Charging Demand Forecasting Method Based on Historical Data

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Abstract: This paper discusses a method for predicting the demand for charging using transaction data combined with data on the growth of the number of electric vehicles. The prediction result of charging demand can be used as an important reference for charging pile planning. The needs of electric vehicles can be divided into three different scenarios, night scenes, work scenes and entertainment scenes. In each scenario, we used Clark's negative exponential equation to describe the distribution of charging demand in space.

1. INTRODUCTION

Electric vehicles have good energy conservation and pollution reduction characteristics, and have become the development direction of the international automotive industry. According to the International Energy Agency (IEA) report, the number of electric vehicles in the world has reached 3.1 million in 2017, and will triple by 2020. It is expected to reach 125 million in 2030 [1]. Among them, China is the world's largest electric vehicle market, accounting for 40% of the world in 2017. The rapid growth of electric vehicles has a great impact on the planning and construction of electric power grids. Accurate estimation of electric vehicle charging demand is an important basis for electric vehicle charging infrastructure construction.

Charging of electric vehicles has a lot of space and time randomness. The quantity of electric vehicles, the type of electric vehicles, the charging and discharging characteristics of batteries, and the initial state of charge (SOC) in a given area are all the factors affecting the charging load of electric vehicles. The current forecast for charging load of electric vehicles mainly includes simulation method based on the Monte Carlo, prediction method of charging load of electric vehicles based on the short-term load forecasting method of the power system, and other methods. The effect of different factors on charging behavior is modeled based on the Monte Carlo simulation method and the influence of various factors on the charging demand can be compared through simulation. [2] This paper mainly analyzes the influence of different types of electric vehicle models, different charging power, different permeability, different charging scenarios. [3] This paper mainly analyzes the impact on electric vehicle charging scale and SOC on charging demand. [4] This paper considers the different effects of electric vehicle type and charging method of charging to demand. Due to the complexity of electric vehicle charging in the actual environment, the Monte Carlo simulation method requires a certain degree of simplification of the model. For example, [5] only considers two types of electric buses and electric...
private cars in the analysis; [6] modeled the power-changing mode, considering the strategy of orderly charging, but did not distinguish different requirements between fast charging and slow charging; [11] considered four models of buses, taxis, official cars, and private cars. Another type of method is based on historical charging data for electric vehicles, using traditional predictions of mathematical tools or related prediction methods that combine artificial intelligence. [7] Utilizes charging data for electric cars and buses as well as traffic data and weather data. [8] Use the method of data mining. It must be pointed out that the current work on the demand for electric vehicles is mostly focused on analyzing the total amount of electric vehicle charging and the distribution characteristics during the day. In the charging infrastructure, on the other hand, the key data are the prediction of the distribution of charging demand in space, and the work in this area is relatively insufficient.

In order to promote the development of charging vehicles, China has already carried out preliminary layout and construction of charging piles around 2007. In this process, the charging pile company has accumulated a large amount of relevant data, including charging pile cost, charging amount of electric vehicles, charging time of electric vehicles and other data. This paper establishes a prediction model of electric vehicle charging demand distribution based on population density distribution, and combines the actual situation of electric vehicle operation which divided into different scenarios, and uses the historical data of charging transaction to determine the parameters of the model, so as to predict the distribution of charging demand.

2. DEMAND DISTRIBUTION MODEL BASED ON POPULATION DENSITY DISTRIBUTION

2.1 POPULATION DENSITY DISTRIBUTION MODEL

Urban geography studies have shown that urban population distribution is regular: population density decreases with distance from the city center which could be described by the famous Clark negative exponential equation [9]

\[ D_r = ae^{-br} \] (1)

In the formula, \( D_r \) is the population density at point distance to the city center (usually the central business district, is CBD) \( r \); \( a \) and \( b \) are constants \( (a \) also known as the CBD intercept, which is positive; \( b \) is the density drop slope, generally Negative value). Actual data from different cities also validate the universality of this equation. In reference [9], data from Beijing and Chicago were compared. Although the population and geographical area of the two cities has a large gap, the population density is consistent with the Clark negative index equation. This reflects the orderliness within the city.

2.2 CAR DISTRIBUTION MODEL

The use of electric vehicles depends on the distribution of the population, and the more people there are, the greater the number of electric vehicles. Assuming that the electric vehicle ownership rate is proportional to the population density, the population density distribution model can be used to describe the distribution model of the electric vehicle. Further, if the difference in charging characteristics of different electric vehicles is not considered, the distribution model of population density can be used to approximate the distribution of charging requirements of electric vehicles.

