Research on Charging Load Modeling and Influence on Distribution Network of Household Electric Vehicle

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Abstract. The impact of large-scale access of electric vehicles on the power distribution network of electric power systems has become increasingly prominent. To solve the problems brought by electric vehicle charging to the distribution system, it is particularly important to predict the charging load of electric vehicles. Based on the travel chain theory, this paper models the charging demand of household electric vehicles. Considering the uncertainty of charging demand in space and time, combined with the Monte Carlo method, taking the typical IEEE33 node power distribution system as an example, this paper simulates the impact of electric vehicle charging load access on the distribution network under different penetration rates and different access modes. The research results show that the charging load of household electric vehicles is usually concentrated in residential areas, and the impact on the overall load characteristics of the distribution network and the node voltage offset is more significant as the penetration rate of electric vehicles increases.

Introduction

In recent years, electric vehicles have become more and more recognized by the public because of their energy-saving and environmental-protection characteristics. These have led to the expansion of the scale of electric vehicles, and in the same time the proportion of household electric vehicles has gradually increased. However, the charging load of electric vehicles has a great randomness, and the charging demand that comes with it is bound to increase, which has an impact on the reliability of the distribution system. Therefore, how to effectively establish the charging model of household electric vehicle charging load is of great significance.

In the research on the demand forecasting of electric vehicle charging, some scholars propose a charging load modeling method based on the distribution of vehicle operation possibilities [1-2]. Some studies combined with the foreign traffic department's household vehicle survey data for travel research [3-4], and simulated the time distribution curve of electric vehicle charging power. In order to further analyze the spatial distribution characteristics of users during the travel process, scholars have proposed to use the travel chain model to study the spatial and temporal distribution of electric vehicles during their daily driving, to construct the simple and complex chains of the daily travel of the owners, and to propose a consideration for driving. Time and route of electric vehicle charging demand forecasting method [5].

In this paper, the electric private car is taken as the research object. Considering the spatial and temporal random distribution characteristics of electric vehicle travel, a method based on the travel chain model for electric vehicle charging demand prediction is proposed. Then, combined with the typical distribution system structure, considering the impact of the charging load of electric vehicles with different penetration rates, quantitative research on the impact of the distribution network on electric vehicles is carried out.
Modeling and Analysis of Charging Load Based on Travel Chain Theory

Study on the Concept and Characteristics of the Travel Chain

The charging load of electric vehicles is closely related to the daily travel of users. The analysis of the travel rules of electric vehicles is the basis of simulating the charging load. The travel chain refers to the form which individuals’ daily driving activities are connected in a certain time sequence [6]. It is generally used to describe the process of returning home after the user has finished the activity and come back home. It is mainly composed of a time chain that characterizes the time distribution and a spatial chain that characterizes the spatial distribution.

The characteristics of household electric vehicles travel are more complicated. In the study, residential areas are used as the starting point in daily travel. The purpose of travel is divided into five categories according to functional areas, including residential areas (Home, H) and work areas (Work, W), Commerce District (Commerce, C), Recreation Area (Recreation, R) and other areas (such as picking up others, going to school, going out for medical care, etc.) (Other, O). According to the number of parking nodes, the travel chain can be divided into two modes: simple chain and complex chain. As shown in Fig. 2, the single-purpose travel mode is called simple chain while the multi-purpose travel mode is called complex chain [5].

Since the feature quantities under different conditions have different distribution characteristics, different probability functions are used for parameter fitting. Firstly, starting from the distribution of the time feature quantity that constitutes the time chain, and focus on the distribution of the first travel time, parking time and mileage. The above feature quantities are greatly affected by the spatial distribution.

