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Fault Diagnosis of Power Electronic Circuits Based on Improved Particle Swarm Optimization Algorithm Neural Network

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ABSTRACT

In the rapid development of high and new technology, the intelligence and integration of modern equipment are constantly improving. Power electronics technology is one of the indispensable key technologies in any high and new technology. In this paper, a power electronics circuit fault diagnosis based on improved particle swarm optimization neural network is proposed, the algorithm design of particle swarm optimization algorithm neural network is introduced, and the improved PS0 algorithm, standard PS0 algorithm, and BP algorithm optimized neural network are applied to the fault diagnosis classification system of rectifier circuits. The results show that the parameters of the basic (particle swarm optimization) algorithm are as follows: the parameter value of the basic PSO algorithm is the number of particles is 30, W decreases from 0.9 to 0.4 linearly with the increase of iterations, and the number of iterations is 300. The BP algorithm uses the traingdx training function. The transfer functions of the hidden layer and the output layer are hyperbolic tangent sigmoid and Purelin function, respectively. The target error $e=0.01$. The superiority and effectiveness of the neural network diagnosis model of the improved PS0 algorithm are shown in this paper. This method can solve the fault diagnosis problem of the double-bridge parallel rectifier circuit.

Index Terms—Improved particle swarm optimization algorithm, neural network, power electronic circuit fault, BP neural network

I. INTRODUCTION

Power electronics technology was formed in the 1970s. With the continuous improvement of circuit topology, control strategies, and the development of power semiconductor devices, passive components, digital signal processor chips, and system integration technology, the efficiency and power density of power electronics systems has been continuously improved [1]. A variety of high-performance, high-complexity power electronic products continue to emerge, with applications covering many fields such as industrial production, automobile manufacturing, energy generation, rail transit, and aerospace, involving almost all aspects of social life [2]. From mobile phones, computer server power supplies, electronic lighting, chargers, to electric vehicles, motor drive devices, photovoltaic inverters, power transmission systems, aircraft secondary power supplies, and so on, power electronic equipment can be seen everywhere. The combination model of wavelet neural network based on integrated moving average autoregression and genetic particle swarm optimization has also been studied, as shown in Fig. 1 [3]. Power electronic devices are usually used as power supplies or motor drives in engineering systems to provide electrical energy for the entire system. They are a key component of the system and have a significant impact on the reliability of the system. Especially in those application areas that require high safety, such as aerospace and weapon systems, its importance is even more self-evident. Therefore, it is of great military and economic significance to study the fault diagnosis technology of power electronic circuits and apply it to practical power electronic devices [4]. Fault diagnosis begins with (mechanical) equipment fault diagnosis, whose full name is condition monitoring and fault diagnosis. It contains two aspects: one is to monitor the running state of the equipment and the other is to analyze and diagnose the faults of the equipment after discovering abnormal conditions. Fault diagnosis technology has a history of more than 30 years of development and has been widely used in aircraft autopilot, artificial satellites, space shuttles, nuclear reactors, steam turbine generator sets, large *power* grid systems, petrochemical processes and equipment, aircraft and ship engines, automobiles, metallurgical equipment, mining equipment, and

