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Spatial and Temporal Distribution Prediction of Urban EV Charging Demand Based on Monte Carlo Simulation and Traffic Situation Big Data

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Abstract*:* Urban electric vehicle (EV) charging pile is a public service facility of urban transportation. Its overall layout planning and construction is a systematic project with high initial investment cost, wide coverage and strong comprehensive, which will have a profound impact on the future development of a city and residents' travel habits. To obtain scientific and effective charging pile layout scheme, accurate and reliable charging demand analysis is indispensable. Based on the research of EV charging behavior, this paper carried out the research on EV charging demand prediction from two dimensions of time and space, and constructed a time-series forecasting model of charging load based on Monte Carlo simulation and a spatial distribution model of charging demand based on traffic situation. The model can effectively and objectively reflect the spatial and temporal distribution characteristics of urban charging demand at the daily scale of planning year, making the output results of the model more accurate and close to the reality, so as to support the research of charging facility layout planning.

Keywords: Monte Carlo simulation, Spatial and temporal distribution, Traffic situation, Big data

INTRODUCTION

In recent years, with the booming production and sales of new energy vehicles in China, car owners have an increasingly urgent demand for charging, and the charging pile industry has entered a period of accelerated development under the tuyere of new infrastructure [N. Ding, *et. al.*, 2019]. As the energy provider of electric vehicles (EVs), charging infrastructure is the prerequisite and important foundation for the development and promotion of electric vehicles. Fast, convenient and economical charging facilities can enhance consumers' willingness to buy electric vehicles. Therefore, the layout and construction of charging infrastructure has long been called the "last kilometer" of electric vehicles, and the planning and layout of charging facilities is closely related to the prediction of charging demand.

Zhang Tianpei et al. took traffic flow as the main factor affecting charging load, weather, typical date, season and other factors as the secondary factors, established load models according to road conditions, and distributed different power to vehicles through different clustering of EV models and states to complete the establishment of dynamic charging load[T. Zhang, *et. al.*, 2021]. Zhang Chenyu et al. proposed a forecasting method for temporal and spatial distribution of charging load based on traffic travel matrix and cloud model to solve the problem of uncertainty of charging location and charging mode in spatial load prediction of electric vehicles, which reflected the randomness and fuzziness of users' decisions in the model, and Monte Carlo simulation is used in the model [C. Zhang, *et. al.*, 2017].

Jun Yang et al. proposed a novel analytic framework for the charging demand of electric vehicles, which considers charging demand is primarily determined by the travel behavior [J. Yang , *et. al.*, 2020].Ye Tao et al. established a mathematical model to optimize the layout of charging infrastructure based on the real-world driving data of 196 battery electric vehicles in Wuhan. Tao Yi et al. mainly discusses the spatial-temporal distribution of EV charging load demands in different urban functional areas and temperatures, they also used Monte Carlo simulations in their models [Y. Tao, *et. al.*, 2018].

Electric vehicles can not travel without the support of electric energy, which determines the convenience and universality of obtaining data from charging piles. Charging piles will become one of the important entrances to vehicle networking in the future, and their data value is worth excavating. It is an inevitable trend to accelerate the deep integration with digital technologies such as big data, Internet and AI [H. Zou, *et. al.*, 2020]. In this paper, traffic big data is applied to the research of electric vehicle charging demand forecasting, and a spatial distribution model of urban electric vehicle charging demand based on Monte Carlo simulation and traffic situation prediction is designed. It can objectively reflect the typical characteristics of the charging demand of electric vehicles in the space-time dimension on the one-day scale, so as to further support the research on the layout of charging piles [Y. Shimin, *et. al.*, 2019].

TIME-SERIES PREDICTION MODEL OF CHARGING LOAD BASED ON MONTE CARLO SIMULATION

Calculation model of EV charging load

Since it is difficult to obtain the real travel track data of urban EVs, the difficulty of EV charging load calculation lies in analyzing the randomness of EV initial charging time and initial SOC [Q. Xing, *et. al.*, 2020]. The calculation idea of EV charging load in this paper is to accumulate the daily charging load curves of single EV in each class according to the charging behavior analysis of different types of EV to obtain the total EV charging load on a daily scale, as shown in the figure below [X. Guo, et. al., 2013].