(1) First travel time

This paper uses the National Household Travel Survey (NHTS2017) as the data base. From the data distribution of the first travel time from the home, it uses the generalized extreme value distribution to fit and has a good fit effect. The probability function of the generalized extreme value distribution is shown in equation (1).

\[
f(t | \mu, \delta) = \frac{1}{\delta} \cdot e^{\left(-\frac{t-\mu}{\delta}\right)^\tau} \cdot \left(1 + k \cdot \left(\frac{t-\mu}{\delta}\right)^{\frac{1-\tau}{\tau}}\right)^{-\frac{1}{1-\tau}} \quad (k \neq 0)
\]

Wherein, respectively, \( t \) standards for the starting time which is setting out home; \( k \) standards for the shape parameter for determining the overall distribution; \( \mu \) standards for the positional parameter for determining the overall distribution maximum value; and \( \delta \) standards for the scale parameter.

(2) Parking time

The total parking time is greatly affected by space. This paper used the generalized extreme value distribution for fitting the parking time in residential areas, commercial areas, leisure areas and other areas. While the parking time in the working area is distributed and presents multi-peak distribution. Therefore, a feature quantity distribution with an unclear distribution pattern can be described for it.
This distribution is usually fitted by a multi-dimensional Gaussian mixture distribution, and the Cumulative distribution function is as shown in equation (2).

\[
f(t | \alpha, \mu, \sigma) = \sum_{j=1}^{n} \frac{\alpha_j}{\sigma_j \sqrt{2\pi}} e^{-\frac{(t-\mu_j)^2}{2\sigma_j^2}}
\]  

Where \( \alpha \) is the proportion of the Gaussian component; \( \mu \)、 \( \sigma \) are the parameters of the Gaussian component.

(3) Mileage

The distribution of the mileage distribution with different starting and ending is highly consistent with the lognormal distribution, hence the lognormal distribution is used for fitting the different mileage conditions.

(4) Space transition probability

Based on the randomness of spatial distribution in daily travelling, this paper uses Markov chain theory [7] to connect different user’s travel destinations with certain timing. This paper uses \( p_{s_{i-1}} \) to indicate the transition probability for the point \( S_i \) to the next point \( D_i \). Finally, the space transfer matrix of different time periods is obtained, as shown in Equation 3.

\[
\begin{bmatrix}
p_{s_{i-1}}(t_s) & \cdots & p_{s_{i-1}}(t_n) \\
\vdots & \ddots & \vdots \\
p_{s_{i-1}}(t_n) & \cdots & p_{s_{i-1}}(t_n)
\end{bmatrix}
\]  

Through the analysis of the above-mentioned different types of spatiotemporal features, the temporal and spatial distribution of the travel process is obtained. The probability density function obtained by fitting is combined with Monte Carlo method to simulate the traffic volume model of electric vehicles.

Modeling of Electric Vehicle Charging Load

Based on the above analysis of the characteristics of electric vehicle travel, this article models the charging load of household electric vehicles. Firstly, simulate the travel characteristics of a single electric vehicle under different travel conditions. Secondly, judge and make a charging decision according to the power demand in the future travel process after each stop. At the same time, the charging mode is selected according to the parking time of the current position, and the charging load of the single electric vehicle is calculated. Finally, the charging demand generated in the corresponding area is superimposed according to the charging time, and the charging load aggregation curve in different spaces is obtained. The specific modeling process is as follows:

(1) Energy consumption model during driving of electric vehicles

Ignoring the influence of external factors on power consumption, the energy consumption and mileage of electric vehicles are regarded as linear. The power consumption in the journey can be calculated by mileage and average power consumption per kilometer. The state of charge (SOC) of the battery when reaching the destination \( D_i \) is updated according to equation (4).

\[
SOC = \frac{1}{B_{ev}} \cdot (E - s \cdot e_0)
\]  

In the above Equation, \( e_0 \) represents the average power consumption per kilometer during the driving of the electric vehicle, in kilometers per hour; \( E \) is the remaining capacity of the electric vehicle when reaching the destination; \( SOC \) is the state of charge of the electric vehicle battery; \( Bev \) is the battery capacity of an electric car.