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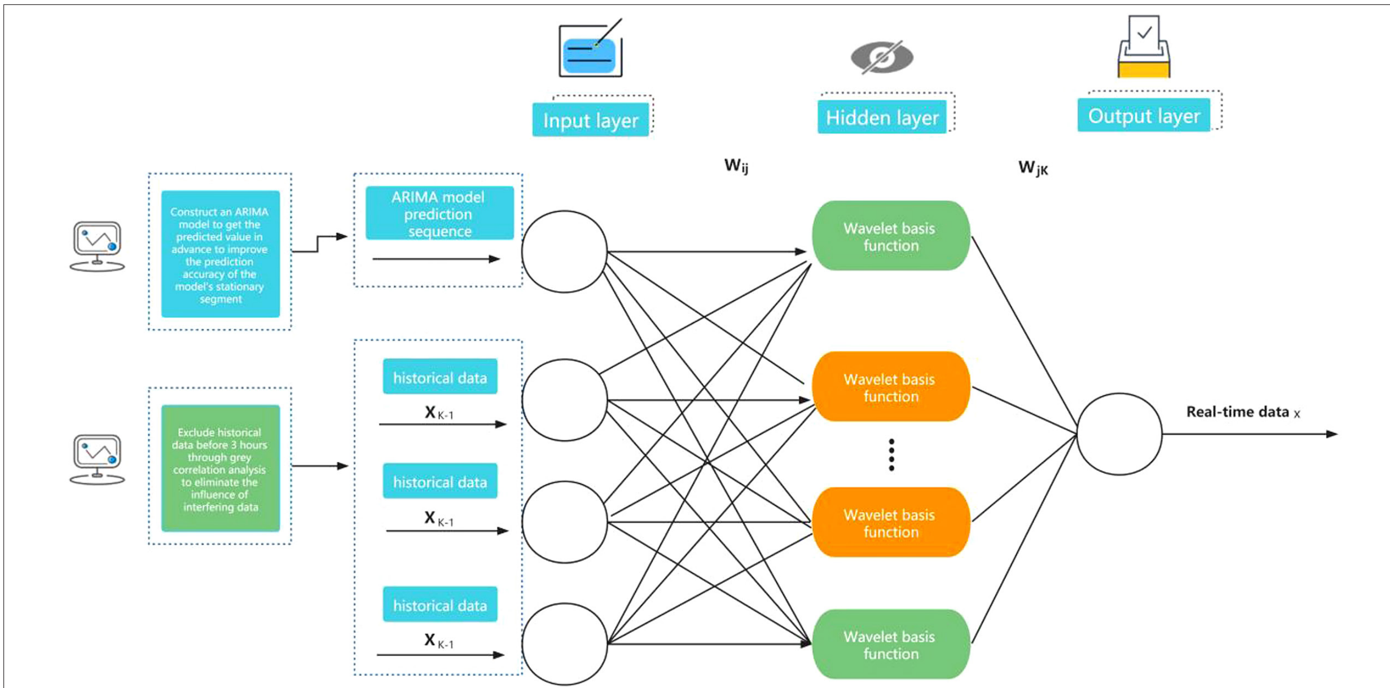

Fig. 1. Combined model of wavelet neural network integrating moving average autoregression and genetic particle swarm optimization.

machine tools. The artificial neural network is developed on the basis of modern neurological research results. It is a network system that imitates the information processing mechanism of the human brain. It is widely connected by a large number of simple artificial neurons; although it is not a human brain, it does reflect several characteristics of human brain function, which can complete functions such as learning, memory, recognition, and reasoning. Because the neural network has the ability of self-learning and fitting any continuous nonlinear function and the ability of parallel processing, distributed information storage, and global action, it has strong advantages in nonlinear problems and online estimation potential, so it is very suitable for fault diagnosis system.

II. LITERATURE REVIEW

For this problem, Yang et al.'s fault diagnosis method based on analytical models mainly uses Kirchhoff's voltage and current law to analyze the circuit and derives the analytical model of power electronic circuits. The fault diagnosis method based on the analytical model detailed is divided into the method based on the state space average model and the method based on hybrid system modeling [5]. Xu et al. used potential circuit analysis to derive the BUCK circuit state space average model based on the connection matrix generated by the component current and voltage and used heuristic algorithms to obtain characteristic parameters that can be used for fault diagnosis and determined the fault type according to the preset fault set [6]. For the real-time fault diagnosis of switching converter circuits, Wang et al. proposed a state space model based on switching converter circuits, which converts the component parameters to be diagnosed into state variables, and uses strong tracking filter to track and estimate the component parameters and states. According to the estimation results and modified Bayes (MB) algorithm, the fault of circuit components is diagnosed in real time [7]. Ukasz et al. established a corresponding fault model for each fault event based on the hybrid logic dynamic model for the inverter circuit , constructed a circuit observer based on the fault model, and calculated the residual error between the observed value and the actual circuit fault event identification vector. The fault identification threshold is used to determine whether the corresponding fault event occurs so as to realize fault diagnosis [8]. Based on the hybrid system theory, Soo-Kyoung et al. established a mathematical model of power electronic circuits and used various algorithms to identify circuit device parameters so as to realize the fault diagnosis of power electronic circuits [9]. Wang et al. developed a fault diagnosis method based on hybrid system theory, used hybrid system model to replace the actual circuit model, and applied it to the field of power electronic circuit fault diagnosis [10]. Bi et al. used the bispectrum analysis of the sampled data to obtain the fault characteristics of the circuit, used the discrete hidden Markov model to distinguish the fault type. They took the fault diagnosis of the main converter of the SS8 locomotive as an example, and the feasibility and effectiveness of the diagnosis algorithm are verified [11]. Li et al. established a fault model for the 12-pulse controllable rectifier circuit based on the rectifier waveform in case of circuit failure. Through the spectral analysis of the failure mode vector, the corresponding fault characteristic parameters are extracted and then the fault is located [12]. Xu et al. proposed an analysis of the harmonic components of output voltage and current for the open and short circuit faults in power electronic converter modules (including three-phase rectifiers, DC-DC conversion circuits, and single-phase inverters). The diagnosis result is obtained by comparing the specified harmonic component with the failure threshold [13]. For the fault diagnosis of DC-DC converter circuit, Gong et al. used wavelet analysis to extract the feature vector of the circuit failure mode and built a fault dictionary based on the center of gravity and radius of the feature vector. In the actual diagnosis, the fault type can be determined by calculating the Mahalanobis distance between the eigenvector of the circuit to be tested and the eigenvector corresponding to the

