Combination Prediction Method of Electric Vehicle Charging Load Based on Monte Carlo Method and Neural Network

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Abstract. In recent years, electric vehicles (EVs) have been widely used. A large number of EVs connected to the power grid will affect the economy and stable operation of the grid. Load prediction of EVs is the basis to solve the above problems. In practical application, the parameters of traditional model are difficult to obtain accurately and the calculation speed is slow. In order to solve this problem, a combination prediction method of electric vehicle charging load based on Monte Carlo method and neural network is proposed in this paper. Firstly, the Monte Carlo model is built to fit the electric vehicle charging load (EVCL) according to the user's behavior characteristics. Then, the neural network is guided by the Monte Carlo model to learn the EVCL under different user behavior characteristics, and the mapping relationship from the basic data to the predicted load is established. Finally, the trained neural network model can realize the EVCL directly and quickly based on the basic data of EVs. The simulation results show that the proposed combined prediction method can realize the prediction of EVCL quickly. It is applicable to the daily total load prediction of large-scale electric vehicle cluster.

1. Introduction
In order to solve the increasingly tense problem of fossil energy and environmental pollution, the development of electric vehicles (EVs) has become an irresistible trend. However, a large number of electric vehicles connected to the power grid will certainly have a huge impact on the reliability, power quality and stability of power system operation[1,2]. To solve this problem, the access amount and fluctuation trend of electric vehicle charging load can be grasped through accurate prediction of electric vehicle charging load (EVCL), so as to arrange orderly charging of EVs to improve the stability of power system.

In this regard, many scholars have conducted full research. In the early stage of the research, EVCL prediction mainly focuses on the simulation of user behavior. Literature [3] considers the impact of road network information on EV driving rules, and uses the travel chain to simulate the random dynamic characteristics of EVs to predict EV charging load. Literature [4] considers the location characteristics of charging behavior and predicts the charging load in a specific area to a certain extent. Although these methods can complete part of the charging load prediction function, it rarely involves the real-time changes of EVCL, and it is uncertain whether it can be applied to the impact of total EVCL on power grid after the mass popularization of EV. In recent years, with the popularity of EVs and the rapid development of deep learning algorithms, the research on load forecasting of electric vehicles has gradually turned to big data. Literature [5] proposed a charging load prediction method for electric vehicles that combines the random forest algorithm with the load data of a single charging
station, divides the characteristic data from different sides. Literature [6] proposed an ensemble method of full wavelet packet transform and neural network for short term electrical load forecasting. Traditional prediction methods rely on accurate data of travel behavior provided by users, which are diversified in form and large in quantity, and have the problem of slow computing speed when dealing with load prediction of large-scale EV clusters. However, the neural network prediction method requires a large amount of historical load information to train the model, and it is difficult to obtain. In order to solve the above problems, a combination prediction method combining Monte Carlo and neural network is proposed. Firstly, the diversified data information of users’ travel behavior is analyzed and processed, and the charging load of EVs is simulated by Monte Carlo method. Then, The load prediction model of sequence to sequence (Seq2Seq) neural network is established. The output of Monte Carlo load simulation is used to guide the neural network to learn data features, and the mapping relationship between multivariate data and EVCL is established. Finally, the trained neural network model is applied to realize the real-time and fast prediction of EVCL. An example is given to verify the rapidity of the proposed prediction method, which is suitable for the prediction of charging load of large-scale EVs.

2. EVCL prediction model based on Monte Carlo

2.1. User behavior

The behavior of users affects the travel behavior of EVs, and the user’s behavior is closely related to their daily living habits. This paper conducts data mining on the results of the National Household Travel Survey (NHTS) in 2017 [7].

