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Fault Detection of Electrical Automation Remote Equipment Based on Data Network

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ABSTRACT

In order to accurately detect the faults of electrical automation equipment, this paper proposes a data-based neural network to diagnose the faults of electrical automation equipment. This study investigates various (Radio Access Network, RAN) architectures such as cloud-RAN, heterogeneous cloud-RAN, and fog-RAN. These architectures are examined in various contexts, including system efficiency, spectrum and energy efficiency, fronthaul capacity, latency, resource sharing and allocation, etc. A neural network structure based on the (back propagation) model is used to perform forward computation on the sampled raw data, error Calculations and errors are backpropagated. On this basis, the self-adaptive learning fault detection algorithm is used to realize the self-adaptive fault detection of automatic electrical equipment. In addition to being able to accurately determine the known state of the device, the algorithm is also able to self-study the state of a non-training sample set, allowing the detection of device failures through adaptation. The experimental results show that the method is reliable, the error detection rate is greater than 0.95, and it has good anti-noise performance.

Index Terms—Adaptive learning, electrical automation, fault detection, neural network

I. INTRODUCTION

At present, the troubleshooting automation of the electrical system is poor, which basically depends on manual monitoring, manual patrol inspection, and manual maintenance, which will waste a lot of human resources, and sometimes it is necessary to cut off a subsystem for offline patrol inspection in the process of patrol inspection. Due to the post-maintenance and the need for manual experience in the troubleshooting process, the fault recovery time is long. At the same time, due to the increasing complexity of the electrical system, the effect of relying on manual inspection for maintenance is poor [1]. Therefore, it is necessary to continuously improve the reliability of the electrical system under complex and harsh conditions. Only by mastering the best intelligent diagnosis means can we ensure that the electrical system operates in a stable and economic state and ensure the normal progress of production activities and personal safety to the greatest extent [2]. With the progress of society and the development of science and technology, automatic electrical equipment is constantly improving, and electrical automation equipment has gradually replaced manpower as the main control component of enterprise operating equipment. However, due to the influence of external environmental factors, electrical automation equipment often has some faults during the operation process, resulting in the equipment not running normally. Therefore, the maintenance personnel needs to detect the electrical automation equipment in real time, find out the failure of the electrical automation equipment in time, and repair it to ensure the normal operation of the electrical automation equipment.

The application of electrical automation equipment has brought great economic benefits to society, and its own development is also very rapid. At present, it is clear that the level of use of electrical automation equipment in the industrial sector is more important and its scope is expanding. Currently, traditional methods for detecting faults in electrical automation equipment include manual inspection and shutdown testing. In the actual operation process, there will be some problems, such as a limited amount of collected information and large error in detection results. As a professional technology capable of early warning and judging faults, fault diagnosis

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technology has made great progress in the fields of machinery and power system and has also obtained many valuable research results [3, 4]. Along with social progress and technological development, automatic electrical equipment is constantly improving. Electrical automation equipment has gradually replaced manpower and became the main control part of enterprise operation equipment. However, due to external environmental factors, the electrical automation equipment may have some defects during operation and the equipment may not be operating properly. Electrical automation technology is a new technical means in the field of electrical information, which is closely related to the modern industrial field and people's life.[5]. Figure 1 shows the remote control and fault diagnostics of electrical automation equipment.

II. LITERATURE REVIEW

In recent years, more and more scientists are researching detection methods and are achieving good results. McDonald and Moyes use the expert system for fault diagnosis. The expert system has strong reasoning and interpretation ability, but the construction and organization calibration of its knowledge base need high requirements and logic, which is difficult to meet in the actual system [6]. Whittington and Flynn proposed using an artificial neural network for fault diagnosis. The neural network has strong learning and generalization ability, and the calculation between neurons is carried out in parallel, so it has good real-time performance. However, neural network algorithm needs a lot of data support, and it is difficult to guarantee the effect in the face of enlightening problems [7]. Lee and others used the partial discharge method and vibration analysis method to carry out state detection and fault diagnosis of the power plant, and comprehensively obtained the operation state of the starting power plant. The improvement of power plant automation makes artificial intelligence methods, modern statistical reasoning methods, and machine learning methods play a leading role in intelligent power plant condition monitoring [8]. Kim used the method of fuzzy set to eliminate the problems of uncertain and incomplete information in the process of fault diagnosis [9]. Jaoura and others proposed a rigid tank way fault detection method based on wavelet packet and back propagation (BP) neural network. First, two typical tank channel faults, step protrusion fault and tank channel joint fault, are simulated, and the vibration acceleration signal of the lifting container is collected. Wavelet packet decomposition is used to analyze the energy of the collected signals and extract the fault characteristic parameters. The fault characteristic parameters are used as the input of the BP neural network, and new test samples are

