Research on Fault Diagnosis Method of DC Charging Pile Based on Deep Learning

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***Abstract*—Aiming at the fault diagnosis of the charging module of the electric vehicle DC charging pile, a fault diagnosis method of the DC charging pile based on deep learning is proposed. First, through circuit simulation, the DC charging pile model is simulated under different faults and different working conditions, and the three input current signals are obtained as fault characteristic parameters. Perform three-layer wavelet packet decomposition and reconstruction of the fault characteristic parameters, calculate the frequency band energy spectrum data through the reconstruction coefficients, and normalize it. Finally, the fault characteristic set is composed of the fault data and the fault result, which is used as a deep neural network (DNN) Model input and verification. After the output layer of the constructed DNN model, a Softmax classifier is added to fine-tune the output fault characteristics and realize fault type recognition. Through the analysis of different types of faults of the charging module of the DC charging pile, the accuracy and effectiveness of the fault diagnosis method is verified, and its accuracy rate can reach more than 95.56%.**

Keywords—DC charging pile, deep learning, wavelet analysis, fault diagnosis

I. INTRODUCTION

With the continuous improvement of the independent innovation level of my country's new energy industry, the DC fast charging technology of electric vehicles has also been developed rapidly and has become a hot research field. As a large and complex charging device, DC charging piles often require continuous high-power operation to charge electric vehicles, which leads to a variety of failures in the DC charging piles. When the charging pile fails, it will greatly reduce the work efficiency in the charging station, affect the company's revenue, and even cause more serious consequences. At present, regular maintenance is used on site to troubleshoot faults. For the cause of the fault, maintenance personnel use experience to detect and repair the fault. This method will lead to a long fault processing cycle, high technical requirements and easy diagnosis errors[1]. Therefore, the introduction of deep learning algorithms and the use of valid data to perform fault diagnosis and analysis on the operating status of DC charging piles are of important research significance.

Literature[2] establishes a fault detection network for charging pile based on BP neural network algorithm, and gives fault maintenance suggestions through fault causes and fault performance. Literature[3] designed a set of fault tree algorithm based on fault tree. When a charge pile fault is detected, the fault tree logic operation is carried out from the top event to the bottom event, so as to screen the fault results. Reference[4] proposed a fault diagnosis method combining expert system and fault tree. Firstly, the fault tree of DC charging pile is established, and the faults of the bottom charging pile are quantitatively analyzed by fuzzy theory. Then the quantitative fault data is uploaded to the expert system, and the fault is qualitative through the inference engine to achieve the purpose of fault diagnosis. Literature[5] is based on random forest algorithm, which is applied to the fault diagnosis of DC charging pile switch module. Wavelet analysis is used to complete the fault feature extraction, and the dimension of the extracted data is reduced before training. The most common DC charging piles are open circuit fault and short circuit fault of power devices. Most power tube devices are equipped with fast fuses. In case of short circuit fault, the circuit enables protection to turn the short circuit fault into open circuit fault[6]. However, there is no perfect treatment method for the open circuit fault of power devices. The above research analyzes the faults generated by the charging pile through different methods, but the circuit of the charging module of the charging pile is complex, and it becomes very difficult to diagnose the faults generated by different components.

In the fault mode of the charging module of the charging pile, the fault diagnosis model of the charging module is established by combining the wavelet packet analysis method and the deep neural network. By simulating different power devices and DC measuring capacitance, the three-phase input current waveform data is decomposed and reconstructed under normal operation and failure conditions, and the energy spectrum fault characteristic data of the reconstructed signal is extracted. The deep learning neural network is used to train the data under different faults to realize the diagnosis and

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identification of the faults caused by the open circuit of the power device and the DC measuring capacitance of the DC charging pile.

II. TOPOLOGICAL STRUCTURE AND FAILURE ANALYSIS OF DC CHARGING PILE

A. DC charging pile topology

The charging module of the DC charging pile mainly includes AC-DC and DC-DC two-level electrical structure[7]. Among them, the VIENNA rectifier circuit is commonly used in the front-end structure, which is responsible for rectifying and correcting the power factor. The latter stage is a phase-shifted full-bridge conversion circuit, responsible for voltage conversion and electrical isolation. When the charging module is working, the front-stage VIENNA rectifier circuit converts the three-phase AC power of the grid into stable DC power and provides it to the subsequent-stage circuit. The latter-stage phase-shifted full-bridge conversion current inverts the DC power input from the VIENNA circuit into AC power. Then it is converted into the required AC power through the transformer, and then rectified and filtered for the second time, and finally output suitable DC power to be supplied to the load for charging[8].

