Research on load modelling of new infrastructure of power system-a case study of electric vehicle

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Abstract. The continuous rapid development of new infrastructure load represented by electric vehicles (EVs) has brought new opportunities and challenges to the power system, as well as new propositions for traditional power system load modelling. It is of great practical significance to study the planning and operation of power systems considering EVs and other new infrastructure loads. Based on the analysis of the real historical data of EVs, this paper proposes an EV load modelling method based on the charging power scenario model. Based on the key variables of EV charging, the proposed model considers the joint distribution model of the uncertainty and correlation of the key variables of EV charging. Power scenarios are aggregated to obtain the EV load curve. Finally, the actual EV charging power data is used to verify the effectiveness of the proposed method.

1 Introduction

In recent years, with the rapid development of new infrastructure construction, new propositions have been brought to the traditional power system load modelling. Among them, as an important part of the intelligent transportation infrastructure, electric vehicles have been developed and gradually become a new load growth point. From 2014 to 2019, the global electric vehicle (EV) ownership continued to grow rapidly at an average annual growth rate of 60% [1], and it will become an important mode of transportation to solve problems such as resource shortage and environmental pollution [2].

At the same time, due to the role of EV energy storage, power system regulation ability can be further improved by improving the intelligent level and collaborative control ability of EV charging infrastructure, and strengthening the integration of charging infrastructure with renewable energy, power grid and other technologies [3]. Therefore, EVs are gradually becoming a hot issue in the field of power system optimization, and the problem of EV load modelling has also become an important aspect of future load forecasting.

However, most of the existing studies assumes that the key variables such as the initial charging time, the initial state of charge (SoC), and the end SoC satisfy conventional mathematical distribution models such as Gaussian distribution, Weibull distribution, and Uniform distribution.

Aiming at the disadvantages of the existing studies in the study of EV load modelling, this paper proposes an EV load modelling based on charging power scenarios. First, the key variables that characterize the charge and discharge power curve of EVs are proposed. Then, based on the historical charging data of EVs, the historical data of key variables of EV charging and discharging are obtained, and the probability density function and cumulative distribution function are modelled. The parameters are obtained from the historical data of key variables in the charge of EVs. Finally, based on the key variable model of EV charging, EV power scenarios are generated through inverse transform sampling. The EV load curve based on the EV power scenarios is obtained.

2 Analysis of key variables of EV charging

2.1 Charging start time

The paper analyses the charging data of the first n times (take n=3) each day, and obtains the probability density histogram (PDH) of the charging start time of the n-th charging on weekdays and weekends, as shown in figure 1.

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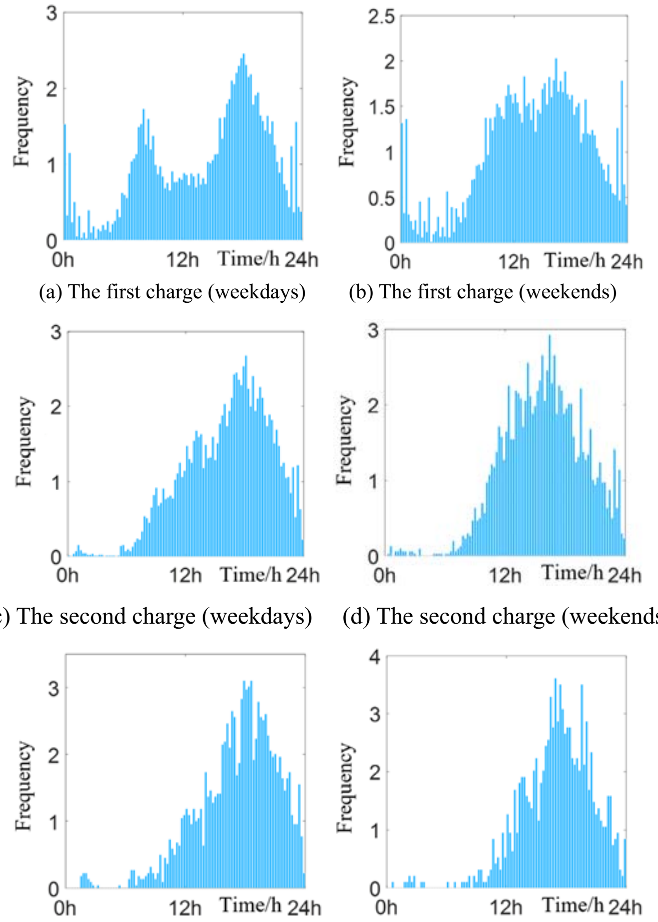

(a) The first charge (weekdays) (b) The first charge (weekends)

(c) The second charge (weekdays) (d) The second charge (weekends)

(e) The third charge (weekdays) (f) The third charge (weekends)

Figure 1. Historical data distribution of EV charging start time.