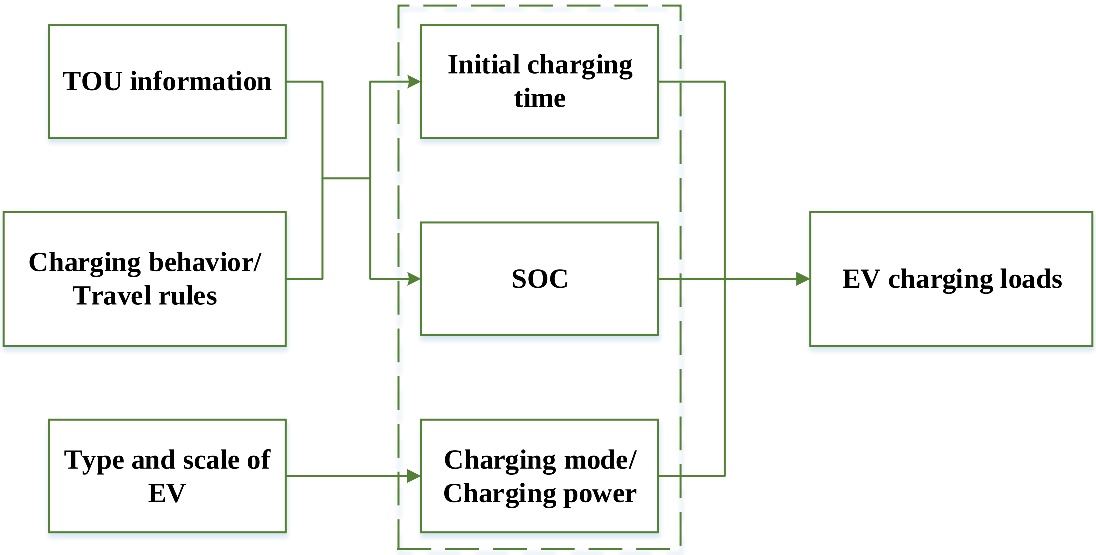

Figure 1 The calculation idea of charging load

The daily charging load is calculated with every minute as a time interval, a total of 1440 minutes. The total charging load of EV at ith minute is the sum of the charging load of all EVs at this moment, and the total charging power can be expressed as:

$$L_i = \sum_{n=1}^{N} P_{n,i}$$

Where, Li is the total charging load in the ith minute, with the unit of MW, i=1, 2, 1440; N is the total number of EV; Pn,i is the charging load of the nth vehicle in the ith minute.

EV charging load prediction based on Monte Carlo simulation

Assuming that the grid does not limit the charging behavior of EVs, there is no need to wait for each charging, and EVs can start charging after being connected to the grid, but some EV charging behavior will have a time limit. To reduce the influence of randomness of parameters, the initial charging time and SOC of a single EV are extracted by Monte Carlo simulation, and combined with the above-mentioned charging mode and charging behavior analysis, a time sequence simulation model of EV charging load based on Monte Carlo simulation is constructed. The calculation steps are as follows [J. Cao, *et. al.*, 2018].

(1) Input the parameters such as the number of EVs, battery capacity and charging power, and set the simulation times N.

(2) According to the distribution of the initial SOC, randomly generate the value of the initial SOC, and calculate the required charging time according to the following formula:

$$t_c = \frac{(1-SOC)C}{P\eta}$$

C is the battery capacity of the EV, P is the rated charging power of the EV, and η is the charging efficiency.

(3) According to the probability distribution of initial charging time, the initial charging time of EV is randomly generated;

(4) From the above three steps, the charging load of a single EV can be obtained;

(5) Convergence judgment, using variance coefficient β to judge the calculation accuracy, the formula is as follows:

$$\beta = \frac{\sigma(\bar{L})}{\sqrt{N}\,\bar{L}_i}$$

$\sigma(\bar{L})$ is the standard deviation of load in the ith minute; $\bar{L}_i$ is the load expectation value of the ith minute. Take the maximum variance coefficient at all time points as the judgment basis, and the maximum value is less than 0.05% as convergence;

(6) Take the average load after N times of calculation and multiply it with the number of this kind of EV to get the charging load.

The input of the model includes the number of EVs, the probability distribution of initial charging time, the probability distribution of initial SOC, the charging period and probability distribution of various charging behaviors, etc [P. Xu, et. al., 2013] . When calculating the charging load of a single EV, if the vehicle has multiple possible charging behaviors, the model will generate a random number that obeys the uniform distribution of U (0,1), and determine the charging behavior of the EV according to the probability distribution of various charging behaviors.