Figure 1 below is the main circuit topology of the DC charging pile charging module, v_a、v_b、v_c are the three input voltages, VT1-VT3 are the power devices of the front-stage VIENNA rectifier, and VT4-VT7 are the back-stage phase-shifted full-bridge converters Power devices. The VIENNA rectifier circuit contains two filter capacitors at the DC side, namely C1 and C2; the phase-shifted full-bridge conversion circuit includes a filter capacitor C_f at the DC side. At the DC output position of the model, set the DC load Ro.

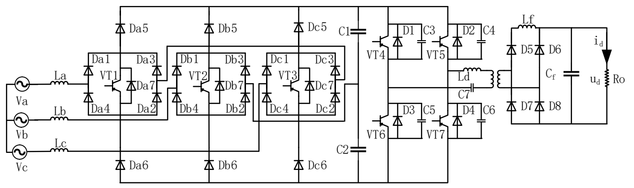

Fig. 1. Main circuit topology of charging module

B. Failure cause analysis

In the actual process, the faults of the charging pile mainly include the communication offline fault, the power device open circuit and the DC measuring capacitance open circuit fault. In the power device open circuit fault, the common situation is that one power device or two power devices have an open circuit, but the probability of multiple power devices in the circuit being damaged at the same time is small, and the open circuit fault of multiple power tubes and DC measuring capacitors at the same time , It is difficult to form a unified fault diagnosis basis. Therefore, this article mainly studies the power device and DC measuring capacitance open circuit fault diagnosis method of the pre-circuit and post-circuit of the charging module.

Under different open-circuit fault states, extract the energy spectrum fault characteristic data of the three-phase input current of the charging pile, and use the DNN model to train the data set composed of various fault data. The trained model can independently perform the input fault data Judge and complete the autonomous identification and positioning of the fault of the DC charging pile.

TABLE I. CHARGING MODULE OPEN CIRCUIT FAULT CLASSIFICATION

Error code	Failure mode	Fault description
F0	Normal	Operating normally
F1	Power device VT1 open circuit fault	Front-end circuit power device
F2	Power device VT2 open circuit fault	
F3	Power device VT3 open circuit fault	
F4	DC measuring capacitance C1 open circuit fault	Pre-circuit capacitance
F5	DC measuring capacitance C2 open circuit fault	
F6	Power device VT4 open circuit fault	Power device of the back stage circuit
F7	Power device VT5 open circuit fault	
F8	Power device VT6 open circuit fault	
F9	Power device VT7 open circuit fault	
F10	DC measuring capacitance Cf open circuit fault	Subsequent circuit capacitance

III. FAULT DIAGNOSIS METHOD OF DC CHARGING PILE

A. Fault data collection and feature extraction

The data required by the DC charging pile neural network fault diagnosis algorithm based on deep learning includes two parts, which are training set data and test set data. The training set data contains data samples for all failure types, and there are multiple data samples for each failure. The operating data of the charging pile in the normal state and the different fault states are obtained by establishing the theoretical model of the DC charging module. Feature extraction is performed on the collected data and processed to form a usable sample set format.

In this paper, the wavelet analysis method is used to decompose and reconstruct the three-phase input current signal[9]. The schematic diagram of wavelet decomposition is shown in Figure 2 below. And extract the fault feature of the energy spectrum of the reconstructed signal to obtain the fault information in the frequency domain. For the data collection of different open-circuit fault points of the charging module, the three-layer wavelet packet decomposition of the collected three input current data is shown in the following formula (1), where a_{k-2l}, b_{k-2l} Is a low-pass filter for wavelet packet decomposition; k, j, l ∈ Z.

$$\begin{cases} d_l^{j,2n} = \sum_k a_{k-2l}\, d_k^{j+1,n} \\ d_l^{j,2n+1} = \sum_k a_{k-2l}\, d_k^{j+1,n} \end{cases} \quad (1)$$