(2) Charging decision model considering the impact of travel demand and parking time adequacy

In most cases, the key to the user’s judgment on whether the electric car needs to be charged is affected by the travel demand. The user calculates the travel mileage and the required power in advance, and determines whether the current remaining power or the state of charge of the battery can meet the travel demand.
While considering the user's travel demand, the problem of the user's long-term parking time in different areas is studied, and the charging mode is determined according to whether the parking time is sufficient or not. When the length of parking meets the length of time required for charging, in order to reduce the impact on battery life, such users use slow charging; if the parking margin of such users is insufficient, the power after the end of the parking time is not satisfied with future travel. Such users become emergency users and need to use fast charging to meet the power demand in a short time.

\[ P_{di} = \begin{cases} 
scP_{di} & \text{if } pt_{di} \geq sct_{di} \\
fcP_{di} & \text{if } pt_{di} < sct_{di} 
\end{cases} \]  

(5)

In the equation, \( P_{di} \) is the charging power selected by the user in the area \( di \); \( sct_{di} \) is the charging time required when the slow charging is used in the area \( di \); \( scP_{di} \) and \( fcP_{di} \) are the slow charging and fast charging power of the regional charging station, and the unit is kW.

(3) Electricity replenishment model

By interactively analyzing the travel characteristics of the electric vehicle and the charging demand, the charging load distribution of the electric vehicle in different regions can be obtained. The charging process of the electric vehicle battery is regarded as constant power charging, and the queuing time at the time of reaching the charging station and starting charging is not considered in the replenishment of the electric quantity, the time of the simulated arrival place is regarded as the starting time of starting the charging. The length of time required for charging is calculated by the charging mode selected by the vehicle state.

\[ ct = \frac{(SOC_{ct} - SOC_{min}) \cdot B_{ct}}{P_i \cdot \eta} \cdot 60 \]  

(6)

After the charging time and the charging power of the single electric vehicle are determined in the area, the charging powers of the plurality of vehicles are superimposed in corresponding charging periods in different regions, and the charging load curves of different regions are obtained.

This paper considers the uncertainty of electric vehicles in time and space, sets up various scenarios according to the difference of electric vehicle access with different penetration rates. In addition, quantitative analysis of the impact of random access of electric vehicles on the distribution system after a typical IEEE33 node power distribution system in different scenarios.

Example Analysis

Parameter Settings

(1) Travel feature study parameter setting

Based on the US Department of Transportation's 2017 Family Travel Survey (NHTS2017) database trippub.xlsx, statistical analysis of travel characteristics was conducted. In this paper, H is set as the starting point and ending point of the trip. The upper limit of the staying node in the travel chain is set to 3, and the electric vehicle can be supplemented when it stays in the four areas of H, W, C, and R. Other areas are only for staying, no charging.

(2) Charging load modeling simulation parameter setting

This paper sets the number of household electric vehicles in a certain area to 40,000; the number of simulations is set to 1000. The electric vehicle battery capacity is uniformly set to 30 kW•h, and the average power consumption per kilometer is 0.21 kW•h/km. A comprehensive charging station with two charging modes is set up in each charging area, and the power parameters are: fast charging and slow charging.

(3) Modeling parameter setting of charging load on distribution system impact study

This paper selects the IEEE33 node typical distribution network system to study the impact of electric vehicle charging load on the power distribution system. The topology structure of the
distribution network system is shown in Figure 5. The system power reference value is set to 10MVA, the reference voltage of the head node is 12.66kV. The parameters are set as follows:

1) Assume that the number of family vehicles in a certain area is 2,000, which are respectively input under the conditions of 0%, 5%, 10%, 15%, and 20%, and calculate the operating parameters of the distribution network.

2) The charging load distributed on each node is calculated as the ratio of the base load of the node to the total amount of the system.

Figure 2. IEEE33 node distribution network system wiring diagram.

Analysis of Results

(1) Analysis of the modeling example of electric vehicle charging load

This paper is based on the MATLAB R2014a and uses the Monte Carlo method to simulate the charging requirements of different regions (the number of simulations is set to 1000). Consider the distribution of charge loads generated by different chain types. Figure 3-4 show the charge demand distribution curves generated by simple chains and complex chains, respectively.

Figure 3. Charging load distribution curve of each area in simple chain travel mode.