2.1.1 Destination of travel. Based on the analysis of the travel purposes of users in the NHTS data set, travel destinations can be divided into five categories: residential area, work area, business area, leisure area and others, which are respectively represented by $A = \{A_1, A_2, A_3, A_4, A_5\}$. User’s behavior is the change of spatial coordinates on a certain time scale, which has a certain randomness. After arriving at the destination, users stop for a period of time, and then start the next trip or end the trip. This kind of continuous random spatial variation can be described by the spatial transition probability matrix. Assuming that the current position is $A_i$ and the travel destination is $A_j$, then the spatial transfer probability from $A_i$ to $A_j$ is expressed as:

$$P(A_i \rightarrow A_j) = P(A_j | A_i) = p_{ij} \quad (1)$$

2.1.2 Initial travel time. The initial travel time of user's behavior is closely related to the initial travel place. According to the statistics of the starting travel places in the data set, it is concluded that more than 90% of the starting travel places are residential areas no matter on weekdays or on rest days. Therefore, when analyzing the travel behavior of users, this paper takes the residential area as the starting travel place. The initial travel time satisfies the multi-dimensional Gaussian distribution:

$$f(t) = \sum_{i=1}^{m} a_i N(\mu_i, \sigma_i^2) \quad (2)$$

In formula (2), $t_i$ is the initial travel time. $m$ stands for dimension. $a_i$ is the weight of the $i$ component. $N(\mu_i, \sigma_i^2)$ is the standard normal distribution.

2.1.3 Mileage of travel. Assuming that the driving duration of a single trip is $t_d$ and $v(t_d)$ is the average speed of this trip. The distance $d$ traveled during this period can be expressed as:

$$d = v(t_d) \cdot t_d \quad (3)$$
According to the law of large numbers and the central limit theorem, it can be approximately considered that the distribution of driving speed satisfies the normal distribution $N(\mu_d, \sigma_d^2(t_d))$ under the condition of $t_d$. In combination with formula (3), it can be known that $d$ satisfies the normal distribution $N(\mu_d(t_d), \sigma_d^2(t_d))$ under the condition of $t_d$, $\mu_d(t_d) = \mu_d \cdot t_d$ and $\sigma_d^2(t_d) = \sigma_d^2(t_d) \cdot t_d$. The probability density function of mileage can be expressed as:

$$f(d) = \frac{1}{\sqrt{2\pi} \sigma_d(t_d)} \exp \left[ -\frac{(d - \mu_d(t_d))^2}{2\sigma_d^2(t_d)} \right]$$

(4)

2.1.4 Parking time. The parking time is related to the travel purpose of the user. According to the classification of different regions, it can be seen from the fitting of the data in the data set that the parking time satisfies lognormal distribution, and its probability density is expressed as follows:

$$f(t_p) = \frac{1}{t_p \sqrt{2\pi} \sigma_p} \exp \left[ -\frac{(\ln d - \mu_p)^2}{2\sigma_p^2} \right]$$

(5)

In formula (5), $t_p$ is the parking time. $\mu_p$ is the expected to park. $\sigma_p$ is the standard deviation of the parking time.

2.2 EVCL prediction model

The state of charge (SOC) of EV battery is usually used to describe the charging demand of EVs. The calculation formula of SOC is as follows:

$$SOC_i = \frac{B_i \cdot SOC_{i-1} - d/t_p}{B_i}$$

(6)

In formula (6), $i$ is the number of trips. $B_i$ is the battery capacity of EVs. $d/t_p$ is the power consumption per kilometer of EVs.

Considering the battery loss and environmental conditions, the initial state of charge of the EV is assumed to be 0.9. After the user finishes each leg of the journey, the SOC of the EV is calculated and a lower limit is set. If the SOC of the current moment is lower than the lower limit, the EV will be charged; otherwise, it will not be charged. After charging, update the SOC value as the starting SOC for the next leg of the trip. The SOC lower limit is set as 0.3.

$$0.3 \leq SOC_i + \frac{P_{Ch}}{B_i} \leq 0.9$$

(7)

$$SOC_{i+1} = \frac{B_i \cdot SOC_i + P_{Ch}}{\eta B_i}$$

(8)

In formula (7), $P_{Ch}$ is the charging power. In formula (8), $\eta$ is charging efficiency.