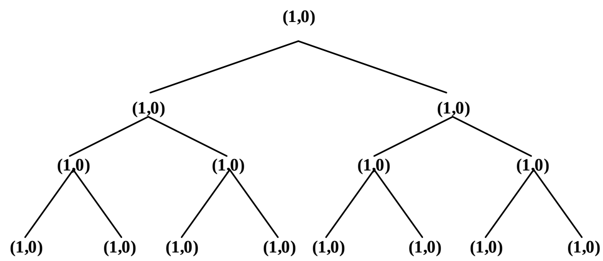

Fig. 2. Schematic diagram of wavelet decomposition structure

The reconstruction of wavelet packet coefficient is shown in the following formula (2) :

$$d_l^{j+1,n} = \sum_k [h_{l-2k} d_k^{j,2n} + g_{l-2k} d_k^{j,2n+1}] \qquad (2)$$

Where h_{l-2k} and g_{l-2k} are the high-pass filter coefficients.

In the third layer wavelet packet decomposition, the decomposition coefficients of eight frequency bands are extracted from low frequency to high frequency, and the energy of each frequency band after wavelet packet decomposition can be expressed as formula (3). Where, $d_{j,k}^{n}$ is the Kth coefficient corresponding to the node $s(j,n)$ after wavelet packet decomposition, and N is the original signal length.

$$E_i = \sum_k^N {d_{j,k}^{n}}^2 \quad i = 1,2,\dots,2^j \qquad (3)$$

Each energy spectrum signal then constitutes the energy spectrum vector. Through each energy spectrum vector of the third layer, the characteristic vector T can be obtained. The expression is shown in formula (4).

$$\begin{cases} E = [E_1 E_2 \dots E_{2j-1}] & j = 0,1,2,3 \\ T = [E_{(3,0)}\ E_{(3,1)}\ \dots\ E_{(3,2j-1)}] & j = 0,1,2,3 \end{cases} \qquad (4)$$

In order to facilitate the calculation and processing of data, and avoid gradient explosion in the process of neural network learning, vector T is normalized to T_1, which is a new feature vector part of the data set.

$$\begin{cases} E_s = \sum |E_{(3,j)}| \\ T_1 = \left[\frac{E_{(3,0)}}{E_s}\ \frac{E_{(3,1)}}{E_s} \dots \frac{E_{(3,j)}}{E_s}\right] \end{cases} \qquad (5)$$

In each fault state, the three-phase input current is normalized by wavelet packet feature vector extraction, and a set of 24-dimensional input variables can be obtained. Due to the fault of the same-arm power device, the wavelet energy spectrum distribution is relatively close. Therefore, on this basis, three input currents are added to generate the current amplitude after the fault, and a 27-dimensional feature vector T_2 is formed as the input data of the deep learning neural network. The following table shows part of the signal feature vector in normal state and some fault.

TABLE II. EIGENVECTORS UNDER NORMAL CONDITIONS AND CERTAIN FAULTS

	Normal Data			A Fault Data		
E0	0.95782	0.96680	0.96814	0.68129	0.70468	0.71549
E1	0.02132	0.01603	0.01349	0.08760	0.07952	0.06617
E2	0.00308	0.00201	0.00313	0.03657	0.03004	0.03131
E3	0.00487	0.00319	0.00384	0.04336	0.04506	0.04004
E4	0.00763	0.00756	0.00807	0.03098	0.02673	0.01873
E5	0.00165	0.00143	0.00107	0.03082	0.03461	0.04026
E6	0.00189	0.00186	0.00134	0.06538	0.04025	0.04984
E7	0.00224	0.00162	0.00146	0.02448	0.03961	0.03877
I	0.25759	0.25717	0.25565	0.23493	0.25258	0.25836

B. Establishment of Deep Neural Network Model

The DNN model is shown in Figure 3. Common four - layer neural network structure.

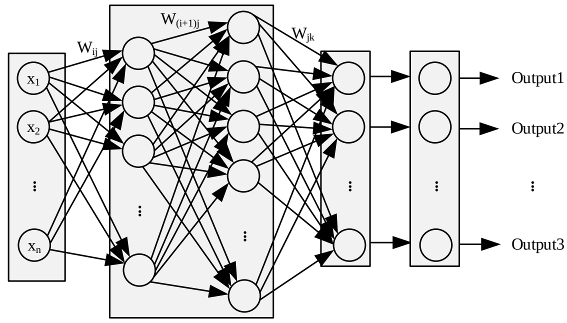

Fig. 3. DNN model structure

In Fig. 3, $X_1, X_2, \dots X_n$ are the input data of the deep neural network. The 27-dimensional feature vector T_2 composed of the reconstructed three-phase input current and each current amplitude is applied to form the training data set and the verification data set. The middle part is two hidden layers, from the second layer data to the third layer data, the third layer data to the fourth layer data need an activation function, here is the Relu function. After output from the fourth layer, the multi-classification problem of faults is involved. Therefore, the fourth layer connects the Softmax function, and the Softmax function determines the final fault type in multiple types of faults according to the results of the output layer.

