Electric Vehicle Charging Fault Diagnosis Based on BP Neural Network

Yuanxing Zhang¹*, Taoyong Li¹, Shuaishuai Zhao²*, Xiangwu Yan², Jing Zhang¹, Xiaohong Diao¹ and Bin Li¹

¹Beijing Electric Vehicle Charging/Battery Swap Engineering and Technology Research Center, China Electric Power Research institute Co., Ltd, Beijing 100192, China
²North China Electric Power University (Baoding), Baoding 071003, China
E-mail: zhangyuanxing1988@163.com; zhao2017shuaishuai@163.com

Abstract. With the popularization and application of electric vehicles, the problem of charging failure is exposed frequently. In order to effectively and accurately determine the type of charging failure and find out the cause of the failure, a method for identifying the charging failure using neural network is proposed. By collecting charging data and using neural network for training, the failure results are obtained through continuous optimization, and compared with the results of preliminary judgment, the superiority and feasibility of BP neural network are verified.

1. Introduction
The development of the electric vehicle industry has been strongly supported and promoted by domestic policies. Due to the need for constant energy supply for electric vehicles, the corresponding interactive technology with the power grid is becoming more and more important. However, in the actual charging process, various charging failures may occur due to different reasons, thereby causing safety accidents. Due to the uncertainty and ambiguity of the cause of the fault, it is often impossible to diagnose the fault of the charging process through the mathematical model of the linear relationship type [1, 2]. The nonlinear mapping function, parallel processing function, good learning ability, and associative memory function of the neural network can be well applied to complex charging systems for charging fault diagnosis. Therefore, the BP neural network is used to identify and judge the charging faults, which simplifies the maintenance process of the operation and maintenance personnel and improves the efficiency of fault diagnosis. It is of great significance to further realize the safe and reliable operation of the charging process [3].

2. Structure of BP Neural Network
The BP neural network method is a kind of multi-layer feed-forward neural network. It is usually composed of an input layer, a hidden layer, and an output layer. The input layer is composed of input neurons composed of input data. The hidden layer can be divided according to the needs of data mining. It is one layer or several layers, and the output layer consists of output neurons that output the results [4, 5].

In the process of data mining, BP neural network mainly includes forward and backward propagation of two information and data transmission methods. Initially, the signal and the data are propagated in a forward direction. If a more suitable output result cannot be obtained, then the error between the actual and desired output results needs to be adjusted. The error signal is back propagated
through the BP neural network structure, and the weights between the neurons in each layer are adjusted and corrected. When the forward and backward propagation of the two steps alternately run to obtain more accurate data mining results, then the process of data mining by BP neural network ends.

The meanings of the parameters of the input layer, hidden layer and output layer of the BP neural network in the paper are shown in the table 1.

| Parameters | Meaning | Parameters | Meaning |
|------------|---------|------------|---------|
| $n$ | Number of input neurons | $W_{ki}$ | Value between input layer and hidden layer |
| $q$ | Number of hidden neurons | $W_{jk}$ | Value between hidden layer and output layer |
| $m$ | Number of output neurons | $\eta$ | Learning rate |

In the process of forward propagation of data and information by BP neural network, from a mathematical point of view, the corresponding formula is as follows:

The output of the hidden layer neuron is shown in (1).

$$Z_k = f_1\left(\sum_{i=0}^{n} W_{ki} \times x_i\right) \quad k = 1, 2, \cdots, q$$

The output of the output layer neuron is shown in (2).

$$Y_j = f_2\left(\sum_{k=0}^{q} W_{jk} \times Z_k\right) \quad j = 1, 2, \cdots, m$$

After the signal and data are initially propagated in a forward direction, if a more appropriate output result cannot be obtained, then the error between the actual and expected output results needs to be adjusted. Then the error signal is back propagated through the BP neural network, and the weights between the neurons in each layer are corrected.

