

The Prediction of Electric Vehicle Charging Load

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Keywords: Electric Vehicle; Load Forecasting; Optimization Algorithm; Driving Rule; Charging Mode

Abstract. Because electric vehicle charging has the characteristics of strong randomness and unpredictability, it will inevitably have a certain impact on the power system. To effectively predict the charging load of electric vehicles can effectively alleviate the impact of electric vehicle charging on the distribution network to a certain extent. An electric vehicle charging load forecasting method using neural network and genetic algorithm is proposed in this paper. This method fully considers the influence of driving rule, charging characteristics, seasonal change, road condition and other factors. Relevant experimental data show that the prediction method has good prediction accuracy.

Introduction

Because the prediction of electric vehicle charging load is the basis of solving the related access problem, the prediction of electric vehicle charging load has become a research hotspot in recent years. Document [1], through Monte Carlo method, simulates when electric vehicles are used, when and when to charge, and the main charging time is obtained, thus the time and space distribution of charging vehicles is obtained. Document [2] analyzes the factors that affect the charging of electric vehicles, gives the charging mode parameters of different types of cars, and then simulates and simulates the charging load of electric vehicles in the future through Monte Carlo simulation and simulation. Two kinds of modeling methods are proposed in document [3]. One is the mathematical formula for fast calculation of load under certain precondition, and the other is a dynamic process method for designing many practical factors. The prediction data obtained after simulation are in good agreement with the actual data.

On the basis of considering the historical curve of electric vehicle charging load and the main factors affecting the charging load, this paper proposes a method to predict the charging load of electric vehicles by using the genetic algorithm to optimize the number of the hidden layer units of the neural network structure and the weight threshold. The empirical evidence has a higher prediction accuracy.

Optimization of Historical Data

The charging load of the electric vehicle is related to the season, the weather and the travel law of the users, so these factors should be taken into account when the charging load is predicted, and it cannot be regarded as a common load. At the same time, we optimize the existing historical data, eliminate abnormal data and fill in some vacancy data to ensure the integrity and accuracy of data. The vacancy data $x_q(t)$ is obtained by formula (1), and the preprocessing formula is as follows:

$$x_q(t) = [x(t-3) + x(t-2) + x(t-1) + x(t-7)]/4 \quad (1)$$

In the formula: $x_q(t)$ —missing data;

$x(t-7)$ 、 $x(t-3)$ 、 $x(t-2)$ 、 $x(t-1)$ —The previous data of the corresponding period.

Determine whether the data is abnormal by using the (2) La compliance method; when a data is satisfied (2), it is judged to be an anomaly, and is removed, and then the data is filled in accordance with formula (1).

$$|x_i - \bar{x}| > 3S \quad (2)$$

In the formula: $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$ —The mean of the sample;

$$S = \left[\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 \right]^{1/2} \text{—Standard deviation of the sample.}$$

After the data optimization, the training sample data are divided into two parts of the earlier sample Q_1 and the recent sample Q_2 , taking into account the increase in the number of electric vehicles that may exist in a certain period of time. Since the sample data in different periods have different influence on the prediction, and the recent sample Q_1 data have a large impact on the prediction, the training sample data are divided into two parts Q_1 、 Q_2 , which account for 70% and 20% of the sample data respectively. 10% of the sample data Q_3 are used to check the prediction ability of the network. That is, the sample data is:

$$Q = [Q_{1,1}, \dots, Q_{1,M_1}, Q_{2,M_1+1}, \dots, Q_{2,M_2}, Q_{3,M_2+1} \dots Q_{3,M}];$$

The input of the historical charge load is the data of the first three days of the day of prediction and the average of the data of the day last week; the input of the historical temperature is the average temperature of the day before the day of prediction; the input of the historical weather is more specific for the forecast day, and the weather is 1, the cloudy day 0.7 and the rainy day 0 on the sunny day. .5, snowy day 0.3; the input of the trip rule is the prediction of working day or holiday, and the input date is 0.7, and the holiday is 0.3.

An Optimization Algorithm

The training process of connection weights of neural networks is a process of decreasing errors. The connection weights of neural networks are generally random initialized into $[-0.5, 0.5]$ interval random numbers. This random number has great influence on network training. Gradient descent method is widely used in neural networks. It is very sensitive to the initial value of connection weights. Because different initial values will produce different training effects, there will be different error values, such as the improper initial value will cause the network concussion so that the network cannot converge, and may make the network converge slow so that the training time is very long, and the same pattern may also make the network fall into the local minimum. A value that cannot reach the global optimal value. In spite of this, there is no mature theory to effectively explain the network connection weights, and a relatively good connection right can be obtained by optimizing the genetic algorithm.