According to the above analysis of user’s behavior and charging behavior, the Monte Carlo method is adopted to simulate the EVCL[8]. The specific calculation process is shown in Figure 1.
The number of EV is N
Initialize n=1, i=1

Start

The number of EV is N
Initialize n=1, i=1

The nth EV
Select the destination, mileage, and parking time for the ith travel
Simulate travel and calculate SOCi
SOCi \leq SOC_{min}

Y

0.3 \leq SOCi + \frac{Pt}{Ri} \leq 0.9

Y

Charge, and update SOC_{i+1}

Generate and superpose the charging power curve

Is it the last leg of the travel?
n=N

N

n=n+1

i=i+1

End

Figure 1. The flow chart of EVCL prediction based on Monte Carlo.

3 EVCL prediction model based on neural network

3.1 Gated recurrent units
Gated recurrent units (GRU) is used to extract the time correlation characteristics of EVCL. GRU retains the gate structure of LSTM network to control the speed of information accumulation. At the same time, it can selectively forget the accumulated information in the cell state. Moreover, GRU has a fast convergence speed in the training process, and it can achieve similar effects compared with LSTM network[9]. The structure of GRU is shown in Fig.2.

Figure 2. Structure of GRU.
GRU consists of input layer, hidden layer and output layer. The hidden layer includes the reset gate and the update gate. Two gating state information can be calculated through the input of the current node and the hidden state transmitted from the previous node, in which \( r \) represents reset gate state information and \( z \) represents update gate state information.

\[
\begin{align*}
    r_i &= \sigma(W_{rx} x_i + W_{rh} h_{i-1}) \\
    z_i &= \sigma(W_{zx} x_i + W_{zh} h_{i-1})
\end{align*}
\]

In formula (9) and (10), \( W_{rx}, W_{rh}, W_{zx} \) and \( W_{zh} \) are the parameters to be trained. \( \sigma \) represents the Sigmoid function used to normalize gated state information to between 0 and 1 to reflect the degree of retention of memory information.

After the gate signal is obtained, GRU splices the reset gate state information with the current input state information, and then scales the data information to the range of -1 to 1 through a tanh activation function. The hidden state information after the reset is as follows:

\[
\tilde{h}_r = \tanh\left(W_{hx} x_i + W_{hh} r_i h_{i-1}\right)
\]

In formula (11), \( W_{hx} \) and \( W_{hh} \) are the parameters to be trained. Finally, the updated gate state information and the reset hidden state information are used to calculate the new hidden state. The calculation formula is as follows:

\[
h_i = z_i \tilde{h}_i + (1 - z_i) h_{i-1}
\]

The trained GRU network can learn the charge-discharge characteristics of EVs and the characteristics of environmental factors that affect the charge-discharge process, so as to provide time-scale features for Seq2Seq deep neural network model.

3.2 Seq2Seq deep neural network

The neural network model is guided by the output of Monte Carlo model. The Seq2Seq model is trained with user behavior data, and the Seq2Seq model is guided to learn the simulation results of Monte Carlo model for EV charging load. Through the training of the model, the parameters of the neural network are obtained. In the basic training stage, the Seq2Seq model can learn the optimal prediction result from the massive basic data. When new data is entered, the model can provide real-time and rapid prediction results. The Seq2Seq proposed in this paper is based on two GRU composite networks to realize the encoding and decoding process. The network structure diagram of Seq2Seq is shown in Fig.3.

![Figure 3. Structure of Seq2Seq network.](image-url)

In the encoding layer, the Encoder encodes the input time series from front to back. It calculates the hidden state at the current moment according to the GRU calculation rules and takes it as input to the next unit. The Encoder assigns the last hidden state to the semantic vector \( C \).

\[
h_i = f(x_i, h_{i-1})
\]
In formula (13), $\hat{h}_i$ represents the hidden state of Encoder layer. $f$ represents the internal operation rules of GRU.
In the decoding layer, the Decoder decodes the encoded information by relying on the semantic vector $C$. The input of GRU is the semantic vector $C$, the decoded output and the hidden state at the last moment. The output sequence is as follows:

$$s_i = f(s_{i-1}, y_{i-1}, C)$$

$$P(y_i|y_{i-1}, L, y_1, C) = g(s_i, y_{i-1}, C)$$

In formula (14), $s_i$ is the hidden state of Decoder layer. In formula (15), $g$ is the mapping function from hidden state to predicted load probability density distribution. The predicted value with the highest probability is selected as the output at time $t$.

$$y_i = \arg \max \left[ P(y_i|y_{i-1}, L, y_1, C) \right]$$

The Encoder of Seq2Seq model is composed of 6 GRUs end to end, with 64 nodes inside each GRU. The network structure of the Decoder is identical to that of the Encoder. The output of Seq2Seq model adopts a fully connected neural network, which outputs EVCL at different times of the predicted day. The number of nodes can be set according to requirements. In this paper, it is set to output once every 15min, and the number of nodes is 96. The cross entropy function is used as the loss function and Adam optimizer is used to optimize the model[10].