C. Model Training and Fault Diagnosis Process

The fault diagnosis process of DC charging pile based on DNN is to train the model by learning the nonlinear similarity measure and using the back propagation[10–12]. After the data training, the Softmax classifier is added to the output layer to adjust the output of the entire neural network and complete the fault point identification of DC charging pile. The type diagnosis process is shown in Fig. 4.

Step1: Obtain the sample data of DC charging pile running in normal state and various faults, and collect the original data by running multiple times under different working conditions.

Step2: The fault feature is extracted from the collected data by wavelet analysis. Finally, the sample data of input DNN model with 27 eigenvalues T_2 in each group is obtained by normalization.

Step3: Using Keras to build the DNN model and initialize the parameters. According to the number of data input features and output structure, the design model has two hidden layers, 27 input neurons, 32 neurons in hidden layer 1, 30 neurons in hidden layer 2 and 11 neurons in output.

Step 4 : In the model, the neuron activation function is the Relu function, and the loss function is the cross entropy. The optimizer used in the iteration is Adam, and the $w_{(n)}$ and $b_{(n)}$ between each layer are initialized to a number close to 0.

Step 5 : 70 % of the data are the training set, and 30 % of the data are the test set.

Step6 : Softmax classifier is added to the feature output layer of the model to fine-tune the network and optimize the network output.

Step7 : Model evaluation. Use test set data to test and evaluate the trained model.

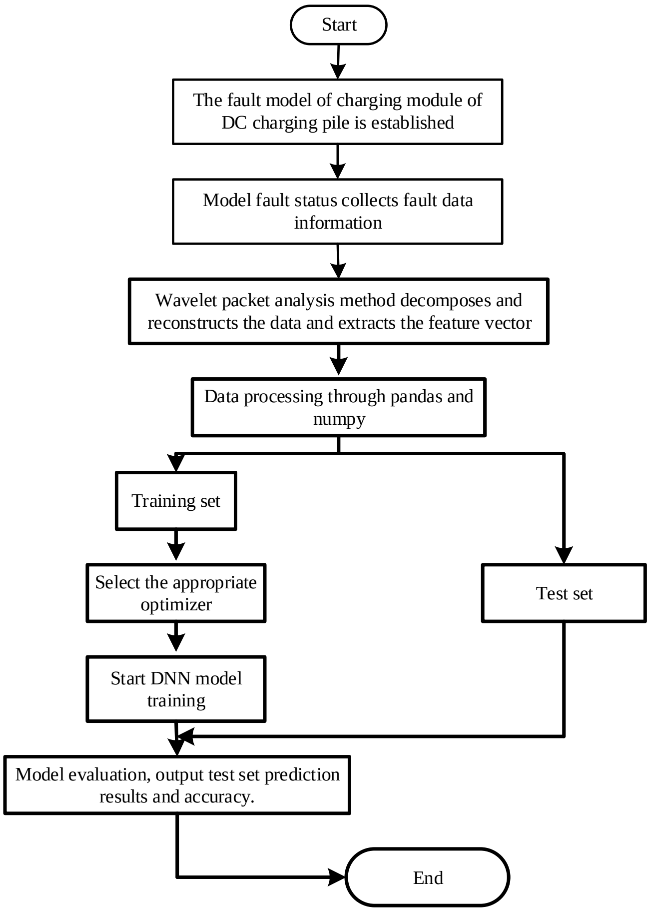

Fig. 4. Fault diagnosis flow chart of DC charging pile

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the method used in this paper, whether the prediction of DC charging pile fault diagnosis is effective. In the process of model simulation, 650 groups of sample data are collected under normal and fault conditions. Before training, 650 groups of data were divided into training set and test set, of which 455 (70 %) group data constituted training set and 195 (30 %) group data constituted test set. F0-F10 is the fault code. The meaning of the fault code is shown in table 1 above. The number distribution of training sets and test sets for 11 faults is shown in the following table III .

