Research on Charging Load Characteristics of EVs Based on Actual Charging Power

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Abstract. With the expansion of the scale of electric vehicles (EVs) and the maturity of fast charging technology and the popularization of fast charging piles, the disorderly fast charging of EVs caused a significant damage on distribution network, the actual charging power of EVs is different from the rated power, the traditional method of using the rated power of the charging pile to forecast the charging load will cause a significant error and affect the dispatching operation of power grid. Based on the actual EV charging curve, this paper establishes a variable power fast charging load model for EVs. The Monte Carlo simulation method is used to simulate the charging load of EV groups. The fast charging loads of EVs with different vehicle types and different battery capacities are compared. The actual variable power fast charging mode of the electric vehicles is compared with the constant power fast charging mode and the slow charging mode, and the charging loads of the three charging modes are significantly different. Finally, the impact of charging load of electric vehicles of different scales on distribution network load is analyzed.

1. Introduction
With the rapid development of the global economy, the problem of global warming and shortage of fossil energy is becoming more and more dangerous. The popularisation of traditional fuel vehicles has been unable to meet the requirements of environmental protection, energy conservation and emission reduction, so it is urgent to develop new energy vehicles. At present, governments around the world have formulated development strategies and introduced new policies to promote the research and development and marketing of EVs [1]. Relevant enterprises actively invest and EV technology rapidly developed.

By the end of 2018, the number of EVs in the world reached 5.4 million, an increase of 64% over 2017. In the whole year of 2018, the global sales of EVs reached 2.01 million, and the share of EVs in the global automotive market reached 2.1%, an increase of 72% [2].

The charging load of EV have a randomness in time and space. The access of large-scale EVs may lead to problems such as increased peak load, partial overload, grid congestion, increased fluctuation and increased investment in distribution networks. It will have a significant impact on the stability of the power grid and the planning and operation of the power system and the operation of the power...
market. On the other hand, EVs can be scheduled and controlled as schedulable loads and energy storage, which can reduce the pressure and improve the reliability of the power grid [3-4].

Therefore, the forecasting and simulation of the charging load of EVs is very imperative. In [5], the existing charging load calculation method is divided into the determination analysis method based on travel demand, the Monte Carlo simulation method and the probability analysis method of charging station charging load, then the three methods were introduced respectively. In [6-8], they use driving pattern data from the National Household Travel Survey (NHTS 2001) to fit the probability density distributions of travel time and daily mileage of household EVs. Then, based on these probability distributions, Monte Carlo simulation is carried out to analyze the charging load of EVs. Literature [9-11] subdivides the types of EVs into buses, taxis, private cars and official vehicles. According to the driving patterns of different types of vehicles, and considering different charging modes such as fast charging, conventional charging and slow charging, the charging load forecasting method of EVs is proposed. In [9], charging time is divided into three types based on the analysis of user behavior, and each factor is obtained by Monte Carlo simulation method. Literature [10,11] proposed several kinds of EV orderly charging control strategies based on peak-to-valley electricity price and considering various user response, which significantly reduced the peak load and peak-to-valley difference of the power grid.

At present, the forecasting of the charging load of EVs is mostly based on the conventional or slow charging mode, and the charging power is assumed to be constant power or evenly distributed within a specific range. Literature [12] proposed that the charging power of EVs changes with time, but its charging power model is only the product of voltage and current, and does not consider the difference between vehicle type and battery capacity, and does not compare the difference of charging loads of EVs with different speeds and the difference of constant power charging and variable power charging. Due to the maturity of EV fast charging technology and the popularization of fast charging piles, EV owners are more willing to adopt fast charging with short time and high efficiency. The disorderly fast charge of the EV will have a considerable impact on the distribution network. Therefore, the accurate simulation and forecasting the real-time charging power of EV, especially in the case of fast charging mode, is of considerable significance to distribution network dispatching and control strategy.

This paper focuses on the fast charging load characteristics of EVs based on actual charging power. Using the data of the charging power of the actual measured new mainstream type of electric vehicles which changes with the battery state-of-charge (SOC), the probability simulation of EVs can be done through Monte Carlo method which extract a single vehicle’s start charging time and mileage. The actual power fast charging loads of EVs with different vehicle types and different battery capacities are compared. And the difference of EVs charging loads with different charging speeds and different scales are compared. The results show that the fast charging load curves are steep more prominent, have more significant peak value and more significant impact on the grid than slow charging load curves; in the case of a small number of EVs, the fast charging mode based on the actual charging curve will not only increase the peak value of the load curve, but also lead to increased load curve fluctuations, and it also have a significant impact on the distribution network scheduling and operation.