SPATIAL DISTRIBUTION MODEL OF CHARGING DEMAND BASED ON TRAFFIC SITUATION BIG DATA

Construction principles of spatial distribution prediction model of charging demand

Charging demand is generated by EVs, and EVs run on urban road network. This paper sets a positive correlation between charging demand and traffic flow on urban trunk road network, and reasonably quantifies the charging demand of urban road network. According to the urban charging load curve obtained by Monte Carlo simulation, the total urban charging demand under the daily scale was calculated.

Considering the availability of data and feasibility of operation, and considering the traffic flow of urban trunk road network as the index needed in this part, this paper optimizes the spatial distribution of charging demand with the help of big data technology: By invoking the intelligent traffic data center interface of Baidu Map, the historical data of the traffic situation of the main road network in the research area are obtained. The related indicator fields are described in the following table. Then, Extreme Learning Machine (ELM) is used to predict the future traffic situation indicators. Finally, entropy weight method is used to calculate the weight of distribution index, so as to complete the distribution of total regional charging demand to the main traffic network [S. Guo, *et. al.*, 2015].

Table 1 Parameter description and value

Field name	Field meaning	Field value
road_name	The road name	/
congestion_distance	Congestion distance (m)	/
speed	Average speed of current road section (unit: km/h)	/
status	Road Congestion evaluation	0: unknown road conditions, 1: smooth, 2: slow, 3: congestion, 4: severe congestion
congestion_trend	Congestion trend from 10 minutes ago	Flat, ease, aggravate

Charging unit division and conversion algorithm

The concept of charging unit proposed in this paper quantifies the distribution of charging demand of urban road network into the charging demand of each charging unit, and obtains the spatial distribution of urban charging demand load[Y. Zhou, et. al., 2015]. Charging unit is divided on the basis of each road section on the road network, and the closed area geographically enclosed by each road section is taken as a charging unit (S). The charging unit transforms the spatial distribution of charging demand on the road section into the spatial distribution within the planning area. Assume that the road section set of the regional road network is A, and the charged electric quantity of the road section is distributed according to the flow weighted distribution. The road network node set is {b1,b2,…,bm}, and the coordinates of each node (Xi,Yi), i=1,2,…,m can be obtained by latitude and longitude conversion; The road network can be divided into n charging units, and the unit set is {S1,S2,…,Sn}. According to the above data, conversion calculation of charging unit demand is carried out. The main calculation steps are as follows:

(1) As road sections are the connection between two nodes of the road network, the charging demand{Na, a∈A} on all road sections of the road network is equally divided to the two nodes forming the road section, and the node power is Na /2. In theory, any node in the road network participates in the formation of at least one road section, so the charging demand of nodes is obtained through accumulation, so the charging demand of road network nodes can be expressed as $Q_i = \frac{\sum N_k}{2}, \forall k \in K_i$, where Ki is the road section set formed by node bi.

(2) An arbitrary charging block is formed by at least three road network nodes connected by road sections, and the charging demand Qi of the road network nodes forming the block is accumulated as

the demand of the charging block. Any node in the road network may participate in the formation of one or more charging blocks, so the charging demand of the node is equally divided into the charging blocks in which it participates, so the charging block demand is $S_j = \sum_{\forall i \in R_j} \frac{Q_i}{c_i}, j = 1, 2, ...n$, where Rj is the node set participating in the formation of charging block Sj, and ci is the number of charging blocks formed by nodes bi in Rj.

(3) In order to better quantify its spatial distribution in the planned area, a certain point in the block is selected by the weighted average method to reflect the charging demand of the block. The coordinates of representative points of each charging block are $(x_j, y_j) = (S_j^{-1} \sum_{\forall i \in R_j} \frac{X_i Q_i}{c_i}, S_j^{-1} \sum_{\forall i \in R_j} \frac{Y_i Q_i}{c_i})$, which can represent the concentration of the charging demand of the charging unit in the sense of geography and geometry.