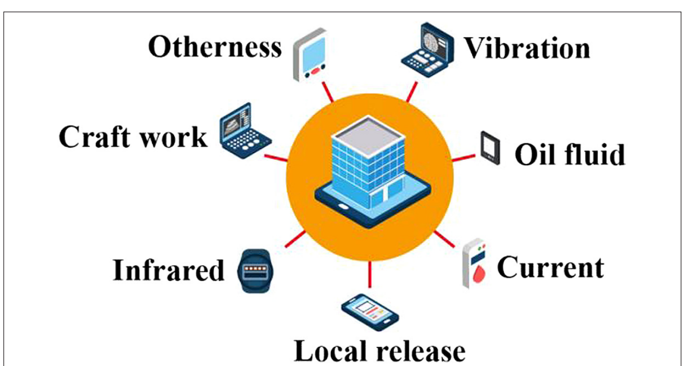

Fig. 1. Remote monitoring and fault diagnosis analysis of electrical automation equipment.

selected to output the fault diagnosis results. However, this method has the problem of low reliability of fault detection [10]. Antos and others proposed a fault detection method of chemical equipment based on fuzzy dynamic fault tree. In this method, the fuzzy dynamic fault tree is decomposed into fuzzy static subtree and fuzzy dynamic subtree, and a quantitative calculation model based on minimum cut set and minimum cut order is constructed. At the same time, the concept of weak triangular norm is introduced to reduce the inaccurate calculation results caused by the diffusion of data fuzziness, so as to realize equipment fault detection. However, this method has the problem of low fault detection rate, and the practical application effect is not good [11]. A method for fault detection of chemical equipment based on fuzzy dynamic fault tree was proposed. The fuzzy dynamic fault tree is decomposed into fuzzy static subtree and fuzzy dynamic subtree, and a quantitative calculation model based on minimum cut set and minimum cut order is constructed. At the same time, a weak triangle is introduced. The concept of the norm is used to reduce the phenomenon of inaccurate calculation results caused by the diffusion of data ambiguity, thereby realizing equipment fault detection. However, this method has the problem of low fault detection rate, and the practical application effect is not good. In order to solve the problems existing in traditional fault detection methods, a fault detection method for electrical automation equipment based on the neural network is proposed. Based on this study, this paper proposes a method for detecting faults in a data network-based electrical automation remote device. The breakdown of electrical automation equipment is divided into five types, the output voltage and input current of the load terminal of the electrical automation equipment are selected at the sampling point, and the initial data are collected at the sampling points. The neural network structure based on the BP model is adopted to carry out forward calculation, error calculation, and error reverse transmission of the sampled original data. The fault detection algorithm of adaptive learning is used to realize the adaptive detection of the fault of automatic electrical equipment. The algorithm not only accurately determines the known state of the equipment but also allows you to independently study the state of the non-training sampling package and detect the adaptability of the equipment.