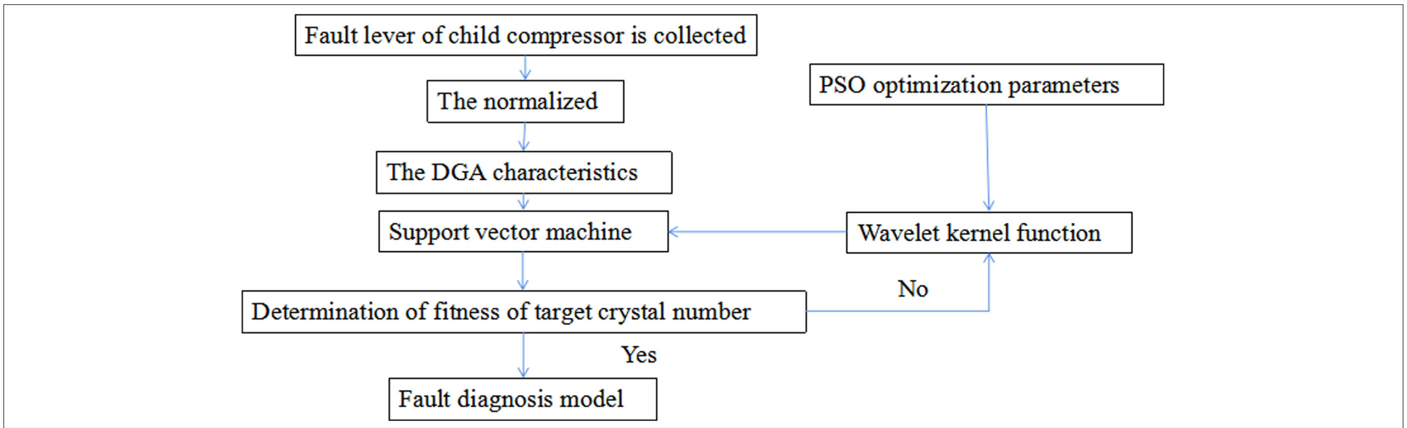

Fig. 2. Wavelet particle swarm optimization -SVM transformer fault diagnosis method based on three-ratio feature quantities.

center of gravity of each fault mode and comparing it with the corresponding fault radius [14]. According to the singularity of the signal generated by the power electronic device in the event of an open circuit fault, Changzhi et al. proposed a fault diagnosis method with wavelet branch detection. The wavelet particle swarm optimization (PSO)- Support vector machine (SVM) transformer fault diagnosis method with three-ratio feature quantities is shown in Fig. 2. Taking the open-circuit fault of a three-phase bridge rectifier circuit as an example, through the wavelet multi-scale decomposition of the output voltage waveform under each fault mode, the correlation dimension is calculated to determine the fault type [15].