After a large number of data analysis and comprehensive consideration of the main influence factor of electric vehicle charging load, the number of input layers of the neural network is 4, which are the historical load of electric vehicle charging, the corresponding historical temperature, the corresponding history weather and the travel law, and the number of output layers is 1, which is the charging load of one day that needs to be predicted.

The genetic algorithm optimizes the structure and connection right of the network at the same time, each encoding contains two parts, the former is the network structure, the latter part is the connection right of the network, and the optimization can save the time greatly. The length of the coding of the connection right (using the real number code) is: $4 \times n + n + n \times 1 + 1 = 6n + 1$ (n is the number of the neural network hidden layer units after the optimization of the genetic algorithm), the weight threshold is listed according to the line, and the weight threshold code is formed, and the genetic algorithm is coded by the network structure coding and the connection weight coding. The specific implementation steps are as follows:

(1) Building up three sample data based on a large number of sample data collection and optimization.

(2) Using the three layer neural network, we use the sample data Q_1 to preliminarily determine the basic solution space $[\delta_{\min}, \delta_{\max}]$ (δ_{\min} 、 δ_{\max} is the minimum and maximum of the connection weight) ;

(3) The error square sum reciprocal is used as the fitness function to optimize the genetic algorithm. The formula is as follows:

$$F(W_1, B_1, W_2, B_2) = \frac{1}{\sqrt{\sum_{k=1}^M (y_k - \bar{y}_k)^2}} \quad (1)$$

W_1, B_1, W_2, B_2 is the weight threshold between the input layer and the hidden layer, the weight threshold between the hidden layer and the output layer, k is the input mode logarithm, and y_k and \bar{y}_k are the sample expected output and the model prediction output respectively, and the M is the size of the sample data.

(4) Coding the basic solution space. Each group of codes is composed of structure and connection right code.

(5) The initial group is composed of N individuals. Each individual is composed of a $6n+1$ network structure code with a string length of 7 and a connection weight code with a string length of 0-1, and the connection weight code is generated in the interval $[\delta_{\min}, \delta_{\max}]$.

(6) Calculation of fitness. The structure and connection weights of the N group neural network are obtained by step (5), and the sample data Q_1 is input, and fitness function is derived from fitness function.

(7) Carry on the operation of selection, cross and variation. The individuals with the maximum fitness value are directly inherited to the next generation, and the other different fitness values are filtered to the next generation of according to the roulette selection method.

(8) The generation of a new generation of groups.

(9) Repeated (6) \rightarrow (8), evolving to K_{\max} generation.

(10) When the optimization is finished, the encoding of the K_{\max} generation is decoded to get a set of network hidden layers and connection weights. On the basis of the structure and connection weight, input sample data Q_2 to find the final set of hidden layer numbers and

connection weights of $\min E_2(W_1, B_1, W_2, B_2) = \sum_{k=M_1}^{M_2} [y_k - \bar{y}_k]^2$.

(11) Finally, we input the sample data Q_3 to test the generalization ability of the neural

network, that is, $E(W_1, B_1, W_2, B_2) = \frac{1}{M - M_2} \sum_{k=M_2}^M [y_k - \bar{y}_k]^2 < \varepsilon$ (ε is the set error).

Example Case Analysis

Taking the data of the charging load of a bus charging station in 2018, and combining the data of temperature, weather and holiday in the year of the year, the load forecast of the charging station is analyzed in accordance with the above steps.

In addition, the method proposed in this paper is compared with the BP neural network method. It can be seen from the table that the method proposed in this paper has high prediction accuracy for three days of random extraction and an average prediction precision of 1.47%, which shows the feasibility of the method.

Conclusion

In this paper, the genetic algorithm and neural network are combined to Prediction of Electric Vehicle Charging Load, so that the electric vehicle charging daily load forecasting is more accurate. After the charge load is superimposed on the conventional load of the power grid, it will bring a series of effects, such as increasing peak valley difference, and harmonics. A large influx of and so on. The short-term load forecasting of electric vehicle based on neural network optimization is helpful to the short-term load dispatching of the power grid.

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