This paper makes the charging decision discrimination by considering the extent to which the user's remaining power meets the travel demand. Household electric vehicles have a small range of daily driving mileage, thus most users can meet daily travel needs by charging power in residential areas. The charging demand generated by the commercial and leisure areas accounts for less than 3%, it contributes little to the overall charging load.

Figure 4. Charging load distribution curve of each area in complex chain travel mode.

The distribution of charge load generated in the complex chain travel mode is significantly different from the simple chain charge load, as shown in Figure 4. The distribution characteristics of
load peaks in time are quite different. The peak value of complex chain charging load is generated at 18:00 in the afternoon, which is delayed by 5 hours compared with the peak of simple chain load (generated at 12:51).

(2) Analysis of the effect of large-scale electric vehicle charging load on distribution network

a. Impact on system load characteristics

The overall load level of the system after superimposing the charging load of the electric vehicle and the basic load of the distribution system under different penetration rates is shown in Fig.5.

![Figure 5. Variation of total load of distribution network under different permeability.](image)

| penetration rate | peak load/kW | Peak load time | Minimum load/kW | Minimum load time | valley-to-peak/kW |
|-----------------|--------------|----------------|-----------------|------------------|------------------|
| 0%              | 3715         | 15:00          | 1920.7          | 7:00             | 3700             |
| 5%              | 3818         | 15:00          | 1936.4          | 7:00             | 3803             |
| 10%             | 3920.9       | 15:00          | 1952.1          | 7:00             | 3905.9           |
| 15%             | 4023.9       | 15:00          | 1967.8          | 7:00             | 4008.9           |
| 20%             | 4126.9       | 15:00          | 1983.6          | 7:00             | 4111.9           |

After the electric vehicle is connected, the load peak, valley value and peak-to-valley difference of the system are increased compared with before the access. And with the increase of permeability, the above-mentioned feature quantity has increased. The charging load brings the highest load growth rate of 11.09% to the distribution system while under the 20% penetration rate. For the early morning period when the base load of the distribution network is low, the impact is weak, and the charging load is small during this period.

b. Impact on system voltage level

The load growth effect of the electric vehicle charging load on the distribution system causes the system node voltage to change. As the number of electric vehicle access increases, the system node voltage will also decrease accordingly. If the access volume is too much, it will cause safe operation problems such as voltage crossing.
The access of the charging load will cause the voltage value of the node to decrease, increasing the voltage offset. Figure 6 shows the voltage variation of node 18 at different permeability. In the figure, from 0:00 to 10:00, the voltage of node 18 is basically the same under different permeability. While the voltage amplitude of node 18 is different under different permeability after 10:00 am, the voltage level shows a downward trend with the increase of access volume. And even when the permeability is 20%, the voltage exceeds the limit from 14:00 to 16:00. The vehicle starts charging after ending the journey at 10:00 am, and 15:00 is the peak time after the load is superimposed, which is consistent with the voltage change of the node.

In order to explore the randomness of electric vehicle charging load distribution in time and space, this paper considers the influence of parking time adequacy on user charging mode selection to establish the spatio-temporal distribution model of electric vehicle charging load. Next, by analyzing the impact of the electric vehicle on the distribution system with different permeability scenarios, the penetration rate is defined as the ratio of the number of electric vehicles in the region to the total number of household vehicles.

**Conclusion**

This paper is based on the travel chain theory, combined with the Monte Carlo method, simulates the impact of household electric vehicle charging load access on the distribution network, the following conclusions can be obtained:

1. The travel chain theory can describe the time-space travel process of household electric vehicles well;
2. Considering the electricity consumption of the electric vehicle during driving, establish a charging decision model that takes into account the travel demand and the parking time adequacy, and simulates the charging load of the electric vehicle under the different travel modes of the Monte Carlo method.
3. With the increase of EV penetration rate, the load of each nodule of the distribution system has a significant growth trend with the access of electric vehicles, and the amplitude of the node voltage also decreases. This is even more significant during the peak charging load. In the future, after analyzing the electric vehicle’s access to the grid effectively, it will evaluate the impact of the grid, and the research on the control strategy of the electric vehicle is extremely important.

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