TABLE III. CATEGORY AND QUANTITY OF FAULT SAMPLE SET

Error code	Number of training samples	Number of test samples	error code	Number of training samples	Number of test samples
F0	35	15	**F6**	42	18
F1	42	18	**F7**	42	18
F2	42	18	**F8**	42	18
F3	42	18	**F9**	42	18
F4	42	18	**F10**	42	18
F5	42	18			

Before the training of sample data, the distribution relationship of sample data is analyzed to understand the layout of original data, which lays the foundation for subsequent DNN model processing and optimization. The sample data are reduced by principal component analysis (PCA), and the original 27-dimensional sample data are reduced to a two-dimensional plane. The feature distribution scatter plot of the reduced-dimensional data is plotted.

The visual scatter plot of sample data features is shown in Fig. 5.

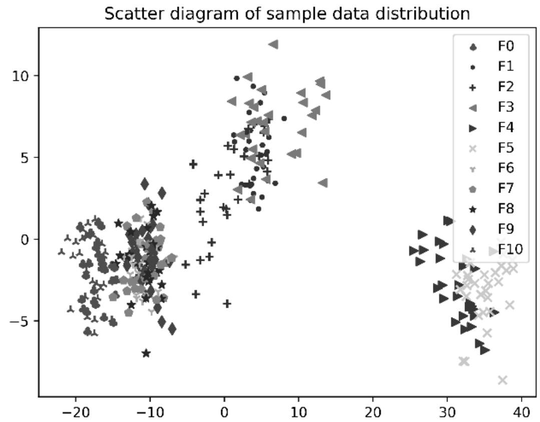

Fig. 5. Scatter distribution of original data

It can be seen from the distribution of 455 groups of sample data in Fig. 5 that the sample data of different faults are bonded together, and the distribution is chaotic, and there is no rule to clearly classify the fault types.

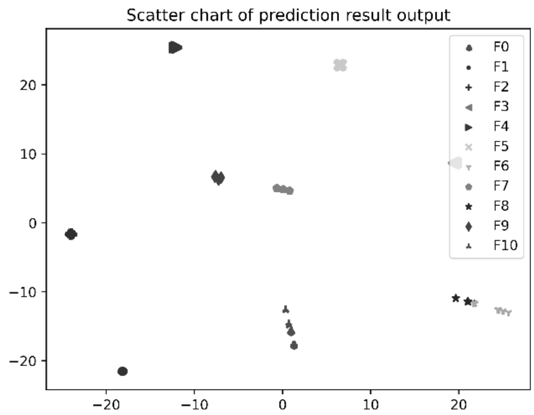

Fig. 6. Scatter distribution of fault characteristics of prediction samples

Figure 6 is 195 sets of test sets. Through the evaluation model, the 195 sets of fault feature vectors are output, and then the vector dimension reduction visualization shows, and the fault result distribution scatter diagram of the test set is obtained. Through the scatter diagram of the results, it can be seen that after DNN model training, different fault states have been clearly classified.

TABLE IV. SOFTMAX FAULT CATEGORY PREDICTION VECTOR

Error code	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
F0	0.981036	0.000000	0.000000	0.000000	0.000000	0.000000	0.000011	0.000000	0.000000	0.000000	0.018953
F1	0.000000	0.999888	0.000111	0.000000	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000	0.000000
F2	0.000000	0.000005	0.999979	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000016
F3	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
F4	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
F5	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
F6	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.885903	0.000000	0.113534	0.000563	0.000000
F7	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000036	0.749143	0.023487	0.227334	0.000000
F8	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.383361	0.000000	0.589804	0.026834	0.000000
F9	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000697	0.032049	0.096657	0.870597	0.000000
F10	0.437913	0.000002	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.562085

