Load Forecasting Mechanism of Electric Vehicle Based on FWA-BP

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Abstract. The rapid development of electric vehicles and the popularization of related engineering applications require us to accurately predict the load of large-scale electric vehicles. In view of the current development status of electric vehicles, this paper first analyses the data basis and method selection of electric vehicle load forecasting. Then, a load forecasting method for large-scale electric vehicles based on FWA-BP is proposed, which fully considers the fluctuation characteristics of electric vehicles. Finally, the method proposed in this paper is verified by a simulation case, and the prediction results prove the effectiveness of the proposed method.

1. Introduction

With the continuous development of the scale of electric vehicles and the continuous derivation of related industrial chains, it is very important to establish an accurate and effective load forecasting mechanism for electric vehicles. Accurate EV charging load prediction, on the one hand, is conducive to the economic operation and energy management of EV charging stations, and provides a reference for urban infrastructure planning and construction. On the other hand, it is beneficial to the optimal power flow of the power system, the economic dispatching of the power grid, and has important significance to the power market transaction and the study of the optimal combination of generator sets.

At present, EV load forecasting methods mainly include EV charging load forecasting method based on short-term power load forecasting method and EV charging load forecasting method based on Monte Carlo simulation. The former method mainly combines the historical charging behavior data of electric vehicles and refers to the short-term load forecasting method in power system load forecasting to predict the charging load demand of electric vehicles. Laws of Monte Carlo simulation are based on the traffic behavior of resident trip survey database, based on the Monte Carlo principle, through simulation the owner traffic habits (including travel habits and charging habits), set up with stochastic mathematical model to predict the probability characteristic of automobile charging time in the future period of time, place, the load demand.

Based on the existing development of electric vehicles and load forecasting technology, this paper first analyzes the shortcomings of classical load forecasting methods, and then proposes a load forecasting method of electric vehicles based on FWA-BP. This method seeks for the optimal number of hidden nodes in BP network through FWA, so as to effectively improve the accuracy of EV load...
prediction. In the last section of this paper, a numerical example is given to verify the results, which show that the method proposed in this paper can effectively improve the accuracy of prediction.

2. Electric vehicle load forecasting method

2.1. Data set construction
Considering the large difference between the Monte Carlo-based forecasting method and the real situation, the electric vehicle load forecasting is carried out according to the short-term load forecasting method in order to minimize the forecasting error and get the actual available load data.

When using the short-term electric load forecasting method, there are two main ways to forecast the data set, one is to use the relevant influence factors as input and the load forecast values as output. However, this approach requires a larger dataset of relevant influence factors and also suffers from the superposition error of multiple forecasts. At the same time, considering that the EV database is under construction and the relevant datasets are not perfect, the first approach is not applicable to EV load forecasting. The second method is based on the historical load data of EVs, which has relatively low data requirements and is predicted by fitting the change pattern of EV loads, and the prediction results are more reliable. The second method is the prediction method used in this paper, which uses past EV load data to predict the development of future EV load.

2.2. Forecasting method selection
The choice of forecasting method is crucial to the forecasting effect, and this section analyzes three methods: multiple linear regression forecasting method, gray system forecasting method and artificial neural network forecasting method.

Regression analysis is an important way to achieve energy demand forecasting, which can reflect the development trend of the dependent variable with the change of the independent variable, and there are many scientific research results using regression methods to carry out analysis and achieve more accurate energy demand forecasting [1,2]. For the prediction of energy demand under the influence of multiple factors needs to combine multiple indicators for analysis and then predict its future energy demand, at this time, multiple linear regression prediction is a more appropriate technique [3]. However, it cannot adapt to data sets with high volatility, and it is difficult to handle multidimensional data to solve the electric vehicle load forecasting problem.

Gray system is a system that already has partly known information and also partly unknown information, which has the advantages of lower data requirements, better fitting effect, and the ability to achieve comprehensive dynamic analysis of the system, and is an effective tool for forecasting work. In the case of unclear system structure and weak existing data base, the use of gray system prediction method can get better prediction results [4]. However, for electric vehicle load forecasting, it has a huge data system and can also analyze the relationship between data by analyzing the interaction between multiple layers of influencing factors in various ways, so gray forecasting is also not applicable to electric vehicle load forecasting.

In fact, BP (Back Propagation) network is also a kind of multi-layer perceptron. It was proposed by a group of scientists led by Rumelhart and Hinton in 1986. Compared with multi-layer perceptron, BP network is a multi-layer feedforward network trained by error inverse Propagation algorithm in addition to feedforward neural network. It is one of the most widely used and successful neural network models. BP network can learn and store a large number of input-output pattern mapping relations without revealing the mathematical equations describing the mapping relations beforehand. Its learning rule is to use the fastest descent method to continuously adjust the weight and threshold of the network through back propagation, so as to minimize the sum of squares of errors of the network. This method has the best robustness and intelligence and is the best method for electric vehicle load prediction.
3. Prediction model based on FWA-BP
FWA (firework algorithm) is an optimization algorithm with high burstiness, local coverage, emergence, distribution parallelism, diversity, expandability and adaptability, which has the characteristics of fast computational speed and high computational accuracy. Using FWA to optimize the number of hidden layer nodes of BP can effectively improve the computational accuracy and efficiency of BP prediction models.