4. Analysis of simulation results
The NHTS database is deeply mined, and the destination of travel, initial travel time, mileage and parking time data in the database are fitted to calculate the probability distribution. Monte Carlo method is used to simulate the total daily charging load data of 10,000 EVs in 30 days, and these data are used as the data set to verify the model in this paper. The data of the first 20 days in the dataset is used as the training set, and the data of the last 10 days in the dataset is used as the test set.
Seq2Seq model has complete research system and powerful expansion ability. It shows a great advantage in dealing with the problem of many-to-many load prediction with different input and output sequences. In practical problems, the input and output sequences of different lengths can be set according to the needs of the actual situation, so as to realize the load prediction of different time scales. Based on the output of Monte Carlo model, neural network is trained according to different types of basic data. The Seq2Seq model is tested with the data from the test set, and the predicted results of one day are shown in Fig.4.

![Figure 4. Total daily charging load of EV.](image-url)
Table 1. Comparison of solution time.

| Method                      | Maximum  | Minimum | Average |
|-----------------------------|----------|---------|---------|
| Combined prediction method  | 0.052s   | 0.045s  | 0.049s  |
| Monte Carlo Method          | 58.043s  | 11.267s | 31.248s |

By predicting the daily total charging load of 10,000 EVs, the calculation time of the proposed combined prediction method and the traditional Monte Carlo prediction method in the real-time application is calculated. The statistical results are shown in Table 1. The calculation time of the proposed combination prediction method can reach the level of microseconds, the average value does not exceed 0.05s. The solution time is stable. However, the average solution time of the traditional Monte Carlo prediction method at a single calculation point is about 30s, and it changes with the change of the number of electric vehicles connected to the grid.

5. Conclusion

Aiming at the difficulty of traditional prediction model in real-time application, this paper proposes a combination prediction method of electric vehicle charging load based on Monte Carlo method and neural network. The simulation results show that the proposed combined prediction model can realize the rapid real-time prediction of electric vehicle charging load. The simulation results show that compared with the traditional Monte Carlo prediction model, the proposed combination prediction method performs well in real-time application. The solution time of the combined prediction method is microseconds, and the solution time is stable. The proposed method has low calculation pressure and short solution time, and can solve the problem of charging load prediction of large-scale EV clusters. At the same time, the combined prediction method has a certain generalization ability which can be used as a charging load prediction method to provide a reference for realizing the real-time optimal dispatching strategy of power grid considering the EVCL.

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References

[1] Z. Darabi, M. Ferdowsi, IEEE Trans Sustain Energy, 4, 501-508 (2011)
[2] L. P. Fernández, T. G. San Román, R. Cossent, C. M. Domingo, P. Frías, IEEE Trans. Power Syst., 26, 206-213 (2011)
[3] M. B. Arias, M. Kim, S. Bae, Applied Energy, 195, 738-753 (2017)
[4] N. G. Omran, and S. Filizadeh, IEEE T Smart Grid, 5, 632-641 (2017)
[5] Y. Lu, Y. Li, D. Xie, E. Wei, X. Bao, H. Chen, and X. Zhong, Energies, 11 (2018)
[6] M. El-Hendawi, Z. Wang, Electr. Power Syst. Res., 182 (2020)
[7] DOT, FHA, NHTS (2017), URL:http://nhts.ornl.gov
[8] J. Munkhammar, M. Shepero, 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe, 1-6 (2018)
[9] W. Ren, G. Xu, Power Syst. Technol., 44, 27-34 (2020)
[10] J. Ba, International Conference on Learning Representations, 1-15 (2015)