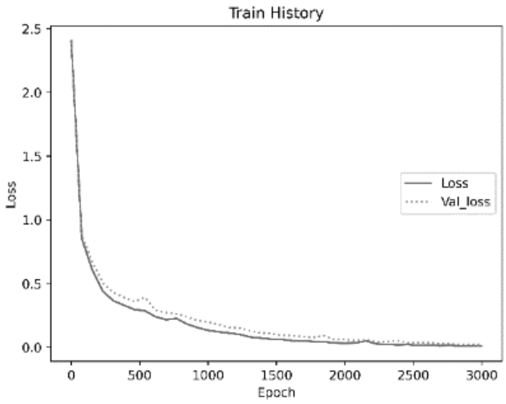

Fig. 7. Curve of training loss rate and verification loss rate

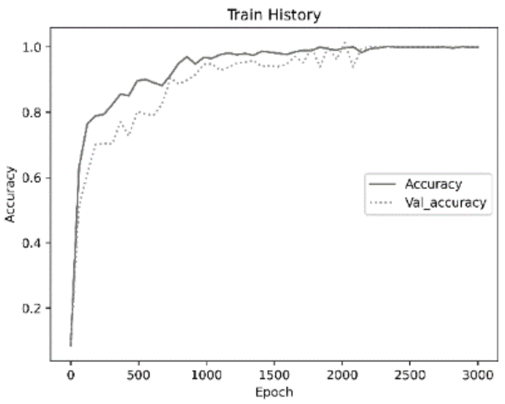

Fig. 8. Curve of training accuracy and verification accuracy

Figure 7 is the relationship between training loss rate and verification loss rate, and figure 8 is the relationship between training accuracy and verification accuracy. From the model training results, it can be seen that with the increase of iterations, the error rate of training and verification is getting smaller and smaller, and finally tends to converge. The accuracy of training and verification is rising and finally tends to be stable. The average fault recognition rate of the model can reach 95.56 %, and the performance is good.

V. SUMMERY

Aiming at the open circuit fault of DC charging pile power device and DC measuring capacitor, this paper proposes a fault diagnosis method of DC charging pile based on deep learning. The wavelet packet analysis method is used to extract the fault feature of DC charging pile. Then the deep learning framework is established by Keras, and the fault diagnosis model of DC charging pile is built with Softmax classifier. Finally, the fault recognition and location are realized. The feasibility and accuracy of the method are verified by simulation. The results show that :

(1) In this paper, the wavelet packet method is used to extract the characteristic distribution of different faults from the DC charging pile charging module. The DNN model can not only solve the gradient explosion problem, but also improve the accuracy of the model.

(2) Using DNN fault diagnosis method, combined with Softmax classifier, the fault diagnosis accuracy of DC charging pile can reach 95.56 %, and the error of the model meets the requirements. Therefore, this method verifies the feasibility of deep learning in DC charging pile fault diagnosis.

REFERENCES

[1] Kang Ning. Research on feature extraction of charging module of DC charging pile[D]. Beijing : Beijing Jiaotong University, 2019.

[2] Sun Yaguang. Research on condition monitoring and fault diagnosis system of high-power charging equipment for electric vehicles [D]. Qingdao University of science and technology, 2020.

[3] Gao Dexin, Liang Ke, Hou Junjie, Yang Qing. Design of mobile monitoring and fault diagnosis system for electric vehicle charging pile [J]. Journal of Qingdao University of science and Technology (NATURAL SCIENCE EDITION), 2019,40 (03): 107-113.

[4] Yang Shasha. Research on DC charging pile fault diagnosis expert system based on fault tree[D]. Beijing: Beijing Jiaotong University,2019.

[5] Wang Qunfei,Lu Xiaoli,Yang Dongjunming. Fault diagnosis of DC-DC module of V2G charging pile based on Fuzzy Neural Network[J]. IOP Conference Series: Earth and Environmental Science,2021,772(1):

[6] Yang Fengkun, Xu Shiming, Zhou Jing, Chen Liangliang. Research on open circuit fault diagnosis of power devices of electric vehicle DC charging pile based on wavelet packet analysis [J]. Electrical appliance and energy efficiency management technology, 2018 (23): 79-85.

[7] Quan Yunliang. Research and design of three-phase three wire Vienna rectifier [D]. South China University of technology, 2014.

[8] Wang Changhe. Research and design of DC charging pile power module [D]. Zhejiang University of technology, 2016.

[9] Zhou Peng. Research on Fault Diagnosis System of high power rectifier [D]. Central South University, 2009

[10] Meng Jianzhong. State detection and fault diagnosis technology of electric vehicle intelligent charging device [D]. Hefei University of technology, 2018.

[11] Wang Yang, Le Jian, Zhou Qian, et al. Inner and outer zone fault diagnosis method of transformer based on wavelet packet analysis and neural network[J]. Electrical Measurement & Instrumentation, 2020, 57(7): 1-7, 15.

[12] Yang Le. Harmonic analysis and suppression of electric vehicle charging station [D]. Xinjiang University, 2020