Case analysis of spatio-temporal distribution prediction of urban EV charging demand: a case study of Yinchuan city

Investigation and analysis on charging behavior of EVs in Yinchuan

The charging load of EVs is not only related to its charging power, but also related to travel rules and charging behavior [B. Liao, *et. al.*, 2017]. Up to now, Yinchuan has gradually formed a certain scale of bus electrification, accelerating the electrification of taxis, business vehicles and special vehicles, and the sustained and steady growth of the number of electric private cars. according to different uses, electric vehicles are divided into five categories: electric buses, electric taxis, electric official vehicles, electric special vehicles and electric private cars.

Considering the guiding effect of TOU electricity price on charging behavior, the charging behavior patterns of these five types of EVs in Yinchuan city were investigated and analyzed. According to the peak-valley time-of-use price table of Ningxia Power Grid implemented since January 1, 2021, the peak hours of Ningxia power grid are 8:00-12:00 and 18:30-22:30. The lowest period is 22:30-6:30; The rest of the time is flat.

Electric buses

According to the investigation of bus operation in Yinchuan, the bus operation time interval is about (6:40,22:00), and the average daily mileage of electric buses in Yinchuan is (150km,200km). BYDK9, the main model of electric buses in Yinchuan, has a range of 250km and a battery capacity of 324kWh.

According to the survey data, the morning work time (7:00,7:50) and afternoon work time (17:00,18:40) are the peak hours of bus operation in Yinchuan city, and electric buses generally cannot be charged during the peak hours. Because bus operation time and route are relatively fixed, and parking places are relatively concentrated, centralized charging can be carried out at comprehensive hubs, bus stations or existing parking lots. Considering safety, road conditions, weather and other factors, to ensure the normal operation of public transport, electric buses should be charged at least once a day during off-peak hours and at night, and at least twice a day. During daytime operation hours, the bus cannot stay for a long time for quick charging; During the night outage period is also the low power consumption period of the power grid, the vehicle is routinely charged.

Based on the above analysis, a reasonable assumption is put forward: electric buses need to be charged twice a day. The charging time of electric buses is 9:00-17:00 during the day and 23:00-6:00 at night. The initial charging time of buses follows uniform distribution, and the initial battery State of Charge (SOC) of each Charge is mainly determined by the daily mileage. It is assumed that the initial SOC of electric buses follows normal distribution N (0.5,0.12).

Electric taxis

At present, electric taxis operating in Yinchuan city mainly include BAIC New Energy EU5, BYD Qin EV, Roewe I5 and other models. Take the main model -- BAIC New Energy EU5 as an example. The driving range of BAIC New Energy EU5 NEDC is 416km, the battery capacity is 60.2kwh, and the fast charging time (30%-80% SOC, 25 ℃ at room temperature) is 30 minutes.

Taxi travel routes have strong randomness and flexibility. The average daily mileage of taxis in Yinchuan is about 155km,200km. Most taxis will respond to the guidance of time-of-use electricity price, so electric taxis are mainly concentrated in 12:00 to 18:30 and 22:30 to 6:30. Due to range anxiety, electric taxis choose to charge twice a day. Generally, they choose quick charging mode during daytime operation and conventional charging mode during night shutdown. The initial charging time followed normal distribution, and the initial SOC followed normal distribution N(0.4，0.12).

Electric official vehicles

Most of the official vehicles in Yinchuan are used by the government or enterprises and institutions, which basically carry out official duties during the day, the driving mileage is within the range of mileage, and they can be recharged once a day, and when the official vehicles do not perform official duties, they can be recharged. therefore, in most cases, there is sufficient charging time, and its charging mode is mostly slow or conventional charging.

At present, most official vehicles are parked at designated parking places at night. It is assumed that the starting time for charging is roughly between the end of work and the next day before going to work, that is, from 18:00 to 7 00, and that it is charged at night at 20u00-the rest time at 7:00 the next day, and the starting charging time obeys N(20,0.52).

Sometimes it is necessary to use semi-fast charging due to emergencies, and the initial charging time obeys a uniform distribution.

Electric special vehicles

Electric special vehicles in Yinchuan are generally electric logistics vehicles, electric sanitation vehicles, etc., with fixed working mode. Their charging mode is similar to that of official vehicles, charging time interval is (20:00,7:00), initial SOC obeys normal distribution N(0.6,0.12), and there is no need to adopt high-power charging mode.