Usually, the determination of the population density is determined according to the distribution of the house. In contrast, the mobility of the electric vehicle needs to be considered in the prediction of electric vehicle charging. According to the characteristics of people's travel, different locations could be chosen for electric vehicles charging. According to the law of human behavior, charging behavior can be divided into several large scenes. Each scenario needs to be described using a modified population density model.

2.2.1 DIFFERENT SCENES OF ELECTRIC VEHICLE CHARGING

The use of electric vehicles has different characteristics depending on different scenes. This section will analyze several typical scenarios to get the charging requirements of different scenarios.

(1) Night scene
The night scene mainly refers to the evening after work. During this time, the vehicle usually stays in the parking lot near the house. The charging car needs to be charged around the user's house. The charging lasts until the next day. In the night scene, the distribution of charging demand is close to the distribution of population density, which can be described by the population density distribution equation.

(2) Work scene
The work scene mainly refers to the time between the morning start work and the evening off work. During this period, the vehicle usually stays in the parking lot near the unit. The charging car needs to be charged around the user's house or unit, and the charging lasts until the off work. Unlike the night scene, the center of the population distribution has changed, and the center of population distribution has become a work-related area.

(3) Holiday scenes
The holiday scene mainly refers to the weekend, and the time of the statutory holiday. During this time, there will be a lot of vehicles going to attractions, shopping malls, users of electric vehicles can choose to charge around the user's house, or they may choose to charge in attractions, shopping malls, etc. Charging time is usually short. The centers of the population distribution become the area of entertainment and attractions.

3. FORECAST OF ELECTRIC VEHICLE CHARGING DEMAND

3.1 Forecast of ownership of various types of electric vehicles
In order to obtain the total amount of electric vehicles in the future, it is possible to predict based on historical electric vehicle quantity data [10]. However, it should be pointed out that due to changes in national policies, predictions that rely solely on historical data will give relatively conservative results. More reliable sources of data should be related cities’ white paper on electric vehicle planning.

3.1.1 Forecasting Process
Different cities have different typical scenes for electric vehicle applications due to different positioning. For example, some cities have more typical entertainment and leisure areas, while others do not have concentrated entertainment and leisure areas. The former has a typical entertainment and leisure scene of electric car charging, while the latter type of city does not have a typical entertainment and leisure scene of electric car charging. Therefore, in practical applications, it is first determined according to the actual data of the city. After determining the typical charging scenario of an electric vehicle, it is necessary to determine the parameters in each scene based on the historical transaction data of the electric vehicle, that is, a and b in the Clark negative exponential equation. Finally, the distribution of demand forecast for electric vehicles is calculated according to the equation. Process Figure is shown in Figure 1.
Fig. 1 Forecast flow chart

3.1.2 Case Analysis
Table 2 shows the distribution of permanent residents in various districts of Hangzhou issued by Hangzhou Statistics Bureau at the end of 2017. According to the data in the table, Jianggan District and Xihu District have significantly more population than neighboring regions. This is in line with the characteristics of these two regions as the core area of the city. For comparison, the historical transaction data of the charging pile was statistically analyzed as follows. The entire city of Hangzhou is divided into square meters of 500 meters by 500 meters. Through the historical transaction data of electric vehicles, the total electric vehicle charging amount calculated in each grid is calculated. Since the number of charging piles is limited and only exists in part of the grid, in order to obtain the charging demand of each grid, it is necessary to establish a linear mapping from the charging pile space to the grid space for the charging transaction. The charging transaction which occurs on the charging pile is assigned to the surrounding grid, and the specific allocation scheme is as follows.

Grid is expressed $G_i$, $i = 1, 2, \ldots, m$, $C_j$ for charging piles, $j = 1, 2, \ldots, n$. The proportion of charging demand of grid $G_i$ satisfied by charging pile $C_j$ is $a_{ij}$, there are:

$$\sum_{j=1}^{n} a_{ij} = 1, \quad j = 1, 2, \ldots, n$$  \hspace{1cm} (2)

use $E(C_j)$ representing the charging amount of charge pile $C_j$, use $E(G_i)$ representation the charging demand of grid $G_i$, there are:

$$E(C_j) = \text{sum}(E(G_i) \ast a_{ij}), \quad i = 1, 2, \ldots, m$$  \hspace{1cm} (3)

| year | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2020 |
|------|------|------|------|------|------|------|------|
| Motor vehicle ownership (10,000 units) | 95 | 110 | 124 | 126 | 234 | 244 | 318 (E) |
| New energy vehicle ownership (10,000 units) | 1.9 | 2.19 | 2.4 | 3.4 | 5 | 7.5 | 23 (E) |
Write the above formula form as a matrix:

\[
E(C) = \begin{bmatrix}
a_{11} & a_{12} & \cdots & a_{1n} \\
a_{21} & a_{22} & \cdots & a_{2n} \\
\vdots & \vdots & & \vdots \\
a_{m1} & a_{m2} & \cdots & a_{mn}
\end{bmatrix} \times \begin{bmatrix}
E(G)
\end{bmatrix}
\]

\[
= A \times E(G)
\]

(4)

Where A is an n*m order matrix and is usually m>>n.