Overall, the start time of the second charge PDH is more to the right than the first charge. That is, time is relatively late. The start time of the third charge PDH is more to the right than the second charge. Comparing the different characteristics of each charging start time PDH on weekdays and weekends, we can see:

For the first charge, the probability density function of the first charge on weekdays and weekends both presents an obvious "multi-peak" form. This is related to the rest habits of EV users and the charging habits that affect them. During the weekdays, users charge their cars for a limited time in the morning or use other attendance methods after charging in the morning to form a peak in the morning. The user recharges after going home at night, forming a peak at night.

Compared to weekdays, the two peaks of the probability density function of the first charge on weekends are adjacent to each other. This may be because EV users have late work and rest schedules on weekends, or the lack of urgent demand for cars, which results in the (first) charging start time distribution being more scattered than weekdays.

On weekdays or weekends, some users charge before going to bed, thus forming a small peak around the early morning.

For the second and third charges, the shape of the probability density function at the start time of the first charge on weekdays and weekends is relatively simple, which is a "single peak" form. In general, the peak time of the second and third charging on weekends is slightly ahead of the peak time on weekdays. This is because EV users use their cars more frequently on weekends, and will charge the second and third times relatively earlier.

2.2 Charging duration

The charging duration refers to the duration between when an EV is connected to the grid and starts charging until the end of charging. The charging duration is from 0 to the theoretical maximum charging time of the EV. The charging duration PDH of the first, second, and third charging on weekdays and weekends is shown in the figure below:

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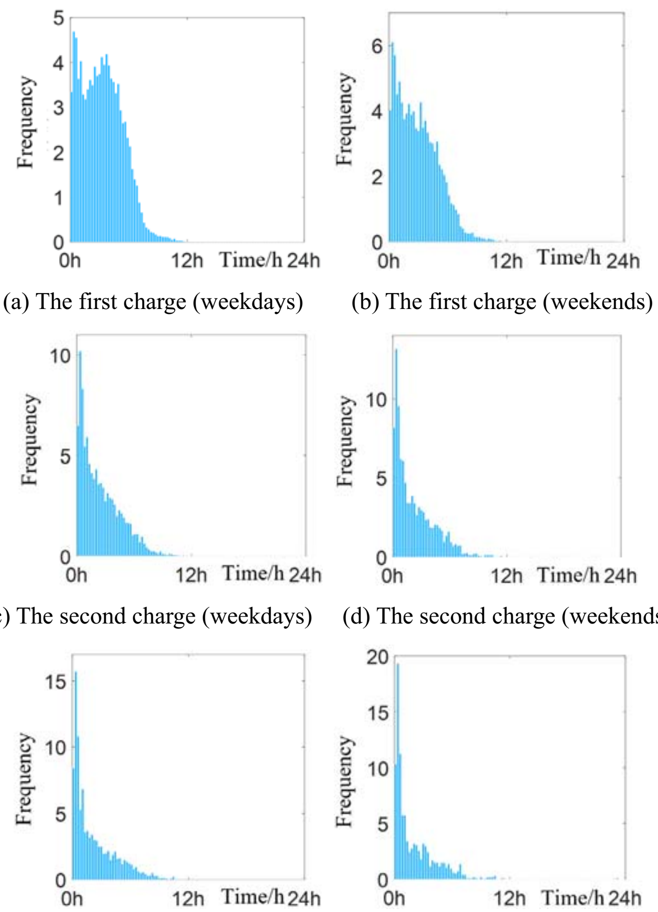


(a) The first charge (weekdays) (b) The first charge (weekends)

(c) The second charge (weekdays) (d) The second charge (weekends)

(e) The third charge (weekdays) (f) The third charge (weekends)

Figure 2. Historical data distribution of charging duration.

It can be seen that, for the charging duration of the first charge, the distribution characteristics of it on weekdays and weekends are quite different. For weekends, the overall trend is that the longer the charging duration, the smaller the probability density. This may be because EV users are eager to use the car on weekends, which leads to a higher probability of charging with a shorter charging duration. For weekdays, there is another peak near the interval of 0.15p.u. to 0.2p.u.. This shows that during weekdays, EV owners have a longer half-weekday charging situation with a continuous charging time of 3.6 to 4.8 hours due to work reasons.

