Power, Energy and Electrical Engineering
M. Deng (Ed.)

doi:10.3233/ATDE240331

Electric Vehicle Charging Demand Prediction and Site Selection Based on Monte Carlo Simulation

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Abstract. In this paper, a data-driven charging demand forecasting and charging station location method for electric vehicles is proposed. Firstly, the daily driving trajectory data of electric vehicles are obtained and analyzed. The user travel characteristic parameters and vehicle charging characteristic parameters are extracted from the data. Then, the user travel activity chain and the charging model of single electric vehicle are built, and the charging demand grid of electric vehicle is built. Using Monte Carlo method to simulate users' daily travel activities. Finally, the time and space distribution of electric vehicle charging load is analyzed through an example, which provides decision-making reference for the new location of charging station.

Keywords. Charging demand, monte carlo simulation, charging station planning

1. Introduction

Compared with traditional fuel vehicles, electric vehicles play an important role in environmental protection and energy adjustment, which is helpful to actively promote the clean and electrified development of transportation industry [1]. However, due to the influence of weather, temperature and other factors, the reliability of electric vehicle travel still needs to be improved. The problem of mileage anxiety is becoming more and more obvious [2]. The charging load of electric vehicles is different from the general electric load. The daily variation range of charging demand load is large. And it is uncertain in space and time, which is closely related to users' travel activities and vehicle driving behavior [3]. This is more challenging to predict the charging load than the conventional load.

At present, when analyzing the charging demand, most of them start from the charging station, which is similar to the traditional power load forecasting method. A demand forecasting model for charging stations is established. When the characteristics of the model are analyzed thoroughly and accurately, the forecasting effect of the model is better. Zheng J.H et al. put forward a two-stage poisson distribution clustering model of electric vehicle charging stations, and obtained the clustering characteristic parameters of electric vehicle charging stations in residential areas through simulation

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experiments[4]. Xie F. et al. established a charging load model based on the daily load data of charging stations[5]. In this study, the mathematical analysis and simulation verification of vehicle charging process are carried out. And nowadays, the charging demand of electric vehicles is increasing exponentially, which greatly tests the accuracy and effectiveness of the model. And because the user's charging behavior will be affected by weather, road conditions and other factors. The travel characteristics and charging characteristics of different types of vehicles are quite different. When it is extended to a wider range of research areas and more complex realistic scenes, the research method based on charging station terminals is no longer applicable[6-9].

In order to solve the above problems, this paper takes electric vehicles as the research object to forecast and analyze the charging demand. A data-driven layout method of electric vehicle charging stations considering charging demand is proposed. The travel characteristic parameters and charging characteristic parameters are obtained from the driving trajectory of the electric vehicle. Construct origin-destination(OD) travel matrix. Analyze the user's getting on and off points. Build a user travel chain. Monte Carlo simulation is used to simulate users' travel activities, and the time-space distribution results of charging demand are obtained. Optimize the location of charging station according to the time and space distribution of charging demand.

2. Prediction of Charging Demand based on Monte Carlo Simulation

In this paper, Monte Carlo method is used to predict the charging load of electric vehicles. Randomly generate the initial travel time and initial SOC according to the probability density function. According to the OD travel matrix, the starting point and destination are assigned to each electric vehicle. Combined with the pre-set charging mode, electric vehicle type and other data, we can simulate the user's activity trip in one day and finally get the time and space distribution of charging demand in one day.

The steps of Monte Carlo simulation algorithm are as follows:

STEP(1): Initialization: Setting the total number N of electric vehicles in the study area, the number of simulated days $Days$ and the battery capacity $battery$ of the vehicle; Determine the fast charging power P_{charg} according to the charging mode;

STEP(2): According to the probability density function, the initial electric quantity C_{p0}, the first trip time t_0 and the initial position O_i are generated;

STEP(3): According to the OD travel matrix, the destination D_i of this trip and the distance Dis_i of this trip are obtained;

STEP(4): Calculate the time Δt_i spent on this trip;

STEP(5): Update the simulation time *t,* the remaining power $C_{p(t)}$ at time *t* and simulation days $Days$;

STEP(6): Judge whether the current vehicle meets the charging conditions, if yes, execute STEP(7), otherwise return to STEP(3);

STEP(7): The generated charging demand is attributed to the grid, and the space-time information of fast charging load is determined;

STEP(8): After charging, update the simulation time t and the remaining power $C_{p(t)}$ at time *t*;

STEP(9): Judging whether the vehicle *j* has completed all the trips, and if so, ending; otherwise, return to STEP (3).