There is a big difference between the fault diagnosis of power electronic circuits and the general analog circuits and digital circuits because the overload capacity of power electronic devices is small, the damage speed is fast, the symptoms before the fault occur are difficult to capture, and the fault information only exists until the fault occurs. In the tens of microseconds before the power failure, real-time monitoring and online diagnosis are required; the power of power electronic circuits has reached thousands of kilowatts, and the method of changing the input and seeing the output used in analog circuits and digital circuits is not suitable. Only the output waveform can be used to diagnose whether there is a fault in the power electronic circuit and what kind of fault because some power electronic equipment contains as many as tens or hundreds of power switching devices, the conventional method of diagnosing one by one is time-consuming and laborious, and cannot meet the needs of real-time diagnosis. Based on the current research, this paper proposes a power electronic circuit fault diagnosis based on an improved PSO algorithm neural network and introduces the algorithm design of the particle swarm algorithm to optimize the neural network. It can be seen from the simulation analysis that the fault diagnosis method proposed in this paper is completely effective for the fault diagnosis of resistive and resistive inductive load in double bridge parallel rectifier circuit, and it is also correct for the fault diagnosis under the rectifier state of back EMF load.

III. METHODS

A. Algorithm Design of Particle Swarm Algorithm to Optimize Neural Network

PSO algorithm parameters are the key to affecting the performance and efficiency of the algorithm. How to determine the optimal parameters to make the algorithm perform the best is itself an extremely complex optimization problem. Due to the different size of the parameter space and the correlation between the parameters, there is no general method to determine the optimal parameters in practical applications. According to the simulation idea of PSO algorithm, the basic PSO algorithm model, the PSO algorithm model with inertia weight, and the PSO algorithm model with shrinking factor are constructed, respectively, and the models are analyzed in detail through a large number of experimental studies The meaning and function of different control parameters in the paper, and the corresponding reference values are determined for them. This paper mainly uses the PSO algorithm to train the neural network to optimize its weights and thresholds [16]. The dimension of the particle position vector X is the sum of the weight and the threshold of the trained network. First, initialize the position vector and then use the PSO algorithm to search for the optimal position to minimize the following mean square error index (fit value):

$$J = \frac{1}{NC}\sum_{i=1}^{N}\sum_{j=1}^{C}\left(y_{j,i}^{d} - y_{j,i}\right)^2 \tag{1}$$

where N is the total number of samples in the training set, C is the number of output neurons of the network, y_{ij} is the ideal output value y of the jth output neuron of the ith sample. j is the actual output value of the jth output neuron of the ith sample. The specific steps of the improved PSO algorithm to train the neural network are as follows:

(1) Determine the topology of the network according to the input and output sample sets of the neural network.
(2) Parameter initialization, C1, C2 take 2.05. The number of particles m = 30, the dimension D is the sum of all the weights and thresholds of the network, the initial particle velocity V and position X are random number between [−1, 1]. Set $V_{max} = V_{max}$ as the maximum value of the variable. Initial inertia coefficient $W(0) = 0.729$, at this time, $a^0 = 3.16a^{-1}$. Set the minimum error and the maximum number of iterations T_{max}.
(3) Calculate the value of the fitness function according to (1), find the optimal position P_{best} of each particle, and the optimal position G_{best} of all particles.
(4) Update the inertia coefficient W. If the mean square error J is not less than the set threshold, and the velocity of all particles is not less than a certain minimum value, the value of velocity v is updated according to the velocity iteration formula. Otherwise,

update the value of speed *v*. Update the position of the particle *x* according to the position iteration formula.

(5) Check whether the speed and position of the particles are out of bounds. If there are any out of bounds, limit the speed and position of the particles.

(6) Determine whether the termination condition has been met. If the maximum number of iterations has reached, or the fitness value has reached the minimum value, the calculation is aborted. Otherwise, go to step (3) to continue execution. It can be seen from the above description that the improved PSO algorithm is used to train the neural network, which avoids the backward propagation process in the original BP algorithm, accelerates the search speed, and prevents the premature convergence of the entire algorithm.

B. Design and Training of Neural Network Structure

Before neural network training, it is necessary to determine the neural network structure. Here, a three-layer BP neural network structure is used, that is, a structure of an input layer, a hidden layer, and an output layer [17]. The number of nodes in the input layer is determined by the number of fault characteristic signals, that is, $N_1 = 6$. The number of code bits of the fault type determines the number of nodes in the output layer. It can be seen from the classification of the fault type that the fault type is identified by a five-bit data code, so the number of output nodes is $N_3 = 5$.