2. Factors affecting the charging load of electric vehicles

The charging load of electric vehicles has a high space-time randomness. And different charging load curves will be generated by considering different affecting factors. At present, the following factors affecting the charging load of EVs are mainly considered [13],

- Battery characteristics: Battery capacity, charging and discharging rate, power consumption per 100 kilometres determine the charging time and charging frequency of EVs.
- User behaviour: The driving habits and travel patterns of vehicle owners are another factor that directly affect the distribution of charging time and space and the charging load, while other factors such as weather, temperature, date type and bus scheduling affect EV charging load by influencing user behavior characteristics [14]. At the same time, buses, taxis, private cars, official vehicles and other vehicles of different uses have different charging demands.
• Charging facilities: Power replenishment modes of EVs can be divided into charging mode and electric changing mode, and charging mode can be divided into fast charging, conventional charging and slow charging. The distribution and quantity of charging facilities will affect the spatial and temporal distribution of the charging loads of EVs through users' charging demands and behaviours. Meanwhile, with the proposal and promotion of vehicle-to-grid (V2G) technology, charging facilities with two-way energy flow will become the mainstream [5]. Currently, the Alternating Current (AC) standard is adopted for conventional or slow charging facilities, while the Combined Charging System (CCS) and the Direct Current (DC) standards are adopted for fast charging facilities.

• The scale of EVs: The overall number of EVs reflects the direction of national policies and people's living standards and the development of the market economy.

• Charging control method: This includes policy regulation and market guidance, such as peak and valley electricity price and grid incentive, and regulating the temporal and spatial distribution of charging load of EVs through some charging control strategies.

This paper mainly considers the first four factors. In order to facilitate the establishment of EVs charging load model, this paper gives the following reasonable assumptions:

- The initial charging time and daily driving mileage of each type of EVs are independent variables.
- Charging end marks of all EVs are SOC=1.
- The last return time of all EVs is the initial charging time.

3. Electric vehicle charging power modeling

3.1. EVs starting charging time and daily driving mileage probability modeling

The travel habits and behaviors of private vehicles owners determine the starting charging time and daily driving mileage of EVs. According to the NHTS 2001, 14% of household vehicles are not be used in one day, and 43.5% of the vehicles have a daily mileage of 20 miles (about 32 km), 83.7% of the vehicles have a daily mileage of 60 miles (about 97 km). After the normalisation of the statistical data, the return time of the final journey and daily driving mileage of the vehicles are fitted as normal distribution and lognormal distribution respectively by the method of maximum likelihood estimation. The results are shown in figure 1, figure 2 and equation 1, equation 2.

![Figure 1. Probability distribution of last return time of private vehicles.](image_url)
By comparing the fitting results in figure 1, it can be concluded that the starting charging time of private EVs satisfies the following normal distribution that the expectation \( \mu_s = 17.6 \); standard deviation \( \sigma_s = 3.4 \), and its probability density function is (1):

\[
f_s = \begin{cases} 
\frac{1}{\sigma_s \sqrt{2\pi}} \exp\left[\frac{(x - \mu_s)^2}{2\sigma_s^2}\right], & (\mu_s - 12) < x \leq 24 \\
\frac{1}{\sigma_s \sqrt{2\pi}} \exp\left[\frac{(x + 24 - \mu_s)^2}{2\sigma_s^2}\right], & 0 < x \leq (\mu_s - 12)
\end{cases}
\] (1)

In equation (1), \( x \) is the starting charging time.

By comparing the fitting results in figure 2, it can be concluded that the daily driving mileage of private EVs satisfies the following lognormal distribution that the expectation \( \mu_D = 3.2 \); standard deviation \( \sigma_D = 0.88 \), and its probability density function is (2):

\[
f_D = \frac{1}{y \sigma_D \sqrt{2\pi}} \exp\left[-\frac{(\ln y - \mu_D)^2}{2\sigma_D^2}\right]
\] (2)

3.2. EVs fast charging power modeling

In this paper, based on the test data of FASTEND website [15], the fast charging power curves of three typical EV models (Kia e-Niro, BMW i3, Nissan Leaf) are selected. Charging power curves are shown in figure 3.
According to figure 3, the charging powers of the three types of EVs are approximated fitted as follows:

\[
P_1(SOC_1) = \begin{cases} 
46 & (0 < SOC_1 < 0.7) \\
37 & (0.7 \leq SOC_1 < 0.76) \\
25 & (0.76 \leq SOC_1 < 0.86) \\
-203.4 SOC_1 + 203.8 & (0.86 \leq SOC_1 < 1)
\end{cases}
\]  