3. Analysis of the Characteristics of Electric Vehicle Travel and Charging

3.1. Travel Activity Chain

Travel activity chain refers to a series of activities and behaviors related to travel. The daily travel trajectory of users can be represented by travel chain. The sequence and content of travel activity chain will be different according to the actual situation and demand.Through the research and mining of travel trajectory data, we can know the daily travel rules of vehicles, such as daily travel time, parking hotspots, parking duration and driving distance [10-12]. The (OD) travel matrix is obtained by calculating the travel chain. Combined with OD travel matrix, the travel activities and charging process of electric vehicles in urban road network are dynamically simulated.

Trajectory data includes three key information: time, place and passenger status. A number of dynamically changing latitude and longitude points constitute the driving track of electric vehicles in one day. $\left(long_i, lat_i, t_i, state_i\right)$ represents the *i* point of the trajectory Ω ; $long_i$ represents the longitude of the *i* point; lat_i represents the latitude of the *i* point; t_i represents the time of the *i* point, $state_i$ indicates the passenger status at the *i* poin, $i = 1, 2, ..., n$,where *n* represents the number of longitude and latitude points of the trajectory.

In order to quickly realize the statistics of charging demand load, the research area is divided into grids. Convert the latitude and longitude of traffic demand location points into grid numbers.Through the analysis of the grid, the traffic demand in the grid is indirectly counted. Grid division is to divide the research area into squares with equal size at a certain interval according to a certain method, and *w* is used to indicate the division interval. When the value of *w* is 0.01, it means that the research area is divided into several grids with equal size at an interval of 0.01°.

3.2. Initial Travel Time and Initial State of Charge

The charging demand of electric vehicles is influenced by driving distance, charging facilities, charging power and charging strategy. It is closely related to the user's travel plan, which is greatly influenced by the daily mileage and time. The initial travel time of electric vehicles affects the charging demand at different times of the day. Therefore, it is very important to predict the charging demand of electric vehicles by accurately fitting the actual starting travel time.

In this paper, it is assumed that the battery state of charge of the electric vehicle when it first trips obeys the normal distribution $N_{SOC}(0.8, 0.1)$. Eq.(1) can be used to calculate the electricity consumption during the first trip C_{P0} , where is the initial SOC.

$$C_{P0} = SOC_{Star} \bullet battery \tag{1}$$

The vehicle will lose energy due to braking, bumps, headwinds and other reasons during driving. Therefore, the energy conversion coefficient η is introduced to represent the power loss caused by various reasons in the actual driving process, and the remaining power of the electric taxi at time t can be calculated by Eq.(2), where η takes a value from 0.9 to 1; $C_{p(t-1)}$ represents the remaining power of the vehicle at time t-1; Δl represents the distance traveled by the vehicle from time t-1 to time t; ΔC_p represents the power consumption per kilometer of the vehicle.

$$C_{pt} = \eta \cdot (C_{p(t-1)} - \Delta l \cdot \Delta C_p) \tag{2}$$

3.3. Charging Time

This paper takes the electric taxi as the research object. According to the travel characteristics of electric taxis, it is the main time period to consider charging when the passenger status is empty. In addition to this time period, dining and lunch break are also good charging time periods.

$$t_{reality} = \begin{cases} tc & t_{\max} > tc \\ t_{\max} & t_{\max} \le tc \end{cases} \tag{3}$$

$$t_{\max} = \frac{C_{p(t-1)} - C_{p(t)}}{P_{charg}} \tag{4}$$

Where $C_{p(t-1)}$ is the electric capacity of the electric taxi at time t-1. P_{charg} is the power of the charging pile, P_{charg}=60kW. $t_{\max}$ is the maximum charging time, that is, the time required for the electric network to get a car from the current charge to full charge. tc is the time available for charging activities when the vehicle is in no-load state.

3.4. Charge State Judgment

Based on the charging characteristics of electric taxis, in order to reduce the time of no-load state, drivers usually choose to use fast charging mode to charge. This paper assumes that the power of the fast charging pile is 60kW. Generally speaking, drivers don't charge their vehicles after they have completely consumed their electricity. When the power of the taxi at a certain moment is lower than the set threshold power, the charging demand is triggered:

$$C_{p(t)} \le \varepsilon \bullet C_{P0} \tag{5}$$

In Eq.(5), $C_{p(t)}$ is the power at time t, ε is the user's mileage anxiety coefficient, and ε obeys uniform distribution, and its probability density function is:

$$f(\varepsilon)=\begin{cases}\dfrac{1}{b-a} & a<\varepsilon<b\\ 0 & else\end{cases} \tag{6}$$