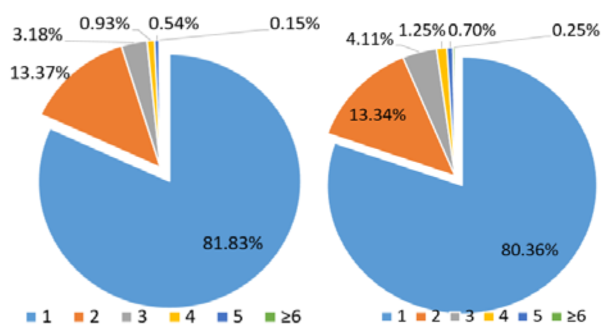
3 Modelling EV load based on key variables

3.1 Analysis of the number of daily charging times of EVs

This paper counts the daily charging of EVs on weekdays (Monday to Friday) and weekends (Saturday to Sunday). The analysis is as follows:

For working days, from the perspective of the number of days with different charging times, the proportions of days with 1, 2, 3, 4, 5, and 5 times or more are 81.83%, 13.37%, 3.18%, 0.93%, 0.54% and 0.15%, respectively. The number of days when the number of charging times is 3 times or less accounts for 98.38%.

For the weekend. The proportions of days with charging times of 1, 2, 3, 4, 5 and more than 5 times are 80.36%, 13.34%, 4.11%, 1.25%, 0.70% and 0.25%, respectively. The number of days when the number of charging times is 3 times or less accounts for 97.80%.



(a) weekdays (b) weekends

Figure 3. Percentage of daily charging times of EVs.

It can be seen that over 97% of the charging records are the first 3 charges of the day, regardless of whether it is a weekday or a weekend. At most 3 recharges occur in more than 97% of the days. Therefore, in the subsequent analysis, in order to simplify the modelling, the charging records of the 4th or more charging are ignored. Assume that there are at most 3 charges per day. Compared to weekdays, the number of EV charging times per day on weekends is relatively high. It is more likely to be charged twice a day and charged three times a day.

By modelling the key variables of the first three charges per day. Based on the scenario generation method, the EV charging power scenarios that obeys the distribution of key variables is obtained. The charging and discharging power of EVs (its own SoC and the charging load from the grid) can be modelled through the scenario generation method.

3.2 Modelling EV load based on key variables

For any EV charging scenario, the load on the grid can be modelled by the above key variables t_{st}^1 , t_{dur}^1 , t_{st}^2 , t_{dur}^2 , t_{st}^3 and t_{dur}^3 (assuming the charging power p_{ch} is known), as shown in Figure 4.

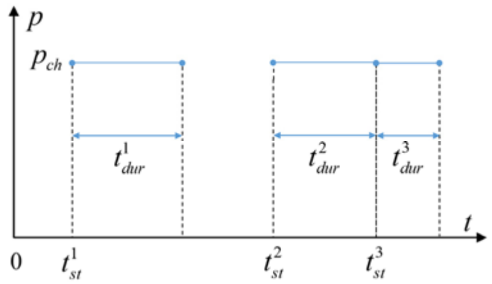


Figure 4. EV load curve of the grid in a day.

As shown in figure 4, the time t and grid load p are the horizontal and vertical axes, respectively. The single EV load modelling is relatively simple. The charging power is the p during the 3 charging period, and the remaining time is 0.

By generating an EV charging scenarios considering six key variables, the EV SoC and charging power can be modelled. Since there is a certain correlation between the key variables in the first, second, and third charging of the EV, it is necessary to consider the correlation of the key variables in the scenario generation. In this paper, the joint distribution method is used to consider the correlation of each key variable, and EV charging power scenarios is obtained through joint distribution sampling.

To simplify the discussion, this paper uses characterization variables $x_1, x_2 ... x_N$, that is, when modelling EV load, $x_1, x_2 ... x_N$ are $t_{st}^1, t_{dur}^1, t_{st}^2, t_{dur}^2, t_{st}^3, t_{dur}^3$ and N=6.

According to Sklar's theorem, for marginal distribution functions, $F_1(x_1)$, $F_2(x_2)$ … $F_N(x_N)$, there is an n-ary Copula function C such that for all $(x_1, x_2 ... x_N) \in [-\infty, +\infty]^N$, satisfies

$$F(x_1, x_2 ... x_N) = C(F_1(x_1), F_2(x_2),\ ...\ , F_N(x_N)) \quad (1)$$

And when $F_1(x_1)$, $F_2(x_2)$ … $F_N(x_N)$ are continuous, the Copula function C is uniquely determined, where $F(x_1, x_2 ... x_N)$ is the joint distribution function of the marginal distribution $F_1(x_1)$, $F_2(x_2)$ … $F_N(x_N)$. Assuming that the total number of variables is N, i=1...N; their respective marginal distributions can be expressed as $F_i(x_i)$, and the marginal distribution of each variable can be obtained through the histogram of historical data.

Based on the Copula theory, the joint distribution cumulative distribution function of all variables can be expressed in the form of the marginal distribution function and the connection function of the respective variables [4], as shown in (1).