Electric private cars

Private cars have short daily journeys, so one charge can basically meet their daily needs. During working days, private cars park for a long time in the parking lot of work units and residential areas, so they can choose to use slow charging or conventional charging. Charging time is mainly from 20:00 to 6:00 in the next day during working hours and after returning home. Because it is in the off state for most of the time, slow charging or conventional charging method is generally adopted. When it stays in shopping malls or other public places for a short time, it needs to use high-power charging method.

Considering the response degree of users to TOU price, assuming that 50% of users will charge when the price is low, the initial charging time follows normal distribution N(23,0.52). For users who choose to charge immediately at the end of driving, the initial charging time follows normal distribution N(19,0.52), and the initial SOC meets normal distribution N(0.6,0.12). The common charging methods, charging power and charging behavior of EVs are summarized as follows.

Table 2 Common charging methods and charging power of EVs

Vehicle type	Charging mode	Charging power /kW
Electric bus	Conventional charging / fast charging	80/120
Electric taxi	Conventional charging / fast charging	40/120
Electric official vehicle	Slow charging / conventional charging	7/40
Electric special vehicle	Slow charging / conventional charging	7/40
Electric private car	Slow charging / conventional charging	7/40/

Table 3 Summary of electric vehicle charging behavior

Type	Charging times	Charging period	Charging probability	Initial charging time distribution	Initial SOC distribution
Electric bus	2	10:00-17:00 23:00-6:00	1 1	Uniform distribution	N $(0.5,0.1^2)$
Electric taxi	2	12:00-18:30 22:30-6:30	1 1	Normal distribution	N $(0.4,0.1^2)$
Electric official vehicle	1	9:00-17:00 21:00-7:00	0.1 0.9	Uniform distribution Normal distribution	N $(0.6,0.1^2)$
Electric special vehicle	1	20:00-7:00	1	Normal distribution	N $(0.5,0.1^2)$
Electric private car	1	8:00-17:00	0.2	Uniform distribution Normal distribution	N $(0.6,0.1^2)$
		20:00-7:00	0.8	Normal distribution	

Time-series prediction of EV charging load in Yinchuan city

According to the modeling idea of charging load time sequence prediction mentioned above, the number of all kinds of electric vehicles, battery capacity, charging power and other parameters in Yinchuan city in 2022 are input into the charging load simulation prediction model based on Monte Carlo simulation, and the typical daily load curve of Yinchuan city in 2022 is shown in the figure.