III. RESEARCH METHODS

A. Fault Detection Algorithm of Electrical Automation Equipment

1) Original Data Acquisition

According to the intelligent fault diagnosis model of electrical automation equipment constructed earlier, discrete fault signals are extracted based on neural network. Considering that the specific fault of the electrical automation equipment cannot be directly judged according to any single fault parameter in the electrical automation equipment, it is necessary to uniformly convert the fault parameters of the electrical automation equipment into discrete fault signals and then perform effective extraction on this basis. Take, for example, a three-phase bridge-controlled rectifier circuit in an electrical automation device, the original data of electrical automation equipment are collected. First, the faults are classified. According to previous experience, in the main circuit of electrical automation three-phase bridge controllable rectifier, it is rare for three and more thyristors to fail at the same time, and the protection circuit turns the circuit short-circuit fault into short-circuit fault. Therefore, it is mainly necessary to study the short-circuit fault of one or two thyristors in the circuit [12, 13]. The faults of a three-phase bridge-controlled rectifier circuit in electrical automation can be divided into five types. The first is the normal working state, the second is that only one thyristor fails, the third is that two thyristors fail, and the fifth is that two cross thyristors fail. Second, set the simulation parameters and trigger pulse. The pulse duty cycle is about 26%. The trigger angles can be 0°, 30°, 60°, 90°, 120°, and 180°. Set the thyristor parameters, set the resistance to 0.15 Ω, the inductance to 1.1 μH, the buffer voltage to 0.11 μH, set the three-phase AC power supply, set the voltage frequency of each phase to 51 Hz, the phase angle mutual check to 120°, the sampling period is 100 s, and the sampling time is controlled at 0–51 ms. Finally, the sampling point is selected. The output voltage and input current contain extremely rich fault information, and these fault information can be easily detected. Therefore, the output voltage and input current of the load end are selected as the sampling point [14]. For numerical features, if the difference between the two eigenvalues is small, the two features can be considered to be very similar, but for categorical eigenvalues, there is no way to say whether they are similar because they must be different, they must not be the same. Since nominal features cannot be calculated mathematically, we can binarize them into numerical features. In the same way, numerical features can also be turned into categorical features through discretization. For example, if the petal length is greater than a certain value, it is category 0, and vice versa. But obviously, some data details are lost this way.

2) Neural Network Structure Based on BP Mode

The faults of electrical automation equipment are divided into five categories, and the output voltage and input current of the electrical automation equipment are selected as sampling points, and the original data are collected at the sampling points; the neural network structure based on the BP model is used to carry out forward calculation on the sampling original data, error calculation, and error reverse transfer. On this basis, the adaptive learning fault detection algorithm is used to realize the self-adaptive detection of the fault of the automatic electrical equipment. The state type of the sample set is learned autonomously, which realizes the self-adaptive detection of equipment faults. The BP neural network mainly adopts a smooth activation function; it has only one input layer and one output layer. The adjacent two layers are connected through the weight coefficient. The processing information in BP neural network flows forward with the layer, but the process of learning the weight coefficient is opposite to the process of information flow. The process of learning the weight factor is the opposite of the information flow process. When learning the weight factor, the weight factor is improved from front to back according to the error between the actual output and the optimal output. The BP network is the most popular and most widely used network among the multilayer transmission neural networks. The BP algorithm is represented by a three-layer conductive neural network [15]. The learning process of the neural network consists of three parts: forward calculation process, error calculation, and error reverse transmission. Taking the three-layer structure as an example, the above process is carried out.

1. Forward calculation process. In this process, the sampling point selection data are input into the neural network, and the original data $O_n = X_n\left(n = 1,2,\ldots,N\right)$ of the load end output voltage and input end current of the three-phase bridge controllable rectifier collected from the sampling point is regarded as the output of each node of the input layer. The hidden layer input is expressed as $I_j = \sum_{n=1}^{N} W_{i,j} O_n + a_n$; the input of the output layer is expressed as $I_m = \sum_{j=1}^{N} V_{i,j} O_n + a_j$; the corresponding thresholds are expressed as a_n and a_j , respectively; and the input nonlinear function is the output of each node. At this time, the following (1)–(3):

$$f\left(x\right) = \frac{1}{\left(1+e^{-1}\right)} \tag{1}$$

$$O_j = \frac{1}{\left(1+e^{-I_j}\right)} \tag{2}$$

$$O_n = \frac{1}{\left(1+e^{-I_n}\right)} \tag{3}$$

1. Calculate the average error. The total average error of all learning samples is expressed as $E = \frac{1}{N}\sum_{k=1}^{N} E_k = \frac{1}{2N}\sum_{k=1}^{N}\sum_{m=1}^{M} e_{km}^2$. In the formula, the number of training samples is expressed as *N*, the number of output neurons is expressed as *M*, and the mean square error of the *k*-th training sample is expressed as E_k. When the network inputs the *k*-th sample, the error of output neuron m is expressed as e_{km}, and the judgment parameter of the training end is expressed as *E* [16].
2. Error reverse transfer. In the process of error reverse transmission, there is an obvious relationship between the adjustment of inter-network weight coefficient and the number of input training samples. Each time the parameters of training samples are input, the inter-network weight coefficient is adjusted accordingly. The adjustment process is carried out in the reverse direction, from output to input [17]. Calculate the weight coefficient between output and hidden layers through (4):

