Research on Fault Diagnosis of DC Charging Pile Power Device Based on Wavelet Packet and Elman Neural Network

Wang Jiajia1, Chen Xingying1,2 and Ji Li1,3

1College of Energy & Electrical Engineering, Hohai University, Nanjing 211100, Jiangsu, China
2Jiangsu Engineering Research Center for Distribution & Utilization and Energy Efficiency, Nanjing 211100, Jiangsu, China
3NARI Group Corporation: State Grid Electric Power Research Institute, Nanjing 211100, Jiangsu, China

1Wang Jiajia: 1805539260@qq.com
2Chen Xingying: xychen@hhu.edu.cn
3Ji Li: jili198504@hhu.edu.cn

Abstract. In order to improve the fault diagnosis accuracy of DC charging pile power devices, a fault diagnosis method based on wavelet packet analysis (WPA) and Elman neural network is proposed in this paper. This method sampled the output voltage signal of DC bus in fault state, decomposed the three-layer db10 wavelet packet and reconstructed the single branch, then calculated the characteristic energy spectrum of the fault signal using the signal in the frequency band, and identified it by Elman neural network. In order to test the diagnostic ability of the model, the PWM rectifier model of DC charging pile is used as an example to simulate and compare with the diagnostic results of standard BP neural network. The simulation results show that the fault diagnosis method based on WPA and Elman neural network has faster diagnosis speed, higher accuracy and stronger generalization ability.

1. Introduction
In the charging process of DC charging piles, the failure rate of power devices accounts for 34% of the failure devices of DC charging piles. The running state of power devices directly affects the normal operation of the whole DC charging piles [1-2]. Among the faults of DC charging piles, open circuit faults and short circuit faults of power devices account for a large proportion [3-4]. For short-circuit faults of power devices, it is usually either monitored and protected by integrated circuits of driving modules [5]. However, there is no perfect solution for open-circuit faults of power devices.

Wavelet analysis is used to realize multi-resolution feature frequency identification, but the applicability of this method is poor [6]. WPA is an improved algorithm based on wavelet analysis [7]. It decomposes the high frequency part without subdivision. In addition, WPA can adaptively select the corresponding frequency band, which improves the time-frequency resolution.

In [8], only single power device fault is studied, and BP neural network has many iterations and slow convergence speed. The traditional BP neural network is a static feedforward network with many parameters setting [9]. As a dynamic recurrent network, Elman neural network overcomes the shortcomings of feedforward network which does not have dynamic characteristics. It has the advantages of fast training speed, simple structure and high diagnostic accuracy.
Based on the advantages of wavelet packet decomposition in signal feature extraction and the characteristics of Elman neural network, a fault diagnosis method for DC charging pile power device is designed, which combines WPA and Elman neural network.

2. Open circuit fault analysis of power devices for DC charging piles

Figure 1 is a schematic diagram of the circuit topology of the PWM rectifier in the DC charging power module. In the figure, \( u_a, u_b, u_c \) is three-phase input voltage, \( L \) is three-phase filter inductor on the AC side, \( Q1 \sim Q6 \) are power devices, \( VD1 \sim VD6 \) are the freewheeling diodes, \( C \) is filter capacitor on the DC side and \( R \) is load on the DC side, \( u_d, i_d \) is DC side voltage and current respectively. Two power devices on each arm work in a complementary manner, and one power device on each arm is on at any time.

![Figure 1. Topology schematic diagram of PWM rectifier circuit.](image)

In the actual operation of the equipment, it is rare that three or more power devices are damaged simultaneously. In this paper, open-circuit faults of single or two power devices are considered. The open-circuit faults of PWM rectifiers are classified into the following five categories.

- no power device fault, indicating normal operation.
- single power device open circuit fault, respectively, there is a fault in \( Q1 \sim Q6 \).
- Open circuit faults of two power devices on the same leg, including \( Q1 \) and \( Q4 \), \( Q3 \) and \( Q6 \), \( Q5 \) and \( Q2 \) faults.
- Open circuit faults of two power devices in the same half bridge, \( Q1 \) and \( Q3 \), \( Q1 \) and \( Q5 \), \( Q3 \) and \( Q5 \), \( Q4 \) and \( Q2 \), \( Q4 \) and \( Q6 \), \( Q6 \) and \( Q2 \), respectively.
- Open-circuit faults of two power devices with different arms, \( Q1 \) and \( Q6 \), \( Q1 \) and \( Q2 \), \( Q3 \) and \( Q4 \), \( Q3 \) and \( Q2 \), \( Q5 \) and \( Q4 \), \( Q5 \) and \( Q6 \), respectively.

3. Fault diagnosis of PWM rectifier based on WPA and Elman neural network

3.1. Open circuit fault feature extraction of power devices based on WPA

The output voltage signals of DC buses under different fault states have different time-frequency characteristics. The output voltage signals of DC buses are decomposed into energy eigenvalues of each node by wavelet packet decomposition, which are different from each other. Therefore, the energy eigenvalues decomposed by wavelet packet are selected as fault eigenvectors.