After the matrix A is determined by prior knowledge, the charging transaction occurring on the charging pile can be distributed to the surrounding grid by formula (4), that is: \( E(G) \) is got form \( E(C) \):

\[
E(G) = A^{-1} \times E(C)
\]

(5)

among them, \( A^{-1} \)Can substituted by Pseudo-reverse of \( A \), that is:

\[
E(G) = [A^T \times (A \times A^T)^{-1}] \times E(C)
\]

(6)

The total electric vehicle charging amount generated in each grid divided by Hangzhou is shown in Fig. 1.

The comparison found that the maximum amount of charge appeared in XiHu district, which is consistent with the population density shown in the table. Comparing the charging history data with the Hangzhou city data, it can be seen that Jianggan District and Xihu District show two different electric vehicle scenes.

**TAB. 2 DISTRIBUTION DATA OF PERMANENT RESIDENTS IN HANGZHOU AT THE END OF 2017**

| area                  | Uptown | Downtown area | West Lake District | Gongshu District | Jianggan District |
|-----------------------|--------|---------------|--------------------|------------------|------------------|
| Population (10,000 people) | 34.8   | 53.1          | 83.1               | 56.2             | 77.2             |

Fig. 2 The total charging power distribution of electric vehicles in the area (the abscissa is the longitude and the ordinate is the dimension)
4. CONCLUSION
The initial construction and operation of the charging pile accumulated a large amount of electric vehicle charging transaction data. This paper discusses a method for using the transaction data to combine the data of the increase of the number of charging vehicles to predict the charging demand. The prediction result of charging demand can be used as an important reference for charging pile planning. We divided the demand for electric vehicles into three different scenes, night scenes, work scenes and entertainment scenes. In each scenario, we used Clark’s negative exponential equation to describe the distribution of charging demand in space.

REFERENCES:
[1] https://www.iea.org/media/topics/transport/Global_EV_Outlook_2017_Leaflet.pdf
[2] Li Jianxiang (2013) Research on Modeling Method of Electric Vehicle Charging Demand Load. Building Electric, 32, 45-48.
[3] Clement, K., Haesen, E. and Driesen, J. (2010) The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. IEEE Transactions on Power Systems, 25, 371-380
[4] Soares, FJ, Lopes, JAP and Almeida, PMR (2010) A Monte Carlo method to evaluate electric vehicles impacts in distribution networks. In: Proceedings of IEEE Conference on Innovative Technologies for an Efficient and Reliable Electricity Supply, IEEE, Waltham, 365-372.
[5] Jing Zhaoxia, Zhong Tongke, Lin Zhilong, et al (2013) The impact of electric vehicle charging behavior on grid load curve. China Southern Power Grid Technology, 7, 80-84.
[6] Luo Zhuowei; Hu Zechun; Song Yonghua; Yang Xia; Zhan Yu; Wu Junyang; Electric vehicle charging load calculation method[J]; Automation of Power Systems; 2011, Issue 14
[7] Mariz B. Arias, Sungwoo Bae, Electric vehicle charging demand forecasting based on big data technologies, Applied Energy, Volume 183, 1 December 2016, Pages 327-339
[8] ES Xydas, CE Marmaras, LM Cipcigan, AS Hassan, N Jenkins, Electric Vehicle Load Forecasting using Data Mining Methods, Hybrid and Electric Vehicles Conference 2013 (HEVC 2013), IET
[9] Wang Fahui, Liu Yu, Wang Wei, Transportation Network and Urban Structure Research——Theoretical Framework and Empirical Cases in China and the United States, Progress in Geography, October 2014
[10] Zeng Ming, Zeng Fanxiao, Zhu Xiaoli, Xue Song, China's electric vehicle ownership forecast based on Bass model, China Electric Power, January 2013
[11] Pan Huan, Qiao Wenjuan, Li Nan, Modeling and Simulation of Electric Vehicle Charging Load Forecasting Based on Monte Carlo Simulation, 2014, 3, 83-91