$$V_{j,n}\left(i+1\right) = V_{j,n}\left(i\right) + \eta O_n \delta_n \tag{4}$$

where $\delta_n = O_n\left(1-O_n\right)\left(d_{p,m} - O_{p,m}\right)$, then calculate the weight factor between the input layer and the hidden layer using (5);

$$W_{i,j}\left(k+1\right) = W_{i,j}\left(k\right) + \eta O_n \delta_n \tag{5}$$

The numerical gain coefficient is expressed as η and the inertia coefficient is expressed as δ. The learning convergence speed is adjusted by two coefficients. Generally, the two coefficients range from 0 to 1. The neural network structure is designed through the BP model, in order to effectively identify whether there is a fault in electrical automation equipment.

3) Fault Detection Algorithm Based on Adaptive Learning

To achieve the purpose of adaptive fault detection of electrical automation equipment, a fault detection algorithm with adaptive learning is proposed, which has the advantage of learning the characteristics of new state types. The detailed process is as follows: the concept of credibility is introduced into the establishment of the neural network structure based on the BP model, and the possible faults in electrical automation equipment are identified according to certain judgment rules by identifying the credibility of results [18]. Take the data selected from the sampling point as the training sample, input the training sample into the neural network, correct the weight coefficient and threshold that have been calculated, and accurately identify the fault in the electrical automation equipment. Assuming that the *i*-th output vector is expressed as $S_i^{'}$, then $S_i^{'}=\left\{b_{i,j}^{'}\right\}, j=1,2,\ldots,z$, where the total number of output vectors is expressed as *z*, and assuming that the reliability is expressed as θ, there is the following formula (6):

$$\theta=\frac{\max\limits_{j=1}\left\{\left|b_{i,j}^{'}\right|\right\}}{\sum_{j=1,z}\left|b_{i,j}^{'}\right|} \tag{6}$$

Among them, the element with the largest absolute value in the *i*-th output vector is expressed as $\max\limits_{j=1}\left\{\left|b_{i,j}^{'}\right|\right\}$, and the sum of the absolute values of each element in the *i*-th output vector is expressed as $\sum\limits_{j=1,z}\left|b_{i,j}^{'}\right|$ due to some errors in the algorithm, when $\sum\limits_{j=1,z}\left|b_{i,j}^{'}\right|$ is less than 1, it is regarded as 1. Normalize the vector to obtain the following formula (7):

$$B'=\frac{b_{i,j}^{'}}{\max\limits_{j=1}\left\{\left|b_{i,j}^{'}\right|\right\}} \tag{7}$$

Set a credibility threshold Ɛ, determine whether an output belongs to a certain state through the credibility threshold and determine the credibility threshold Ɛ through the state algorithm error and the similarity between samples. According to the known reliability, evaluating the reliability of neural network output results is helpful to detect the faults of electrical automation equipment [19]. In the fault detection of electrical automation equipment, there are five types of fault feature quantities. The five types of feature quantities are used as the input vector of the neural network. The whole fault detection process is mainly to select the equipment state feature vector and classify it in the fault feature vector space, so as to realize the purpose of detecting the fault of electrical automation equipment. The characteristic quantities of these five fault types and their corresponding state codes are used as training samples, and the fault detection algorithm of adaptive learning is implemented to independently learn the state types of non-training sample sets, update the reliability threshold in the learning process, and have the accurate detection function of new states of automation equipment [20]. According to the extracted discrete fault signals, the intelligent fault diagnosis and positioning of electrical automation equipment are carried out, and the intelligent and effective fault diagnosis of electrical automation equipment is realized. First, obtain the target value of the corresponding fault point according to the failure mode, then use the neural network technology to select the transfer function of the middle layer and the number of neurons as the control core of the neuron, and finally, use the neural network algorithm to calculate the fault diagnosis amplitude to analyze the fault data. Taking the fault diagnosis amplitude as the basis for intelligent fault diagnosis of electrical automation equipment.