By analyzing the daily travel data of vehicles, the time period that meets the charging requirements is extracted. The Curve Fitting toolbox of matlab is used to fit the data, and Gaussian distribution is selected to get its fitting curve function, such as Eq.(7). At this time, SSE=0.0003778, R-square=0.9943.

$$f(x)=4.878\cdot 10^{15}\cdot \exp(-(\frac{x-(-140.8))}{28.4})^2)+324.4\cdot \exp(-(\frac{x-(-602.5))}{224.7})^2) \tag{7}$$

4. Example Analysis

The research object of this paper is electric taxis. The data set contains GPS records of 100 electric taxis located in Beijing from August 2 to 6, 2020. The main data format is shown in Table 1.

Table 1. Vehicle trip data format description

Field Name	Field Type	Data Example
ID	Varchar	1
Date	Datetimes64	2020-08-02 12:55:36
longitude	Float64	116.564244
latitude	Float64	40.070921
angle	Int64	194
load	Int64	0
speed	Float64	53.2

In order to avoid the interference of noise data in the original data set on the experimental results, it is necessary to preprocess the original data: delete the data with missing values, remove duplicate values, screen out the data that are not in the research area, and delete the data with a passenger distance less than 500 meters. Visualize and analyze the data after the data preprocessing is completed.

Fig. 1 shows the change of the daily average order quantity of 100 electric taxis. The driving track points of 10 electric taxis are given in Fig. 2.

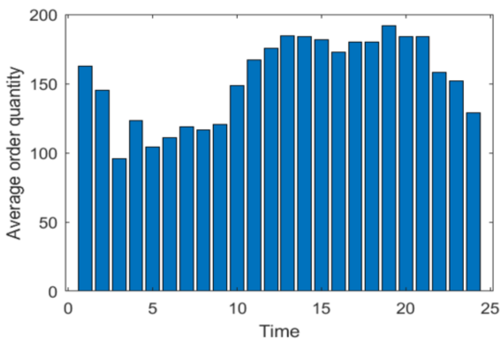

Figure 1. Average daily order quantity.

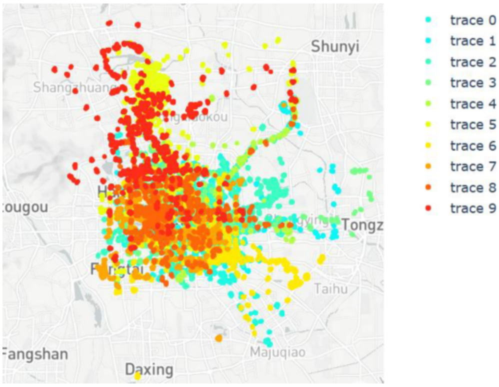

Figure 2. Track points of 10 electric taxis.

A two-dimensional matrix is established to count the data of passengers getting on and off, and the value of the matrix indicates the number of passengers getting on and off. Latitude and longitude are divided by 0.01. Select the corresponding color according to the weight of passengers getting on and off, and draw the map of passengers getting on and off stations at all times, as shown in Fig.3-Fig.4.The darker the color, the more passengers get on and off at this point.

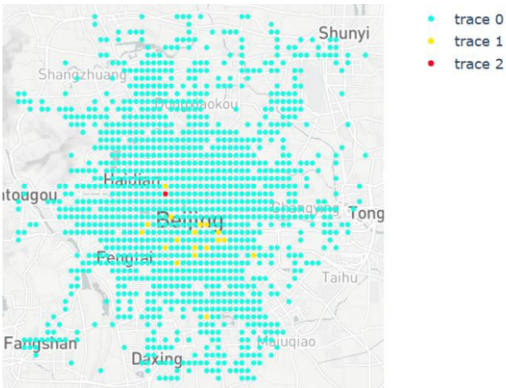

Figure 3. Distribution map of passenger boarding points.

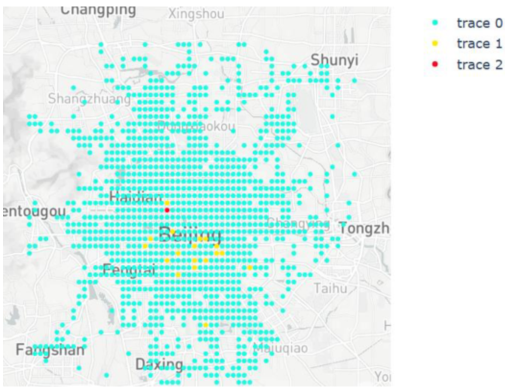

Figure 4. Distribution map of passenger drop-off points.