In this paper, the DC bus output voltage signal is decomposed by three-level wavelet packet. In the energy spectrum of wavelet packets, the sum of squares of signals in each frequency band is selected as a sign of energy. Therefore, the energy of each band after the wavelet packet decomposition can be expressed as:

\[
E_i = \sum_{k} d_{j,k}^n \quad i = 1, 2, \cdots, 2^j
\]
where, \( d_{j,k}^n \) denotes the Kth coefficient corresponding to the node \( S_{(i,j)}^k \) decomposed by the wavelet packet, \( N \) denotes the length of the original signal, and all \( E_i \) forms the wavelet packet energy spectrum vector, as shown in formula (2):

\[
E = \begin{bmatrix} E_0 & E_1 & \cdots & E_{2^j-1} \end{bmatrix} \quad j = 0,1,2,3
\]

At the same time, the energy spectrum eigenvector of wavelet packet is constructed by using the third level energy spectrum vector.

\[
T = \begin{bmatrix} E_{(3,0)} & E_{(3,1)} & \cdots & E_{(3,2^j-1)} \end{bmatrix} \quad j = 0,1,2,3
\]

In order to facilitate data computation and processing, normalization of feature vectors is performed on [10].

\[
E_s = \sum E_{(3,m)} \quad m = 0,1,\cdots,7
\]

\[
T' = \begin{bmatrix} \frac{E_{(3,0)}}{E_s} & \frac{E_{(3,1)}}{E_s} & \cdots & \frac{E_{(3,7)}}{E_s} \end{bmatrix} \quad m = 0,1,\cdots,7
\]

Where, vector \( T' \) is the normalized eigenvector. As the input of neural network, the open circuit fault diagnosis of DC charging pile is realized by neural network identification.

3.2. PWM rectifier fault diagnosis model based on Elman neural network

As a typical local regression network, it is a feedback neural network with strong computing power. Elman neural network consists of input layer, hidden layer, undertaking layer and output layer. Network structure is shown in Figure 2. The approximation ability of Elman neural network is better than that of general static network, and its convergence speed is fast. It can overcome the shortcomings of long training time and high computational complexity of BP network. In this paper, Elman neural network is used to identify the open-circuit faults of power devices according to the fault eigenvectors.

**Figure 2.** Elman neural network structure diagram.

3.3. Open circuit fault diagnosis for power devices of PWM rectifier

The open circuit fault diagnosis steps of PWM rectifier based on WPA and Elman neural network are as follows:

1. Establish the PWM rectifier model controlled by SVPWM, and simulate it according to the five types of faults, so as to get the DC bus output voltage signal of DC charging pile;
2. Choosing the appropriate wavelet basis function, the voltage signal is decomposed into three layers of wavelet packet, and the signal characteristics of each frequency band on the decomposition layer are extracted respectively;
3. The wavelet packet decomposition coefficients are reconstructed in 8 subdivision bands and the signals in each frequency band range are extracted;
According to formula (1), the energy values of each frequency band signal are calculated, and the energy of frequency band is normalized according to formula (3-5), thus the fault eigenvector $T'$ is obtained;

(5) The input of Elman neural network is $T'$ obtained by step (4) and the network parameters are set. The network is trained by Elman neural network training algorithm until the error requirements are met. Then the output of the test is compared with the target output to locate the fault.

4. Simulation results analysis

4.1. Fault feature extraction

In this paper, the simulation model of PWM rectifier based on voltage and current double closed loop SVPWM control is established by MATLAB. According to the fault analysis results in Table 1, the simulation analysis is carried out separately. The input three-phase AC voltage of PWM rectifier is 380 V. The DC side output voltage amplitude is 600 V. The grid frequency is 50 Hz. The inductance L is 0.15 mH. The capacitance C is 4000 mF. The load current is 2.78 A. The resistance R is 225 Ω and the switching frequency is 3.2 kHz. The signal waveform of normal state and different fault states is obtained, as shown in Figure 3.

![Image](image-url)

**Figure 3.** Simulation signal waveform of normal, Q1, Q1Q4, Q1Q3 and Q1Q6.

4.2. Fault diagnosis

The data of DC charging pile in each of the five kinds of states are obtained by 100 groups. Wavelet packet decomposition is used to extract the fault eigenvalues of the response as samples. Table 1 is the output of one group.

| fault type   | $E_1$  | $E_2$  | $E_3$  | $E_4$  | $E_5$  | $E_6$  | $E_7$  | $E_8$  |
|--------------|--------|--------|--------|--------|--------|--------|--------|--------|
| normal       | 0.9994 | 0.0156 | 0.0150 | 0.0115 | 0.0125 | 0.0106 | 0.0136 | 0.0117 |
| Q1 fault     | 0.9998 | 0.0119 | 0.0061 | 0.0088 | 0.0060 | 0.0079 | 0.0074 | 0.0070 |
| Q1Q4 fault   | 0.9968 | 0.0270 | 0.0297 | 0.0342 | 0.0306 | 0.0286 | 0.0316 | 0.0368 |
| Q1Q3 fault   | 0.9999 | 0.0098 | 0.0064 | 0.0052 | 0.0047 | 0.0044 | 0.0063 | 0.0059 |
| Q1Q6 fault   | 0.9991 | 0.0227 | 0.0143 | 0.0142 | 0.0177 | 0.0143 | 0.0154 | 0.0149 |

