charging stations.

6.3.1. Analysis of Simulation Results of Charging Station Selection Considering EV Interaction

Table 3. Comparison of EV charging station selection results in Scenario 2 and Scenario 3

EV serial number	Index	Charging station2	Charging station7	Charging station15
6	Without consideration of impact.	356.028	645.955	655.728
	Consider the impact.	579.818	829.266	797.507
9	Without consideration of impact.	217.268	913.145	919.106
	Consider the impact.	353.837	1172.281	1117.831
12	Without consideration of impact.	83.347	282.371	50.974
	Consider the impact.	135.736	362.504	670.103

In scenario 1, although the gravitational selection model without user interaction can correct the deviation caused by users selecting charging stations at the shortest distance, it is not comprehensive to consider users' charging station selection solely based on factors such as the number of charging piles, efficiency and user's state of charge. Therefore, in scenario 2, the simulation analysis is carried out considering the mutual influence of users, and the simulation results are shown in Table 3. The selection of charging station and route selection are shown in Figure 2.

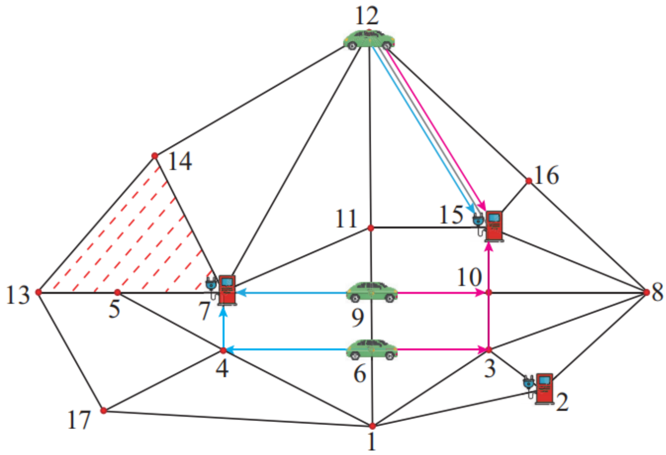


Fig 2. Selection of charging stations in Scenario 1 and Scenario 2

As can be seen from Table 4 and Figure 2, due to the mutual influence of EV selection in the region, there are more queuing EVs in charging station 15, so the attraction of charging station 7 to EV6 increases from 645.955 to 829.266, which is higher than the attraction of 797.507 between charging station 15 and charging station 15. Therefore, the choice of EV6 changes from charging station 15 to charging station 7. Similarly, the selection of EV9 changed from charging station 15 to charging station 7, while EV12 chose not to change. Therefore, EV cluster selection will have a great impact on the attractiveness of charging stations, resulting in changes in the temporal and spatial distribution of EV charging load. Therefore, the mutual influence of multiple EVs cannot be ignored when studying the selection of EV charging stations.

6.3.2. Comparative Analysis of Node Charging Load

In order to further analyze the influence of different charging stations selected by EV users on the charging load of nodes, the charging power of nodes 15 and 7 under the same working day is compared and analyzed, and the results are shown in Figure 3.

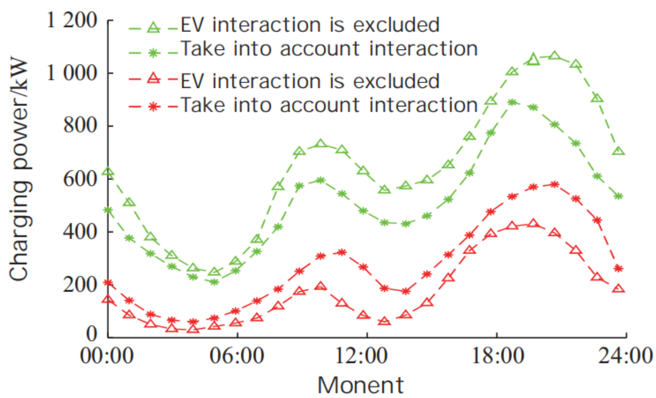


Fig 3. Charging power comparison between node 15 and node 7

As can be seen from Figure 3, when the mutual influence of EV users is considered, the overall charging power of node 15 decreases, while the overall power of node 7 increases, especially during peak hours. This is due to the fact that although charging station 15 is larger and more convenient, after taking into account the interaction among users, a large number of EVs gather at node 15 to charge during peak hours, resulting in traffic congestion and increased queuing time. At this time, the attractiveness of charging station 15 decreases, causing part of its load to shift to node 7. The simulation results verify that the gravity-based charging station selection model can take into account users' aversion to congestion and queuing, and more accurately calculate the charging load of charging stations at different locations.

6.4. Analysis of Calculation Results of Spatial-Temporal Distribution of EV Charging Load

On the same working day, the prediction results of charging load in the region proposed in this paper taking into account vehicle-road-station-network multi-party integration were compared with the conventional prediction method[12] and the prediction method based on Markov decision process (MDP) random path simulation[13]. The simulation parameters were set according to the parameters in this paper, and the simulation results were shown in Figure 4.