Set the overall error of the data sample to $E$, the expected value is $C_j^l$, the calculation formula is shown in (3).

$$E = \frac{1}{2} \sum_{l=1}^{n} \sum_{j=1}^{m} (C_j^l - Y_j^l)$$

For the final actual output value and the expected value to be within the allowable error range, the total error $E$ needs to be adjusted and changed, so that the weight between the hidden layer and the output layer is adjusted. The specific formula is shown in (4).

$$\Delta W_{jk} = -\eta \frac{\partial E}{\partial W_{jk}} = \sum_{l=1}^{n} \left(-\eta \frac{\partial E_l}{\partial W_{jk}}\right)$$

Can also be expressed as (5).

$$\Delta W_{jk} = \sum_{l=1}^{n} \sum_{j=1}^{m} (C_j^l - Y_j^l) f_2'(S_j) \cdot Z_k$$

Correspondingly, the weight between the input layer and the hidden layer needs to be adjusted. The principle of adjustment is the same as that of adjusting the weight between the hidden layer and the output layer. The specific formula is shown in (6).
\[ \Delta W_{kl} = -\eta \frac{\partial E}{\partial W_{kl}} = \sum_{i=1}^{n} (-\eta \frac{\partial E_i}{\partial W_{kl}}) \]  

(6)

Can also be expressed as (7).

\[ \Delta W_{kl} = \sum_{i=1}^{n} \sum_{j=1}^{m} \eta (c_j^i - y_j^i) W_{jk} f_2'(s_j) f_1'(s_k) \cdot x_l \]  

(7)

The trend analysis method draws a specific data type from the massive and complex big data that needs to be analyzed, and draws the corresponding level of the data level, the changing trend and the changing law through the chain or the year-on-year method. According to the trend of the curve or the level of the vertical axis of the curve, you can do a preliminary data analysis of the charging data.

3. Example Application

Select the charging history data of a vehicle in a certain accident, and use trend analysis method to represent the charging voltage, current, SOC and maximum voltage of the battery collected by the battery management system over time as shown in Figures 1 and 2:

**Figure 1.** Analysis curve of the trend of total voltage, current and SOC with time

**Figure 2.** Trend curve of monomer's highest voltage with time

It can be seen from the figure that the previous constant current on the BMS side will be fully charged in the SOC during the constant voltage charging process. The highest voltage of the monomer obviously exceeds the limit of 3.75V. In order to better verify the fault conclusion, the BP network method is used to further Failure analysis.

The preliminary analysis of the data using the above graph can make a preliminary judgment on the health status of the electric vehicle at a specific moment. Combined with the BP neural network calculation method to carry out further data mining on related data. The parameters of the established BP network are shown in Table 2:
Table 2. BP neural network parameters

| BP neural network parameters | Parameter value | BP neural network parameters | Parameter value |
|----------------------------|----------------|-----------------------------|----------------|
| Input layer neuron         | 5              | error                       | <0.001         |
| Hidden layers              | 1              | Learning rate               | 0.1            |
| Hidden layer neuron        | 4              | Maximum learning times      | ≤1000          |
| Output layer neuron        | 2              |                              |                |

After determining the structural parameters of the BP network, the data monitored at a certain time on the BMS side is selected as sample input. The accuracy of the learning process results is shown in Figure 3:

![Figure 3. BP network accuracy](image)

It can be seen from the accuracy results in the above figure that the results obtained by data mining on the selected data samples are more accurate and reliable.

Under the premise that the accuracy is guaranteed, the weight of each index is calculated by extracting the data between the input layer, hidden layer and output layer in the BP neural network structure. Then, using the index weight vector, combined with the relatively fuzzy comprehensive evaluation theory, the data analysis of the data mining is carried out, and the charging failure level is determined according to the principle of maximum membership. Then analyze the cause of the fault based on the fault diagnosis results and the original collected data, and locate the faulty module.

The weights between the input layer, hidden layer and output layer in the BP neural network structure used in this paper are shown in Table 3.