The number of hidden layer nodes is the main factor that determines the learning ability and generalization ability of the neural network, and it also affects the simulation time required by the neural network in fault diagnosis [18]. There is no strict theoretical basis for the selection of the number of hidden layer nodes. It need be adjusted through a series of simulation experiments. If the number of hidden layer nodes is too small, then the generalization ability of the network is poor, and even the network learning cannot converge at all [19]. If there are too many hidden layer nodes, then the training time is too long, the network structure is complex and huge, and the problem of transition training may also occur. Selecting the minimum number of hidden layer nodes that meet the required performance for fault diagnosis can achieve an ideal diagnosis effect [20]. For the same set of training samples, this paper selects a variety of different structural combinations to train the neural network. First, the expression method of the network topology is defined: the hidden layer neurons use the S-shaped hyperbolic tangent function, namely the Tan-sig function, the output layer neurons use S-type logarithmic function, namely Logsig function [21]. The training times and misjudgment rate of different structure combinations are shown in Table I.

TABLE I. TRAINING OF NEURAL NETWORK

Serial Number	Number of Hidden Layer Nodes	Iterative Steps	Misjudgment Rate %
1	12	268	4
2	15	196	1
3	18	231	2
4	20	241	1

It can be concluded from Table I that considering the number of iteration steps and the complexity of the network, the number of nodes in the hidden layer may choose $N_2 = 15$ as the ideal number.

IV. RESULTS AND ANALYSIS

Before training a neural network, it is necessary to determine the neural network structure used. The three-layer BP neural network structure is adopted here, that is, the structure of an input layer, a hidden layer, and an output layer is adopted. The number of nodes in the input layer is determined by the number of fault characteristic signals, that is, $N_1 = 6$. The number of fault type codes determines the number of nodes in the output layer. According to the fault type classification, the fault type is identified by a five-bit data code, so the number of output nodes is $N_3 = 5$. The number of nodes in the hidden layer is the main factor that determines the learning ability and generalization ability of the neural network and also affects the simulation time required for the neural network to diagnose faults. There is no strict theoretical basis for the selection of the number of hidden layer nodes. It must be adjusted through a series of simulation experiments. If the number of hidden layer nodes is too small, the generalization ability of the network is poor, and even network learning cannot converge at all. The number of hidden layer nodes is too large, the training time is too long, the network structure is complex and huge, and there may be problems of transition training. Selecting the number of hidden layer nodes that meets the required performance and has the least number for fault diagnosis can achieve an ideal diagnosis effect.

In total, 520 groups of data are extracted from the fault waveform characteristic signal, of which 400 groups of data are used as learning samples to train the neural network and 120 groups of data are used to test the network [22]. In order to analyze the validity and superiority of the experimental results, under the same level and structure, for the same set of non-training samples, the improved PS0 algorithm, basic PS0 algorithm, and BP algorithm in this paper are used for the fault diagnosis of the double-bridge parallel rectifier circuit. The error curve of training is shown in Fig. 3 and Fig. 4. The

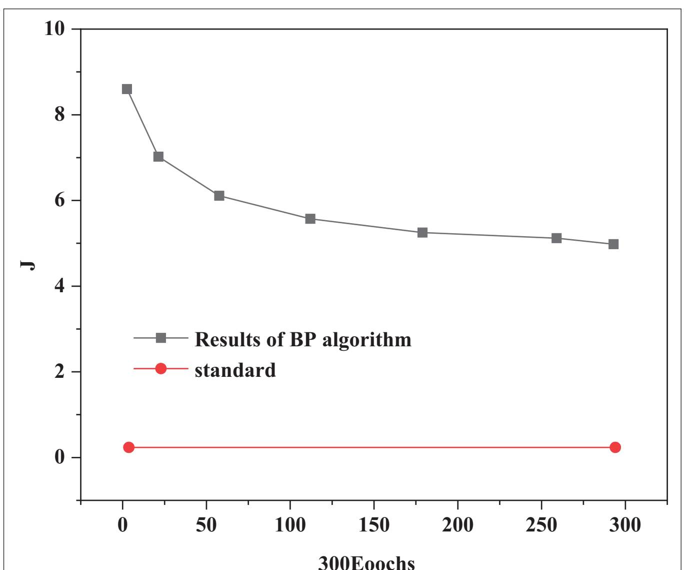

Fig. 3. BP algorithm training results.