IV. RESULT ANALYSIS

Experiments are needed to test the effectiveness of the proposed neural network-based electrical automation device fault detection method. Since the number of input level nodes in a BP network depends on the number of input data, the number of input level nodes is 4 and the number of output level nodes is 4 [21]. The number of hidden layer nodes is not constant and can be adjusted if necessary. The number of hidden layer nodes is given by (8):

$$n=\sqrt{n_1+n_0}+\beta \tag{8}$$

Because learning the BP neural network often requires repeated training, the error value gradually becomes zero, so as to achieve the prediction effect. Due to the different weight coefficient components of the BP neural network, the results will have errors. Therefore, it is necessary to train it, and the output is as follows (9):

$$u=\sum W_i X_i=W_1X_1+W_2X_2+\ldots+W_nX_n \tag{9}$$

where $X_1,\ldots,X_n$ are the sample input signals, X_i is the sample output signal, $W_1,\ldots,W_n$ are the weight coefficients, and the final output result is the training sample network weight coefficient.

A. Network Training Results

Figure 2 shows the training sample network weight coefficient, actual deviation training results, and error elimination process when using this method to detect the three-phase bridge controllable rectifier of a certain type of electrical automation equipment. Figure 2(a) is used to describe the weight coefficient and deviation training, and Fig. 2(b) is used to describe the error elimination.

It is obvious from Fig. 2(a) that the weight coefficient is inversely proportional to the deviation. With the decrease in the weight coefficient, the detection deviation gradually increases. When the weight coefficient is 0.11, the deviation is zero. Therefore, in order to reduce the detection deviation, an appropriate weight coefficient should be selected. In Fig. 2(b), when the number of training steps is close to 300 steps, the error is almost zero, that is, the error accuracy meets the requirements. Moreover, with the reduction of error, there are more training steps, so when the error meets the detection requirements, the error accuracy should be reduced, so as to shorten the number of training steps and reduce the detection time. It can be seen from Fig. 2 that the method in this paper uses the neural network to detect electrical automation equipment, which has a high nonlinear fitting ability. Although there are many training samples and many types of electrical automation equipment faults, the overall detection process has good error elimination efficiency. When considering the elimination of detection errors and deviations, the detection time and detection accuracy should be considered, and the appropriate weight coefficient and training steps should be selected to improve the detection efficiency and shorten the detection time [22, 23, 24].

B. Voltage Fault Detection Effect

Set the voltage sample vector at the load end of the experimental three-phase bridge-controlled rectifier device as $k \quad K_1K_2K_3$ to form the sample characteristic vector. After normalizing the vector, select six kinds of fault voltage samples output by the thyristor load end as the detection samples, namely GZ1, GZ2, GZ3, GZ4, GZ5, and GZ6. This method is used for voltage fault learning and detection. The results are presented in Table I.

The status codes 1–7 in Table I verify that the detection results of this method for known faults are good, and 8 is an unknown input vector to be detected. It can be seen that the reliability of 1–7 input vectors is higher than 0.97, that is, they have high reliability; Assuming