Table 3. Weight Table

| Hidden layer neuron | Input layer neuron | Output layer neuron |
|---------------------|--------------------|--------------------|
|                     | 1                  | 2                  |
|                     | 3                  | 4                  | 5                  |
| 1                   | 1.4246             | -2.0294            | -8.8924            | -0.8087            | -2.2687            | 0.9450             | -0.9428            |
| 2                   | -0.0620            | -0.1943            | -1.0310            | 1.6328             | -0.2593            | -0.7548            | 0.7170             |
| 3                   | -1.4563            | -1.5254            | -0.7780            | 0.3361             | -0.3696            | 0.0188             | -0.0238            |
| 4                   | -1.1454            | -0.9342            | -0.1630            | 0.2077             | -1.0343            | -0.3462            | 0.5768             |

When using the relevant structural coefficients for weight calculation, the values of the following indicators need to be calculated.

\[
r_{ij} = \sum_{k=1}^{P} W_{ki} \frac{1 - e^{-x}}{1 + e^{-x}}
\]  

(8)
Among them, the meaning represented by \( r_{ij} \) is the correlation significance coefficient; the meaning represented by \( R_{ij} \) is the correlation coefficient; and the meaning represented by \( S_{ij} \) is the absolute influence coefficient. In the above index calculation, the final absolute impact coefficient obtained is the weight of the corresponding index contained in the sample data.

Collect the index samples of the BMS side including the charging weight, the highest temperature of the monomer, the lowest temperature of the monomer, the highest voltage of the monomer, and the calculation result of the index weight of the lowest voltage of the monomer:

\[
\begin{bmatrix}
0.0766 & 0.4019 & 0.2607 & 0.2481 & 0.0128
\end{bmatrix}
\]

Then carry out fuzzy comprehensive evaluation, multiply the single-factor evaluation matrix with the weight vector calculated previously. The determination of the single-factor evaluation matrix needs to first determine the relevant data evaluation level. The evaluation levels determined according to the needs in this article are five evaluation levels of health, normal, hidden danger, defect and failure. Combining these five evaluation levels and the number of samples, the relevant single-factor evaluation matrix finally determined according to statistical principles is as follows, where the abscissas correspond to the charging voltage, the highest temperature of the monomer, the lowest temperature of the monomer, the highest voltage of the monomer, respectively And the minimum voltage of the monomer, the ordinate corresponds to health, normal, hidden danger, defect and fault.

\[
\begin{bmatrix}
0.0250 & 0.0455 & 0.1192 & 0.4229 & 0.3874 \\
0.0488 & 0.1395 & 0.2565 & 0.3016 & 0.2536 \\
0.0463 & 0.0816 & 0.1467 & 0.6010 & 0.1244 \\
0.0426 & 0.1523 & 0.2756 & 0.2082 & 0.3213 \\
0.0295 & 0.1473 & 0.2297 & 0.3197 & 0.2468
\end{bmatrix}
\]

The result of fuzzy operation is: \([0.0455 \ 0.1208 \ 0.2218 \ 0.3660 \ 0.2469] \]

According to the principle of maximum membership, it can be seen that the charging state has reached the charging defect state, and the fault state has approached or reached the charging fault state. Collecting the original data of the index and further index analysis can clearly see that the highest voltage of the monomer is seriously exceeding the specified limit. Through the analysis of the fault by the charging expert group, it was found that the fault was eventually caused by the BMS program sleeping and the charge termination message was missed, which triggered the fault. The analysis results are relatively consistent with the results of the trend analysis method.

4. Conclusion
This paper studies and analyzes the problem that the charging network is complicated and the charging failure is difficult to judge. Through the use of BP neural network training, the weight of possible parameter indicators is determined, and finally the fuzzy analysis theory is used to diagnose and identify the fault level. The implementation example shows that the BP neural network can more accurately position the index weights, and then can more accurately identify the charging fault level, which brings certain guarantees for the charging safety of electric vehicles.

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