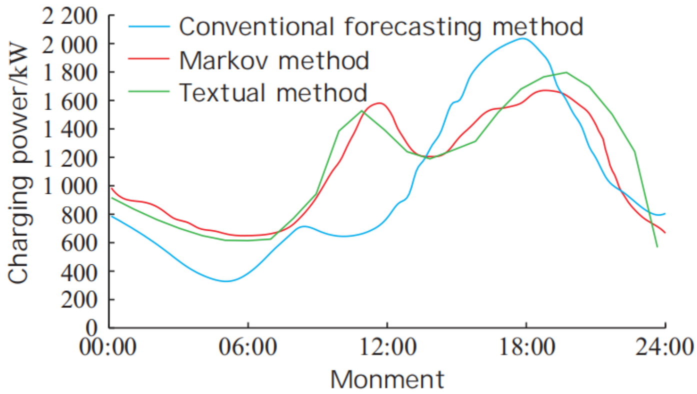
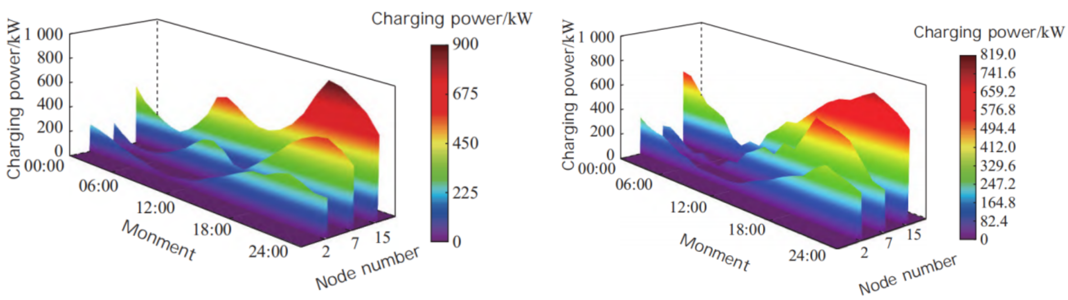


Fig 4. Regional charging power in working days

As can be seen from Figure 4, under the influence of vehicle-road-station-network factors, most EV users start activities at around 08:00, EV power decreases, and charging power within the region begins to rise, reaching the first peak at around 11:00. At about 14:00, the charging power rises again significantly, and the demand peaks in the day at about 20:00, and then gradually declines. The peak load of the day is concentrated around 12:00 noon and 20:00 PM.

In order to further analyze the load characteristics of each major node, the charging loads of nodes 2, 7 and 15 in the same working day and rest day are selected, as shown in Figure 5 .



(a) Working day (b) Day off

Fig 5. Comparison of charging power between nodes on rest days and working days

As can be seen from the simulation results, taking working days as an example, the peak power of node 15 (charging power of 896kW) and node 7(charging power of 581kW) is 132.7% and 50.9% higher than that of node 2(charging power of 385kW), respectively. This is because node 15 and node 7 are located at the intersection of industrial areas, commercial areas and residential areas. Compared with node 2, which is located in residential areas, the charging demand is wider. At the same time, because the charging station of node 15 has the largest scale, its charging load is the largest.

Taking node 15 as an example, there is a double-peak phenomenon in working days, the highest charging load appears at 20:00, the daily peak-valley difference is 685kW, and the bimodal peak-valley difference is 301kW. On rest days, due to the user's late travel, the peak of the charging load is offset, which appears at 21:00, and the load is concentrated in the night, and the charging load is at a higher level from 18:00, the load peak is 819kW, and the daily peak-valley difference is 665kW.

7. CONCLUSION

In order to accurately calculate the spatio-temporal distribution of EV charging load in the region, this paper takes into account multiple factors such as EV, road network, charging station and power grid, establishes the EV user charging station selection model, and realizes the spatio-temporal distribution prediction of charging load in the region. The following conclusions can be drawn through simulation examples.

(1) Changes in ambient temperature will affect users' travel intention, leading to changes in EV quantity of different travel chains. The travel chain correction model established in this paper can solve the calculation deviation caused by taking EV quantity as the number of trips.

(2) The gravity-based charging station selection model can effectively describe the changes in the spatio-temporal distribution of charging station scale, driving distance, queuing time, traffic congestion and the interaction between EVs, and more accurately predict the spatio-temporal distribution of EV charging load.

(3) The scale and location of charging stations have a great influence on their charging load. From the perspective of EV users, this paper reversely analyzes the influence of charging stations at different locations on the spatio-temporal distribution of EV charging states, which can provide a theoretical basis for EV orderly charging strategy and charging station planning.

The proposed method solves the problem that the traditional method does not fully consider the user's travel intention and the choice of charging station, which leads to the inaccurate prediction of the spatial-temporal distribution of charging load. However, the scale of the road network in this example model is small, and the influence of weather type and electricity price on the travel characteristics of EV users has not been considered. In the follow-up study, the temporal and spatial distribution of EV charging load under multi-regional large-scale network and distribution network, taking into account the influence of weather type and electricity price, will be studied.

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