Similarly, the joint distribution probability density function of all variables can be expressed as:

$$f(x_1, x_2 ... x_N) = c(F_1(x_1), F_2(x_2),\ ...\ , F_N(x_N)) \cdot \prod_{i=1}^{N} f(x_i) \quad (2)$$

3.3 Modelling EV load of the grid

Based on the joint probability distribution scenario of each key variable of EV charging, the grid load curve of EV can be obtained respectively. By taking the weighted average of the grid load curves of EVs, the grid load curves of EVs can be obtained. By considering the predicted number of EVs in a certain place, that is, multiplying the number of EVs on the basis of the SoC curve of a single EV and the grid load curve of EVs, the SoC curve of EVs in a certain place and the grid load curve of EVs are obtained.

4 Case study

4.1 Data and parameter

4.1.1 Data source

The historical data of EVs used in this paper comes from study [5]. Including the historical data records of each EV charging. The main information includes the charging start time, the charging duration. As mentioned earlier, the model in this paper only considers the first three charges and is modelled according to the 6 key parameters proposed in Section 2.

4.1.2 Model parameters

In this paper, Gaussian Copula function is used to model the joint distribution of key variables in EV charging. For weekdays and weekends, this paper generates 500 EV grid load power scenarios, and weighted average to obtain the EV load curve.

4.2 EV charging load scenario

According to the model proposed in this paper, three charging is considered to generate EV charging load scenarios, and the three scenarios are shown as shown in the figure. Among them, the first scenario (blue) and the second scenario (green) are both one-time charging

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scenarios that occur at night. The difference is that the charging time of the first scenario exceeds 24h. In the third scenario (red), two charges occurred, in the morning and in the evening.

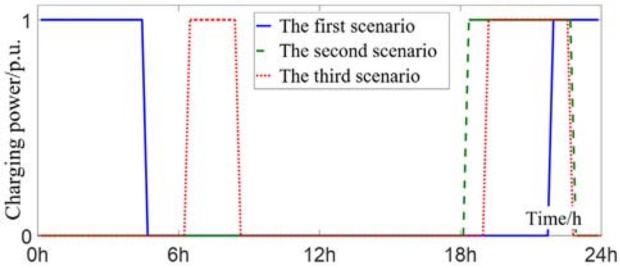
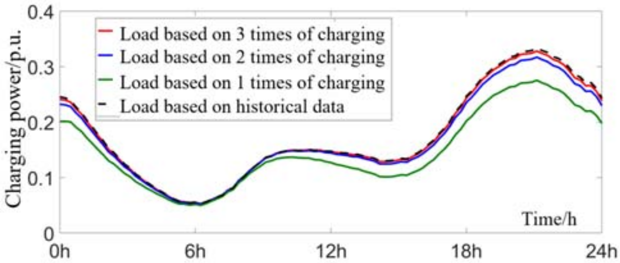


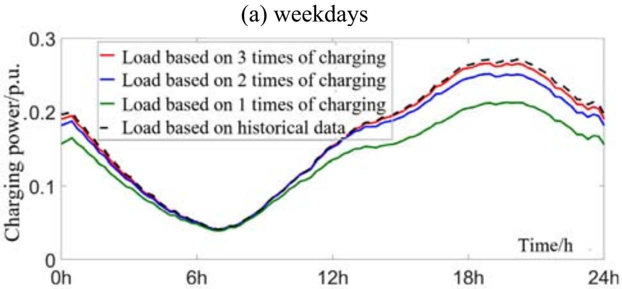
Figure 5. EV grid load scenarios in a day.

4.3 EV load modelling under different charging times

Considering the key variables of three times, two times and one charge respectively, 500 EV daily grid load power scenarios are generated, and the weighted average daily load curve of EVs is obtained, as shown in the figure below. For comparison, based on historical data and considering all charge and discharge times, the EV load curve is obtained as a comparison benchmark.



(a) weekdays



(b) weekends

Figure 6. EV charging load considering different charging frequencies.

As shown in figure 6, when the key variables of three charging are considered, the load model is closest to the load curve based on historical data. When only considering the key variables of two charges and one charge, the load curve will be underestimated to a certain extent, especially during the evening peak period.

Comparing the load curves of EVs on weekdays and weekends, it can be found that in addition to the evening peak charging period on weekdays, there is also a smaller peak during the noon period. This is because users are more likely to commute by EVs in the afternoon on weekdays. At noon on weekends, the load curve decreases in the afternoon on weekdays. Due to the relatively flexible user time on weekends, the shape of the EV load curve is closer to the classic unimodal distribution model, such as the Gaussian distribution.

5 Summary

Based on the key variables of EV charging power, this paper obtains the EV curve scenarios, and further obtains the EV grid load curve. The study found that variables such as the initial charging time and charging duration of EVs have obvious statistical characteristics, and they are different on weekdays and weekends. Considering the key variables of three charging and considering the correlation between the key variables is of great significance to improving the accuracy of the EV charging model.

In the following research, we will further consider the impact of EVs' temporal and spatial distribution and seasonal characteristics on the charging and discharging of EVs, and refine the study of EVs' load models on the power system.

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