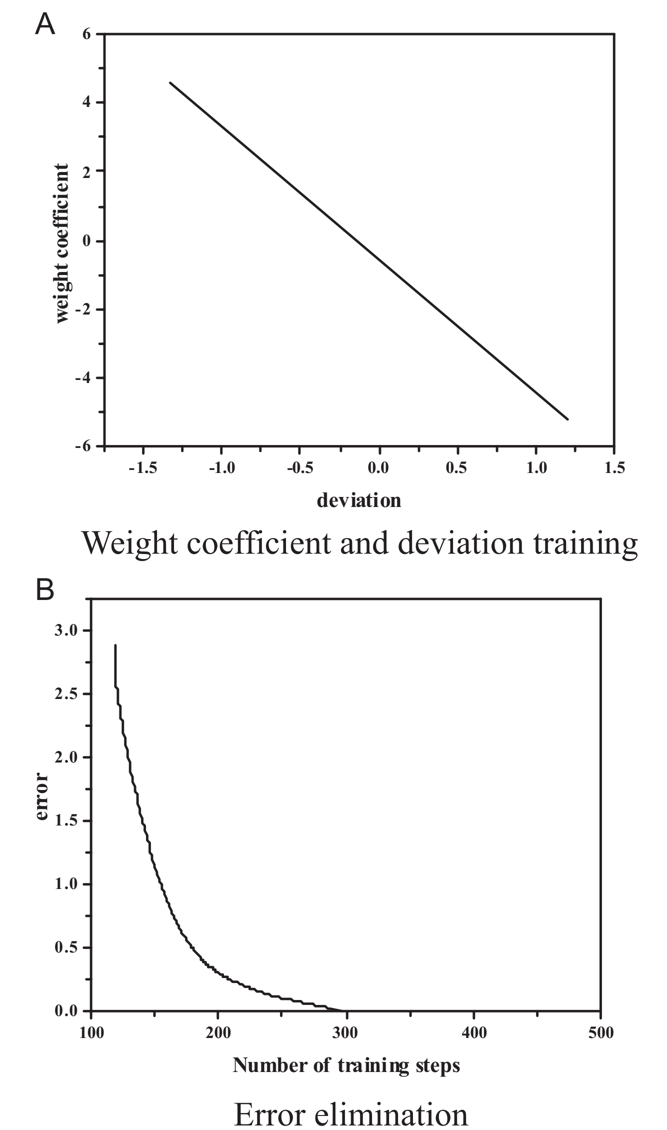

Fig. 2. Training results of neural network. (a) Weight coefficient and deviation training. (b) Error elimination.

TABLE II. RETEST RESULTS OF SAMPLE VECTOR TO BE TESTED

	Network Output	Reliability
8	8	0.99

a confidence threshold of 0.65, it can be seen that the output result of the input vector to be identified in the table is the output result of state code 3, and the confidence is 0.53, which is less than the confidence threshold of 0.65, indicating that the detection result is inaccurate. It is necessary to update the weight coefficient and threshold, re-detect it, and re-detect it to obtain the detection result of the sample vector to be tested [25, 26] (Table II).

It can be seen from Table II that after resetting the weight coefficient and threshold, the reliability of the sample to be identified is 0.99, which is greater than the reliability threshold of 0.65. The output result of the vector of the sample to be identified has high reliability, which shows that this method can accurately identify new samples and effectively detect the voltage fault at the load end of the new three-phase bridge controllable rectifier.

C. Current Fault Detection Effect

Input the test sample into the fault detection method and compare the test result with the actual fault vector. If the test result exists in the fault vector, the equipment fault corresponding to the test result is the test fault. If the test result is not in the fault vector, the test result is wrong. Eight operating conditions of the load end current of the experimental three-phase bridge controllable rectifier are selected as the test samples, and the fault detection results of this method are obtained (Table III) [27].

It can be seen from the table that the detection efficiency of the current fault at the load end of the three-phase bridge controllable rectifier diagnosed by this method is more than 0.95, which has a high detection efficiency, which is more consistent with the actual fault, indicating that this method can accurately detect the current fault at the load end of the three-phase bridge controllable rectifier. As can be seen from Table III, for distribution network fault identification, the wavelet packet method shows a certain identification speed and generalization ability, but its accuracy is low when identifying short circuit fault. The fuzzy diagnosis method shows a strong generalization ability and accuracy, which is also corresponding to its principle.

TABLE I. VOLTAGE FAULT LEARNING SAMPLES AND TEST RESULTS

		K_1	K_2	K_3		
Status Code	Fault Sample		Network Input		Network Output	Reliability
1	Normal	0.77	0	0.45	1	0.99
2	GZ1 fault	1	0	1	2	0.98
3	GZ2 fault	0.88	0	0.87	3	0.98
4	GZ3 fault	0.77	0	0.11	4	0.99
5	GZ4 fault	0.81	0	0.74	5	0.98
6	GZ5 fault	0.84	1	0.73	6	0.97
7	GZ6 fault	0.73	0	0.71	7	0.98
8	Sample to be identified	0.97	0	-0.34	3	0.53

TABLE III. FAULT DETECTION RESULTS

	Test Sample							
	1	2	3	4	5	6	7	8
Detection output	0	0.99	0	0	0	0	0	0.97
	0	0	0.95	0	0	0	0	0.96
	0	0	0	0.97	0	0	0	0
	0	0	0	0	0.94	0	0	0
	0	0	0	0	0	0.99	0	0
	0	0	0	0	0	0	0.98	0
	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0
Detection result	Normal	HN1 fault	HN2 fault	HN3 fault	HN4 fault	HN5 fault	HN6 fault	HN1 and HN2 fault

However, the algorithm itself is slow, and we can see that the calculation speed of the wavelet packet method and fuzzy diagnosis method is far behind the method in this paper.