Divide the study area according to the interval of 0.01 degrees. According to statistics, there are 3150 nodes. There are 33304 OD pairs. Table 2 is a partial example of the edge matrix, where Source is the boarding point. Target is the drop point. Trip is the weight value, that is, the traffic volume from the starting point to the end point.

Table 2. Edge matrix

Source	Target	trip
0	6	1.0
1	7	1.0
1	8	2.0
...	...	...

Table 3 is a partial example of the node matrix. Long indicates the node longitude, Lat indicates the node latitude, and id indicates the node serial number in the OD pair.

Table 3. Node matrix

Long	Lat	id
113.36°	39.69°	0
113.37°	39.69°	1
...	...	...

In order to see the change of the weight value in OD alignment more intuitively, Fig. 5 is drawn according to the weight trip column of the Edge matrix in Table 2.

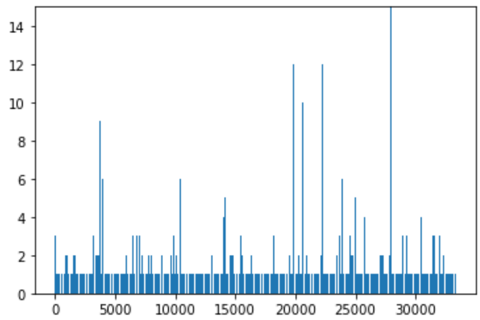

Figure 5. The change of OD to weight value.

Next, the degree of each node of the travel network is analyzed. Because the image is a directed graph, the distribution of in-degree, out-degree and degree is drawn.

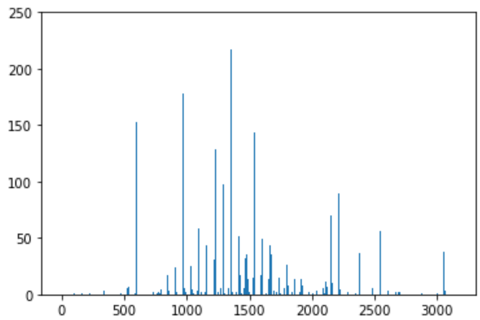

Figure 6. Weight distribution of node progress.

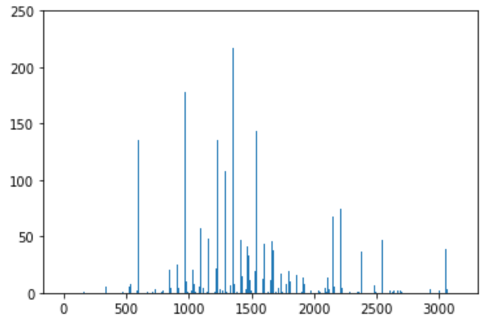

Figure 7. Weight distribution of node outcomes.

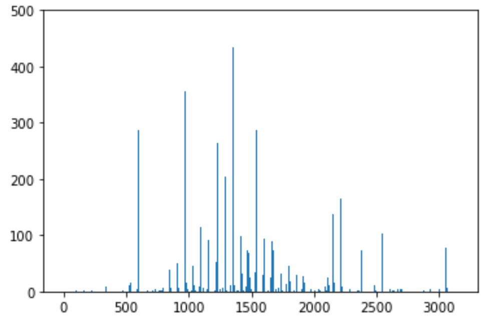

Figure 8. Weight distribution of node degree.

As can be seen from the above figure, hot spots are mainly concentrated between node 1000 and node 1500, regardless of the in-degree, out-degree or degree of nodes. Generally speaking, the traffic flow of electric taxis in the downtown area within the city limits is a little larger.

Monte Carlo simulation is used to simulate the daily travel and charging activities of electric taxis, and the demand distribution is counted according to time-location respectively. The number of electric taxis set in this paper is:100. Divide the research area according to 0.05 degrees to determine the charging demand grid.

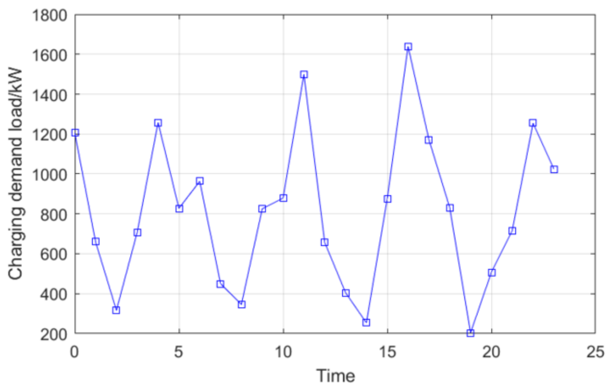

Figure 9. Charging demand load.