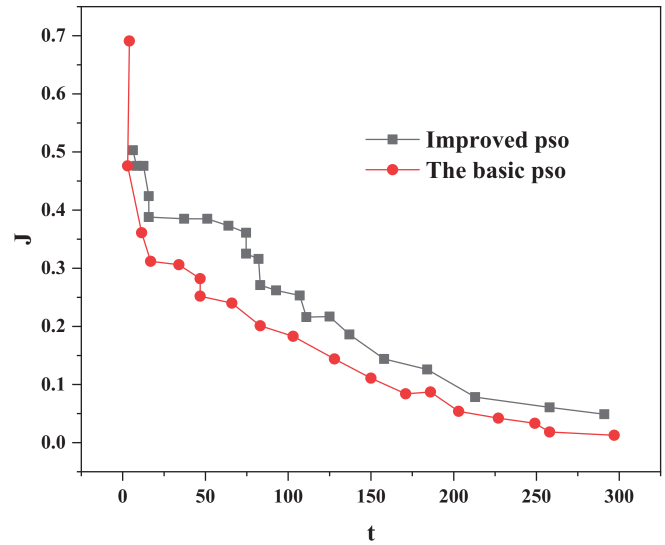

Fig. 4. PSO algorithm training results.

performance indicators of various algorithms in the test results are shown in Table II.

The parameters of each algorithm in the experiment are set as follows: the parameter value of the improved PSO algorithm is the number of particles is 30, $W(0)=0.729$, at this time, $a^0=3.16a^{-1}$, $C_1=C_2=2.05$, $V_{min}=1e-3$, target error e = 0.0l, number of iterations $T_{max}=300$. The parameter value of the basic PSO algorithm is the number of particles is 30, $C_1=C_2=2.05$, and W decreases linearly from 0.9 to 0.4 with the increase of iterations, and the number of iterations is 300 times [23]. The BP algorithm uses the traingdx training function. The transfer functions of the hidden layer and the output layer are hyperbolic tangent sigmoid and Purelin function, respectively, and the target error e = 0.01.

In Fig. 3, the dotted line is the result of the basic PSO algorithm, and the solid line is the result of the improved PSO algorithm in this paper. It can be seen from the above two figures: Under the same level and structure, for the same set of training samples, the standard BP algorithm is slow and has poor accuracy, while the improved PSO algorithm can get higher accuracy and faster speed. Compared to the basic PSO algorithm, its training speed and accuracy are also improved [24].

It can be seen from Table II that compared with the pure BP algorithm fault diagnosis, the training time of the improved PSO algorithm neural network method in this paper is reduced by nearly one-third, avoiding falling into the local minimum, and the accuracy has been greatly improved. Compared with the basic PSO algorithm diagnosis, the method in this paper also has higher accuracy and higher fault correct rate. It can be seen that the improved PSO hybrid algorithm neural network fault diagnosis method in this paper effectively reduces the training time, greatly improves the diagnosis accuracy, and can effectively improve the accuracy of the fault diagnosis and the learning efficiency of the neural network [25, 26].

TABLE II. COMPARISON OF EXPERIMENTAL RESULTS OF DIFFERENT ALGORITHMS

Algorithms	Training Time (s)	Error	Correct Rate %
BP	48.7312	0.2359	88
PSO-BP	18.6199	0.0594	92
Proposed method	17.8101	0.0121	97

PSO, particle swarm optimization.

In the case of adding 5% white noise, non-training samples are used to verify the trained PSO algorithm neural network. For the completeness of comparison, the eigenvectors obtained from load change and input voltage change are selected to verify the network. (1) In the case of resistive and resistive inductive loads added with 5% white noise, different resistance values and eigenvectors obtained at different input voltages are selected to verify the established PSO algorithm neural network. The diagnosis results of the neural network are compared with the actual fault types, and some of the results are listed in Tables III. The output result of 1–5 digits