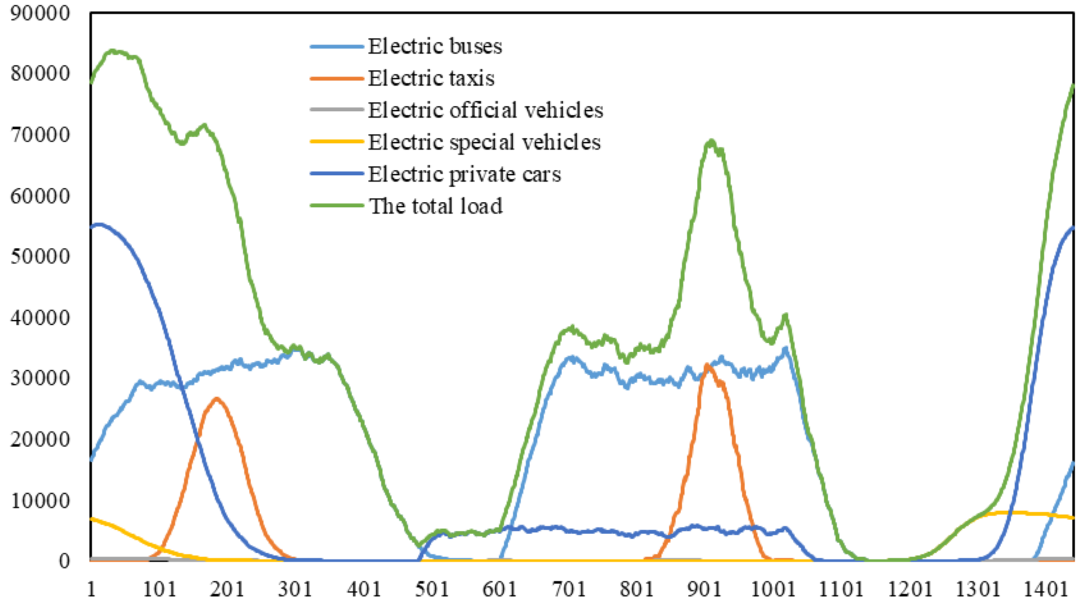

Figure 2 EV charging daily load curve in Yinchuan city in 2022

From the perspective of different types of EVs, due to the large number of electric private cars, and their charging time is concentrated in working hours and night rest periods, forming a peak around 0 o 'clock; Due to the special service characteristics, electric taxis use more frequency of quick charging, so they account for a large proportion in the total load curve. Electric taxis reach the peak load at around 3:20 am and 3 pm, reflecting the guiding role of TOU electricity price. Although the scale of electric buses is also large, their charging behaviors are scattered in off-peak operating hours, so the peak period of the charging load curve of electric buses is complementary to the urban morning and evening peak periods. Due to the small amount of electric special vehicle and electric business vehicle and the small charging power, this type of charging load is small and relatively stable.

From the perspective of the total load curve, the daily charging load curve of Yinchuan city fluctuates greatly, concentrated in two time ranges from 9:30 pm to 5 am and from 11:30 am to 5:30 pm, which reflects the guiding role of TOU mechanism on the whole. According to the daily charging load curve integral of Yinchuan city, the daily charging power of Yinchuan city is 785569.13kW·h.

Study on Spatial Distribution of EV charging demand in Yinchuan city

According to the charging load curve, the daily total charging demand of Yinchuan city in planning year is calculated. Combined with the modeling idea of spatial distribution prediction of charging load, this paper assumes that the charging demand is positively correlated with the traffic flow of urban trunk road network. First, the charging demand of urban road network is reasonably quantified. Then the distribution of charging demand of urban road network is transformed into the charging demand of each charging unit.

Taking some areas of Yinchuan municipal district as the research object, this paper analyzes the spatial distribution of charging demand, which is bounded by Wenchang North Street-Wenchang South Street in the west, Yinchuan roundabout highway in the south, Lijing South Street-Lijing North Street in the east and Helan Mountain East Road-Helan Mountain Middle Road-Helan Mountain West Road in the north. The specific scope of the study area is shown in the following figure. Among them, there are 26 road section nodes, 41 road sections and 16 charging units, including a to z. The schematic diagram of the trunk road network structure is shown below. The longitude and latitude coordinates of each node of the road network are transformed into the plane Cartesian coordinate system, and the topological structure of the trunk road network in Yinchuan is obtained.

Figure 3 Node information and charging unit division of Yinchuan main road network

The traffic situation data set of the trunk road network in Yinchuan during the evening peak on October 16, 2021 was obtained by calling Baidu Map Intelligent Traffic data Interface, with a total of 8142 pieces of data. Considering the influence of the changes of traffic network, vehicle ownership and road conditions in Yinchuan in 2022, a random coefficient is introduced, and then the ELM algorithm is used to predict the traffic situation of the evening peak trunk road network in Yinchuan one day in 2022. The research on the distribution of total charging demand in Yinchuan mainly considers the road congestion distance, the average speed of the current road section and the road length, and the weights of the three indicators are shown in the table below.

Table 4 The entropy weight of the index

Index	**The length of the road #km**	**Traffic situation indicator - Congestion distance #m**	**Traffic situation indicator - Speed #km/h**
Weight	0.133222983	0.470633815	0.396143201

According to the weight determined by entropy method, the regional charging demand is allocated to each road section, and the spatial distribution prediction result of charging demand in Yinchuan can be obtained. The red circle in the following figure marks the location of the representative points of the 16 charging units, that is, the location of the charging demand point in the study area, which can reflect the geographical and geometric concentration of the charging demand of the charging unit.

Figure 4 The position of the representative point of the charging unit

The power demand and representative point coordinates of the charging unit are shown in the following table, which specifically describes the node composition and geographical location description of the charging unit.