It is not difficult to see from Fig. 9 that the demand for fast charging of electric taxis is unbalanced in time distribution. Multiple charging load peaks occur in one day. And at 16: 00, the charging demand load reaches the daily maximum.

In order to better understand the load changes of different grid demand points with time, we have conducted a deeper analysis. Fig. 10 shows the changes of the charging load of 130 grid points of charging demand in one day, from which it can be seen that the charging load of the grid point located in the city is much greater than that in other areas. And the closer to the city center, the greater the demand for charging load.

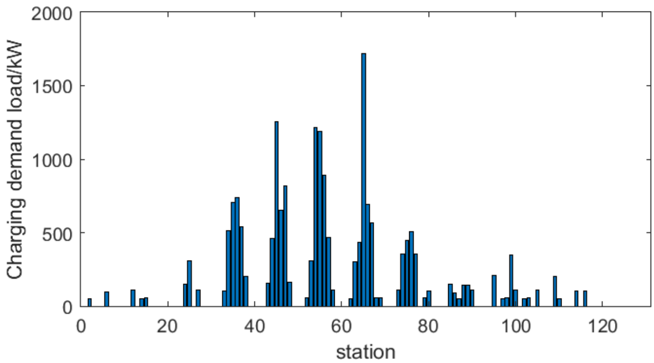

Figure 10. Charging load of 130 grid demand points.

According to statistics, there are 60 grid points with charging events among 130 charging demand points. The specific locations of these sites are shown in Fig. 11. Through simulation and analysis, these potential hot spots of charging demand are found, and charging stations can be planned and built here, which can effectively meet the charging needs of users. The black circle in Figure 11 shows the location distribution of a certain brand charging station in the research area. The green circle is the predicted hot spot of charging demand. On the whole, no matter the actual distribution of charging stations or the predicted results, the charging demand is concentrated in the central area of the city. The closer to the center, the more charging stations there are, and the greater the charging demand is.

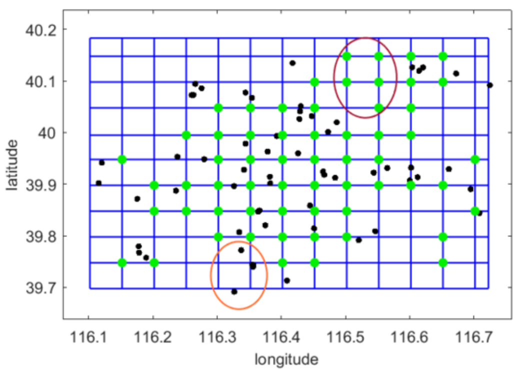

Figure 11. Location distribution of 60 grid points with charging events.

In some local areas, the actual construction location of charging stations is inconsistent with the predicted results. For example, the red circle is mostly a hot spot for charging demand, and no actual charging station is built in the red circle. In the orange circle, most of them are actually built charging stations. Too many charging stations are concentrated in a narrow area, which is not conducive to improving charging efficiency. Therefore, in the subsequent construction of charging stations, we can refer to the location distribution of charging demand hotspots.

At the same time, we also made an in-depth analysis of one of the grid points. Fig. 12 shows the change of charging demand load at grid point 65 in one day.

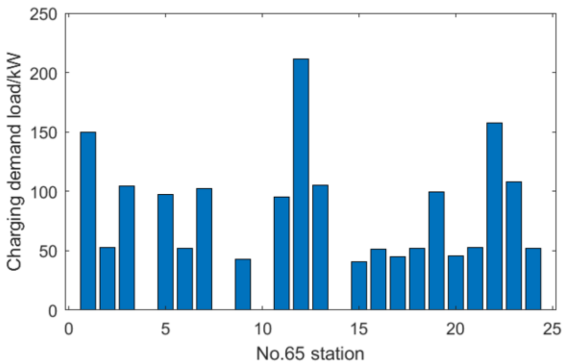

Figure 12. The change of charging demand load of grid point 65 in one day.

5. Conclusion

This paper mainly studies the temporal and spatial distribution and site selection of electric vehicle charging demand prediction. Through the travel data, three parameters involved in the realization of charging demand prediction are described emphatically: initial travel time, charging duration and charging state. The travel characteristics of users and the charging characteristics of vehicles are analyzed by using OD travel matrix. Simulate the process of electric vehicle charging demand, obtain the time and space distribution of electric vehicle charging demand, and analyze the charging load of each charging station. When it is necessary to build a new station, priority can be given to building stations in these hot spots of charging demand.

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