(3)

\[
P_2(SOC_2) = \begin{cases} 
-166.3 SOC_2^2 + 75.97 SOC_2 + 38.17 & (0 \leq SOC_2 < 0.35) \\
44 & (0.35 \leq SOC_2 < 0.64) \\
-119.3 SOC_2 + 118.6 & (0.64 \leq SOC_2 < 1)
\end{cases}
\]  

(4)

\[
P_3(SOC_3) = 35.9 \exp\left(-\left(\frac{SOC_3 - 0.08845}{0.2933}\right)^2\right) + 30.79 \exp\left(-\left(\frac{SOC_3 - 0.5758}{0.4345}\right)^2\right)
\]  

(5)

In equation (3)-(5), \(P_1(SOC_1)\) is the charging power of Kia e-Niro with 64kWh lithium polymer battery under 50kW charging pile; \(P_2(SOC_2)\) is the charging power of BMW i3 with 22kWh lithium ion battery under 50kW charging pile; \(P_3(SOC_3)\) is the charging power of Nissan Leaf with 24kWh lithium battery under 50kW charging pile; \(SOC_1\), \(SOC_2\), \(SOC_3\) is the real-time charging state of three types of vehicle batteries.

### 3.3. EVs state-of-charge calculation modeling

\[
SOC_i(t) = SOC_i(t-1) + \frac{P_i(SOC_i(t-1)) \Delta t}{C_i} / 60
\]  

(6)

In equation (6), \(SOC_i(t)\) is the charging state of the \(i\)-th EV battery at time \(t\); \(P_i(SOC(i))\) is the charging power of EVs, which is obtained by the equation (3)-(5); \(\Delta t\) is the unit charging time set in the simulation and its value is 1min; \(C_i\) is the battery capacity of the \(i\)-th EV.

### 3.4. Fast charging time modeling of EVs under actual charging curve

EV charging time model in general constant power charging mode is as follows:
In equation (7), $T_c$ is the length of charging time; $D$ is the daily driving mileage; $W$ is the power consumption of 100 kilometres; $P_c$ is the charging power of a EV.

Due to the change of charging power with SOC under the variable power charging mode, the above charging time calculation equation is no longer applicable. The total charging time length $T_{cc}$ in variable power charging mode needs to be solved by the following equations:

$$\frac{DW}{100} = \int_{0}^{T_c} P(SOC(t))dt$$

Equation (8) is discretized and becomes equation (9). Here $T$ is the time length of EV that has been charged.

### 3.5. Fluctuation index

In order to show the fluctuation of the load, a fluctuation index is proposed here, defined as follows:

$$S = \frac{\max \sum_{i=1}^{m} (maL(i) - miL(i))}{\max(L)}$$

In equation (10), $L$ is the charging load or grid load; $maL$ and $miL$ are local maxima and minima of $L$; $m$ is the quantity of the maxima or minima.

### 4. Charging load simulation of EV group based on Monte Carlo method

The charging load of the EV group samples at a specific time is the sum of the charging powers of all EVs at that time. The equation is as follows:

$$P_\Sigma = \sum_{j=1}^{N_1} P_{j1} + \sum_{k=1}^{N_2} P_{2k} + \sum_{l=1}^{N_3} P_{3l}$$

In equation (11), $N_1$, $N_2$, $N_3$ are the number of samples for the three EV groups respectively.

According to the EVs charging load simulation model in section 3, the Monte Carlo method is used to extract the initial charging time and the daily driving mileage of each samples. The simulation steps are shown in figure 4:
Initial the number of sample number and maximum daily mileage of each EV

Read the charging power curves and the probability density function of starting charging time and daily driving mileage of each EV model

$t=0(T=1440)$

$n=1$ (The total number of the samples is $N$)

Determine the SOC and initial charging time of EV according to the daily driving mileage

According to the charging power characteristics of EV, determine the charging power of the number $n$ vehicle at the $t$ time and record in an $N\times 1$ matrix

$t\geq T$

Yes

$n\geq N$

No

$t=t+1$

$n=n+1$

Add all calculated $N\times 1$ matrices

$n<n$

Yes

Stop the calculation and output the result

Figure 4. Simulation flowchart of charging load of EV group based on Monte Carlo method.

5. Simulation results and analysis

In this section, three types of EVs (Kia e-Niro, BMW i3 and Nissan Leaf) mentioned in subsection 3.2 with typical fast charging power characteristics are the research objects. The maximum mileages of three EVs is 485km, 240km, 250km, and battery capacitances are 64 kWh, 22 kWh and 24 kWh. The difference between the actual fast charging loads of EV groups of different types is compared. And the charging loads difference between different scales and different charging schemes of EV groups are studied. At the same time, taking the typical daily load curve of Shanghai in 2018 as an example, the impact of EVs of different scales on the load curve of the distribution network is studied.