D. Equipment Operation Status Analysis

By comparing the methods in this paper, wavelet packet method and fuzzy diagnosis method [28], it is analyzed that after three methods are used to detect the fault of the experimental three-phase bridge controllable rectifier, the device operates in normal state, high temperature state, and low temperature state. The results are shown in Table IV [29].

It can be seen from Table IV that this paper method was used to detect faults in three-phase bridge-controlled rectifiers, the operation time of the device under high temperature is only 4.95 Ms. The operation time in low temperature state and normal temperature state is much lower than that of the other two methods, which shows that the operation efficiency of the device can be significantly improved after using this method to detect the fault of three-phase bridge controllable rectifier.

TABLE IV. OPERATION STATUS ANALYSIS RESULTS

		Running Time/ms		
		Normal State	High-Temperature State	Low-Temperature State
Paper method	Start	3.25	2.09	2.64
	In operation	5.01	4.95	4.35
	End	2.09	2.24	1.97
Wavelet packet method	Start	11.36	10.28	10.88
	In operation	13.24	12.95	12.47
	End	10.02	10.57	9.94
Fuzzy diagnosis method	Start	23.25	21.55	22.52
	In operation	28.71	27.43	27.32
	End	22.92	22.58	21.55

E. Detection Rate Analysis

Compare the detection rates of the three methods under different interference signal-to-noise ratios. The comparison results are shown in Fig. 3 [30].

According to the analysis of Table IV, when the interference signal-to-noise ratio is 2 dB, the maximum detection time of this method is 6.51 ms, when the external signal-to-noise ratio is 39 dB, the shortest detection time for this document method is 4.23 ms. Under various interference-to-noise ratios, the detection time of the wavelet packet method is between 28.58 ms and 35.25 ms and that of fuzzy diagnosis method is between 15.28 ms and 23.17 ms. Comparing the detection time of the three methods, it can be seen that this method has the highest detection rate and the best prediction performance and can effectively realize the high-efficiency detection of electrical automation equipment faults. The fault detection algorithm of adaptive learning is adopted to realize the adaptive detection of automatic electrical equipment faults. The reliability and detection rate of the detected faults are both higher than 5%, so the algorithm can not only accurately detect the known state of the equipment, but also self-learning the state type of the non-training sample set, realizing the adaptive detection of equipment faults, and the method has good anti-noise performance.

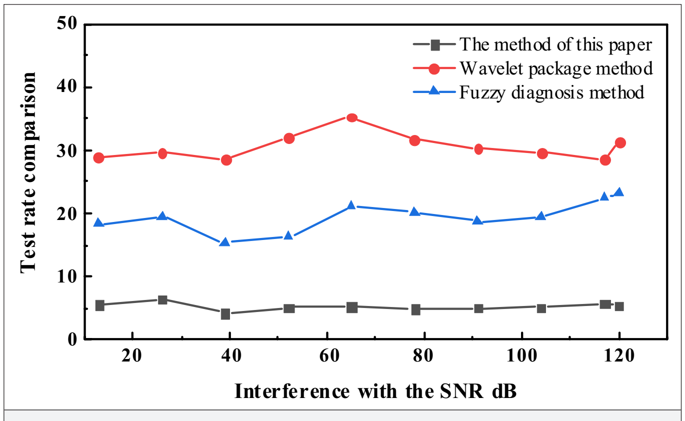

Fig. 3. Comparison of detection rates.

V. CONCLUSION

With the continuous development of automation technology, electrical automation is widely used in industrial enterprises. How to efficiently and accurately detect the faults in electrical automation equipment has become a research hotspot. The designed fault intelligent diagnosis technology can not only complete the tasks that the traditional fault intelligent diagnosis technology cannot complete but also provide academic significance for the design of the fault intelligent diagnosis technology of electrical automation equipment with the fault diagnosis model as the core. In the experimental part, through the network training results, it can be seen that when detecting the fault of electrical automation equipment, this method should consider eliminating the detection error and deviation, combined with the detection time and the required accuracy, select the appropriate weight coefficient and training steps, and shorten the detection time while improving the detection efficiency. At the same time, this method can accurately detect the voltage and current faults at the load end of the thyristor, has high adaptive learning ability, can accurately identify new faults, and has high reliability. Combined with the earlier analysis, this method has the best performance in detecting the fault of electrical automation equipment.

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