Table 5 Basic information about the charging unit

Serial number	Nodes	Charging demand (kW·h)	Longitude	Latitude
1	a、b、h、g	14199.05	106.1334	38.49474
2	b、c、i、h	17834.51	106.1517	38.49257
3	c、d、j、i	12423.25	106.2008	38.48748
4	d、e、k、j	49857.78	106.2466	38.49402
5	e、f、l、k	117525.6	106.2868	38.49441
6	g、h、i、n、m	19128.22	106.1638	38.48184
7	m、n、p、o	27570.35	106.1602	38.47276
8	i、j、q、p、n	37699.5	106.1947	38.47493
9	j、k、r、q	40615.14	106.237	38.47268
10	p、q、t、s	33779.95	106.1982	38.46374
11	q、r、u、t	48837.37	106.2343	38.45901
12	k、l、v、u、r	130535	106.2811	38.45445
13	o、p、s、x、w	41768.21	106.1572	38.45343
14	s、t、y、x	28162.83	106.1993	38.43937
15	t、u、y	31376.15	106.2296	38.44719
16	u、v、z、y	134256.2	106.2818	38.42754

The following picture shows the thermal map distribution of charging demand in the main areas of Yinchuan. It can be found that the electricity demand of the unit is not only related to the size of the area, but also plays a key role in the process of electricity distribution. Because the basic information of urban road network and the information contained in traffic situation are fully considered in the power distribution, this method can accurately reflect the spatial distribution characteristics of electric vehicle charging demand in Yinchuan.

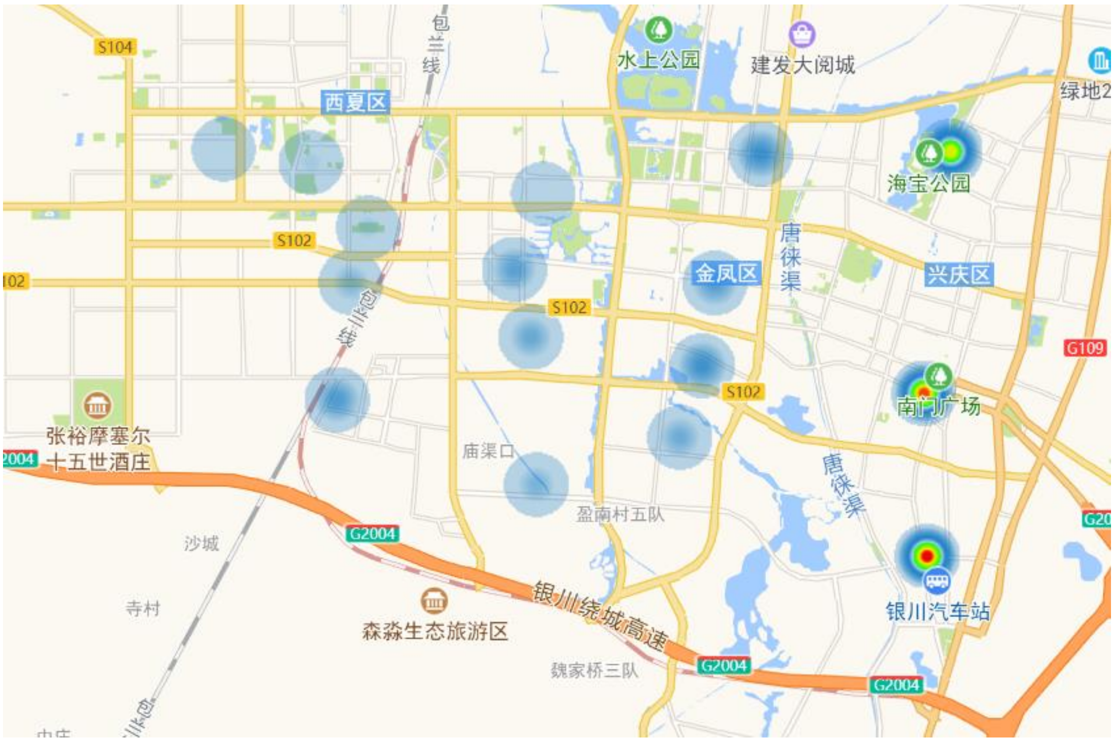

Figure 5 Thermal chart of charging demand in Yinchuan city

CONCLUSION

In this paper, a method from time series prediction of charging load to spatial distribution prediction of charging demand is proposed. Big data technology is applied to the research of regional charging demand forecasting: Monte Carlo simulation is used to predict the changing trend of charging load, then big data and charging unit conversion algorithm are used to obtain the spatial distribution characteristics of regional charging demand, finally take Yinchuan City in 2022 as an example. The calculation results can effectively and objectively reflect the changing characteristics of urban charging demand in the two dimensions of time and space under the one-day scale of the planning year, which has important reference value for the layout planning of charging facilities.

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