5.1. Comparison of fast charging loads of EVs in three types

In this example, the EVs are divided into three groups, each of which has 10,000 vehicles. The EVs in the same group have the same type, namely the Kia e-Niro, the BMW i3 and the Nissan Leaf. The charging loads of the three EV groups in one day are simulated as follows:

Figure 5. Three types of EV group daily charging loads.
Figure 5 shows that the three charging power curves have significant differences due to the difference in battery capacity and maximum mileage of the three types of EVs. From the battery capacity and maximum mileage of EVs, the power consumption per 100km of Kia e-Niro, BMW i3 and Nissan Leaf can be roughly calculated to 13.34 kWh, 9.17 kWh and 9.6kWh respectively, and the ratio of the three corresponds to the curve height ratio. Therefore, it will cause significant errors without considering the actual EV type and battery difference, and the simulation of this example is more practical for actual grid scheduling and load forecasting.

5.2. Analysis of charging load characteristics of EV Groups under different charging schemes
In order to compare the impact of the charging load of the EVs on the grid load under different charging modes, the three types of EVs are selected in the 1:1:1 mix, and this example calculate the charging loads when using the following three charging modes for 3,000, 30,000, and 300,000 EVs respectively:

(1) Fast charging according to the actual charging curves under the rated 50kW fast charging piles;
(2) Constant speed fast charging with a rated power of 50 kW;
(3) Slow charging with a uniform distributed power between 2 kW and 3 kW.

The charging load daily variation curves of the three modes are shown in figure 6-8.

The results show that:
(1) When the EVs are in slow charging mode with a power uniform distributed between 2 and 3 kW, the charging load curve is gentler, the power fluctuation is smaller, the peak value of the curve is smaller, and the time of occurrence of the peak value is later than that of the fast charging mode.
(2) In the two fast charging modes, the peak-to-valley difference of the charging curve is more considerable, and the short-term power fluctuation is relatively large, especially in the case where the number of EVs is small. Figure 6 shows that when 3,000 EVs are charging, the maximum fluctuation value is 261 kW and the fluctuation index \( S = 18\% \) in mode (1), and the maximum fluctuation value is 648 kW and the fluctuation index \( S = 35\% \) in mode (2).

(3) There are also significant differences in the charging power curve and the maximum charging power in the two fast charging modes. For example, when only 3,000 vehicles are charging, the maximum power difference between the two fast charging modes is 592 kW. When 30,000 vehicles are charging, the maximum power difference between the two charging modes is 2435 kW. When 300,000 vehicles are charging, the maximum charging power of the two fast charging modes differs by 21651 kW. It can be seen that if the constant power charging mode is adopted in the distribution network operation and scheduling to do the simulation and forecasting of the charging power will cause a significant error with the actual value.

5.3. The impact of EVs fast charging load on the distribution network

By the end of 2018, the number of motor vehicles in Shanghai had exceeded 3 million. It is estimated that the increasing number of EVs is expected to exceed 30\% in the next five years. Therefore, this example uses the typical daily load data of Shanghai in the summer of 2018. The three types of EVs are combined in a 1:1:1 mix. A total of 100,000 and 300,000 EVs are added to analysis the impact to the peak load in Shanghai when charging in variable power disordered fast charging mode. The original load and total load during peak load time are shown in figure 9. It shows that after adding 300,000 EVs, the peak value of the distribution network load curve is increased by 70 MW, and the difference is significant. Therefore, it is very important to carry out accurate simulations for specific models and specific charging power characteristics in the study.

![Figure 9. Partial diagram of the typical daily load curve of Shanghai after adding EVs.](image)

6. Conclusion

Based on the actual variable power fast charging characteristics of multi-type EVs, this paper extracts the initial charging time and daily driving mileage of EVs through Monte Carlo simulation method to simulate the actual variable power fast charging load of EVs. The fast charging loads of EVs with different vehicle types and different battery capacities are compared. Moreover, the actual variable power fast charging mode is compared with the rated constant power fast charging and slow charging modes. The results show that when the rated charging power of the EV charging pile is constant, if the charging load of the hybrid EV group is calculated only by the rated power, a significant error will occur. At the same time, the actual variable power fast charging mode has a more significant impact
on the grid than the conventional or slow charging mode, and the actual variable power fast charging load variation law of different EV types are different. Therefore, using the actual power fast charging characteristic curve of different EV types to simulate the charging load of the EV group will improve the accuracy and practicability of various research and analysis.

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