TABLE III. 1-12 EXPERIMENTAL OUTPUT VALUES AND EXPECTED VALUES

Serial Number	Y5	Y4	Y3	Y2	Y1	Expected Values
1	0.002	0.102	0. 046	0.046	0.998	0 0 0 0 1
2	0.007	0.231	0.982	0.982	0.104	0 0 0 1 0
3	0.009	0.163	0. 899	0.899	0.921	0 0 0 1 1
4	0.010	0.036	0.027	0.027	0.041	0 0 1 0 0
5	0.013	0.165	0.142	0.142	0.944	0 0 1 0 1
6	0.043	0.158	0. 887	0.887	0.217	0 0 1 1 0
7	0.123	0.214	0. 956	0.956	0.934	0 0 1 1 1
8	0.056	0.948	0.134	0.134	0.142	0 1 0 0 0
9	0.022	0.953	0.285	0.285	0.996	0 1 0 0 1
10	0.034	0.972	0.897	0.897	0.156	0.1010
11	0.054	0.969	0.998	0.998	0.866	01011
12	0.036	0.102	0.023	0.023	0.049	01100
13	0.278	1.000	0.945	0.968	0.867	0 1 1 1 1
14	0.235	0.978	0.896	0.798	0.365	0 1 1 1 0
15	0.158	0.953	1. 000	0.264	0.942	0 1 1 0 1
16	0.966	0.354	0.213	0.145	0.068	1 0 0 0 0
17	1.000	0.153	0.078	0.081	0.966	1 0 0 0 1
18	0.977	0.021	0.036	0.895	0.135	1 0 0 1 0
19	1. 000	0.209	0.162	0.325	0.825	1 0 0 1 1
20	0.973	0.102	0.991	0.017	0.026	1 0 1 0 0
21	0.985	0.314	0.994	0.142	0.867	1 0 1 0 1
22	0.856	0.235	0.987	0.953	0.136	1 0 1 1 0
23	0.998	0.012	0.898	0.952	0.935	1 0 1 1 1
24	0.987	0.913	0.007	0.152	0.143	1 1 0 0 0

is rounded up to make it 0 or 1. The corresponding fault diagnosis result can be found through the six-digit code [27-29].

It can be seen from Tables III that the actual output value is basically consistent with the expected output value, and the fault diagnosis accuracy rate is above 97%. The experimental results show that under resistive and inductive loads, the trained network has certain anti-interference ability, has good generalization ability to other samples, and can carry out quite accurate fault diagnosis.

V. CONCLUSION

The fault diagnosis of power electronic circuits is of great significance to the power system. Based on previous researches, this paper studies the fault diagnosis of power devices in double-bridge parallel rectifier circuits and proposes an idea of using a neural network optimized by improved PSO to diagnose faults in rectifier circuits. When the load is a DC motor, in the rectification state and the inverter state, collect certain fault waveform data for spectrum analysis, and then verify the trained PSO algorithm neural network. The simulation verification results show that the fault diagnosis is wrong, most of which occur when the back-EMF load is in the inverter state. From the above simulation verification analysis, the fault diagnosis method proposed in this paper is completely effective for the fault diagnosis of resistive and resistive inductive loads in double-bridge parallel rectifier circuits and is also correct for the fault diagnosis under the rectifier state of back EMF load. The method in this paper can hardly correctly judge the power device failure in the inverter state. This is mainly because the fault waveform at this time is very different from the rectified output waveform, and the fault characteristic has changed. This is the direction for further study: how to select the fault characteristics in the inverter state and select more learning samples to train the network, so that the network is more complete and has a wider application range.

In this paper, the application of artificial neural network to the fault diagnosis of circuits has been discussed, and certain results have been obtained. The next research work focuses on the following improvements:

(1) Using a better PSO algorithm, this paper only improves the adjustment method of the weight of the PSO algorithm. At present, there are many improvements to the PSO algorithm. For example, multiple groups can be used to make the algorithm achieve better results.
(2) Aiming at the problem of extracting fault characteristic signals of multiplexed rectifier circuits, wavelets can be used to extract faulty characteristic signals of multiplexed rectifier circuits, so that the faulty characteristic signals are more accurate and concise.
(3) Simulation and experimental verification show that the correct rate of fault diagnosis has not reached 100%, and how to optimize the learning sample design of the neural network needs further research.
(4) Further study about the fault diagnosis of the back EMF load in the rectifier circuit when it works in the inverter state and other types of loads is required.

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