The training samples of Elman network contain input data and target output. In the training sample of Table 1, the input vector is 8 dimensional PWM rectifier fault eigenvalue. The sample data has eight eigenvectors and five fault types, so the number of nodes in input layer and output layer of Elman neural network is set to 8 and 5 respectively. Considering the performance and speed of the network, the number of hidden layer nodes is 15, the transfer functions of hidden layer and output layer are set to transig and logsig, the target error is set to 0.001, the maximum iteration is 2000, and the learning rate is set to 0.05.
The standard BP network and Elman neural network are used for training respectively. The result is shown in Figure 4 and Figure 5. Through the learning curves of the two networks, it can be seen that the learning steps of BP network are too many, and 1440 steps can reach the target precision. The learning steps of Elman network are about 25% of that of BP network, and the learning speed of Elman network is faster than that of BP network, which is more suitable for real-time operation.

**Figure 4.** Curve of training error of neural network with iteration number of BP neural network model.  
**Figure 5.** Curve of training error of neural network with iteration number of Elman neural network model.

### Table 2. Comparison of diagnostic output results between Elman and standard BP network models

| fault type          | Target output | Elman output | Standard BP output | absolute error |
|---------------------|---------------|--------------|--------------------|----------------|
|                     |               | Elman       | Standard BP       |                |
|                     |               | output      | output             |                |
|                     |               | absolute    | absolute           |                |
| normal              | 1             | 0.9968      | 1.0556             | -0.0032        | 0.0556         |
|                     | 0             | -0.0063     | 0.0512             | 0.0013         | 0.0512         |
|                     | 0             | 0.0044      | 0.0071             | 0.0044         | 0.0071         |
|                     | 0             | 0.0045      | -0.1128            | 0.0045         | -0.1128        |
|                     | 0             | 0.0271      | -0.0151            | 0.0271         | -0.0151        |
| Q4 fault            | 1             | 0.9957      | 1.0335             | -0.0043        | 0.0335         |
|                     | 0             | -0.0062     | 0.0405             | -0.0062        | 0.0405         |
|                     | 0             | -0.0011     | -0.0301            | -0.0011        | -0.0301        |
|                     | 0             | -0.0155     | -0.0587            | -0.0155        | -0.0587        |
|                     | 0             | 0.0016      | 0.0097             | 0.0016         | 0.0097         |
|                     | 0             | -0.0104     | 0.0195             | -0.0104        | 0.0195         |
| Q3Q6 fault          | 1             | 1.0007      | 0.9759             | 0.0007         | -0.0241        |
|                     | 0             | 0.0103      | -0.0038            | 0.0103         | -0.0038        |
|                     | 0             | -0.0014     | -0.0001            | -0.0014        | -0.0001        |
|                     | 0             | -0.0197     | 0.0138             | -0.0197        | 0.0138         |
|                     | 0             | -0.0053     | -0.0466            | -0.0053        | -0.0466        |
| Q4Q6 fault          | 0             | 0.0051      | -0.0197            | 0.0051         | -0.0197        |
|                     | 1             | 1.0155      | 1.0606             | 0.0155         | 0.0606         |
|                     | 0             | 0.0018      | 0.0116             | 0.0018         | 0.0116         |
|                     | 0             | 0.0350      | 0.0236             | 0.0350         | 0.0236         |
|                     | 0             | -0.0279     | -0.0049            | -0.0279        | -0.0049        |
| Q4Q3 fault          | 0             | 0.0115      | 0.0030             | 0.0115         | 0.0030         |
|                     | 0             | 0.0206      | 0.0082             | 0.0206         | 0.0082         |
|                     | 1             | 0.9998      | 0.9748             | -0.0002        | -0.0252        |

The diagnostic results of Elman and standard BP network diagnostic model are shown in Table 2. It can be seen that the maximum absolute error of standard BP network diagnostic model is -0.1128, while the maximum absolute error of Elman network diagnostic model is -0.0350. Comparing the results of Table 2, Elman network is more effective in fault diagnosis, more accurate in diagnosis and better in diagnosis performance.

### 5. Conclusion
A fault diagnosis method of DC charging pile power devices based on WPA and Elman neural network model is proposed. The fault signal is analyzed and processed by WPA to improve the accuracy of the data and highlight the details of the signal data. The simulation results show that the convergence speed is faster, the training accuracy and the diagnostic accuracy are higher, and the diagnosis performance is better. Meanwhile, simulation experiments have verified the correctness of this method.

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