In 2010, Ying Tan and Yuanchun Zhu proposed about the fireworks algorithm at the First International Conference on Intelligence [5], and the main computational flow of this algorithm is shown in Figure 1.

![Diagram of fireworks algorithm](image)

Figure 1. Calculation flow of fireworks algorithm

Its calculation process is shown in Figure 1.
Initialize the data. The contents of the initialization data include
\[ x_{ij}(0) = x_{ij}^L + rand (0.1) \left( x_{ij}^U - x_{ij}^L \right) \] (1)

Where, \( x_{ij}(0) \) is the spatial position of the individual fireworks of the early generation; \( x_{ij}^L \) and \( x_{ij}^L \) are the upper bound and lower bound of dimensionality respectively; \( rand(0.1) \) represents the generation of random numbers in the position greater than 0 and less than 1, \( i = 1, 2, \ldots, N \), \( j = 1, 2, \ldots, n \).

2) Explosion operator. Explosion intensity is an important value, and is reflected by the number of sparks, its equation is as follow.
\[ N_i = \hat{N} \cdot \frac{Y_{\text{max}} - f(X_i) + \varepsilon}{\sum_{i=1}^{N}(Y_{\text{max}} - f(X_i)) + \varepsilon} \]  

(2)

Where, \( N_i \) is the number of sparks of the first firework, \( \hat{N} \) is the constant controlling the total number of sparks, \( Y_{\text{max}} = \max f(X_i) \) is the fitness value of the individual with the worst fitness, \( f(X_i) \) is the fitness value of the individual, and \( X_i \) is the minimal constant preventing the denominator from being 0.

And explosion amplitude is another important value, and its equation is as follow.

\[ A_i = \hat{A} \cdot \frac{f(X_i) - Y_{\text{min}} + \varepsilon}{\sum_{i=1}^{N}(f(X_i) - Y_{\text{min}}) + \varepsilon} \]  

(3)

Where, \( \hat{A} \) is the explosion amplitude range of the first firework, \( \hat{A} \) is the constant limiting the maximum explosion amplitude, and \( Y_{\text{min}} = \min f(X_i) \) is the adaptive value of the individual with the best fitness.

3) Mutation operator. Here we mainly use Gaussian variation.

\[ x_{ij} = x_{ij}g \]  

(4)

Where, \( g \sim N(1,1) \) is a Gaussian distribution with mean and variance of 1.

4) Mapping rules.

A mapping rule is an algorithm that, by some means, maps a spark beyond the boundary to a limited range, as shown in Equation 5.

\[ x_{ij} = x_{ij}^U + \left\lfloor x_{ij} \right\rfloor \% \left( x_{ij}^U - x_{ij}^L \right) \]  

(5)

Where, \( \% \) represents modular operation, \( x_{ij} \) represents the position of the \( i \) individual on the \( j \) dimension, and \( x_{ij}^U \), \( x_{ij}^L \) represent the upper and lower bounds of the boundary on the dimension respectively.

5) Select operation. The selection operation is based on distance selection and random selection.

\[ R(X_i) = \sum_{q=1}^{K} d(X_i, X_q) = \sum_{q=1}^{K} \|X_i - X_q\| \]  

(6)

Where, \( R(X_i) \) is the sum of the distance \( X_i \) from all other individuals, \( d(X_i, X_q) \) is the Euclidean distance between any two individuals, \( K \) is the position set of all sparks after Gaussian compilation.

\[ p(X_i) = \frac{R(X_i)}{\sum_{q=1}^{K} R(X_q)} \]  

(7)

Where, \( p(X_i) \) is the probability of \( X_i \) being selected.

Then, FWA algorithm is used to optimize the number of hidden nodes of BP neural network, which can improve the accuracy of prediction results of BP neural network.
4. Case Study
In this paper, the data of January in winter in Region A is taken as an example, and the data of 28th is taken as the training set to complete the load prediction on 29th. The prediction structure is shown in Figure 2.

![Figure 2. Load prediction results based on FWA-BP](image)

The results show that the forecast average relative error is less than 9.11%, and the forecast average absolute error is less than 2.51MW, which realizes the accurate prediction of electric vehicle load and has engineering practical value.

5. Conclusion
In view of the current situation of the rapid development of electric vehicles, this paper starts from the current situation of electric vehicle load prediction, firstly analyzes the data set selection and method selection for electric vehicle charging load prediction; Then, based on the load prediction method of electric vehicles, the model optimization design is made. FWA is used to optimize the number of nodes in the hidden layer of BP to improve the calculation speed and accuracy. Finally, the simulation results demonstrate the effectiveness of the proposed model.

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