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A Method for Transformer Fault Diagnosis Based on IWOA-BPNN

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Abstract: In order to improve the accuracy of transformer fault diagnosis, an improved whale optimization algorithm (IWOA) combined with back propagation neural network (BPNN) is proposed in this paper. Firstly, since the initial population is generated randomly, and the quality of the initial population has a direct impact on the performance of the algorithm, chaotic mapping (CM) is used to initialize the population of the whale optimization algorithm (WOA), which is conducive to expanding the search scope and finding the optimal solution. Secondly, inertia weight is a key parameter in WOA, and a fixed weight will lead to a decrease in computational efficiency, which is not conducive to global optimization. The larger the inertia weight, the easier it is to get the global optimal solution. The smaller the inertia weight, the stronger the local optimization ability. The introduction of adaptive inertia weight (AIW) in WOA can improve the global optimization ability and avoid the local optimization. Finally, the weights and thresholds of BPNN are updated by using IWOA, and the BPNN model with optimized parameter values is obtained and applied to transformer fault diagnosis. The experimental results show that IWOA-BPNN model has higher diagnostic accuracy and faster iteration speed than BPNN and WOA-BPNN model, and can effectively diagnose transformer faults.

Keywords: Whale optimization algorithm; Chaos mapping; Adaptive inertia weight; Transformer; Fault diagnosis.

1. Introduction

Due to the continuous growth of power supply demand, the importance of power facilities in various industries is gradually highlighted, and transformers are the key components of these facilities. The failure of a power transformer will affect the stable operation of a power grid, resulting in very large economic losses and even endangering people's lives [1]. Therefore, it is very important to diagnose the fault type of transformer quickly and accurately.

At present, many intelligent algorithms have been applied to fault diagnosis, such as immune algorithm, differential evolution algorithm, extreme learning machine [2], support vector machine [3] etc. However, the above algorithms also have some defects in solving fault problems. For example, immune algorithm has the problem of large network scale and complex calculation, differential evolution algorithm will cause premature convergence and easy search stagnation. The classification performance of support vector machine is largely affected by parameters.

Aiming at these defects, the back propagation neural network (BPNN) is applied to power transformer fault diagnosis and has a successful precedent. But BPNN has a disadvantage. The convergence speed is slow, and it is easy to fall into local optimum. When the number of machine learning samples is large and the relationship between input and output is relatively complex, the convergence rate of the network is slow, so the convergence accuracy is not ideal, or even cannot be convergent at all. In order to further improve the detection accuracy, the intelligent optimization method is used to adjust the network weight and threshold to avoid falling into the local optimum.

With the rise of artificial intelligence, intelligent optimization algorithm has been widely used in practical problems because of its advantages of easy implementation and simple structure. In order to improve the classification performance of neural networks, some examples include fruitfly optimization algorithm [4] and sparrow search algorithm [5] are applied to the optimization of neural networks. Zou et al. use fuzzy C-means clustering particle swarm optimization (PSO) algorithm to optimize the parameters of BPNN and solve the problem that the training of neural network tends to converge to the local minimum [6]. Liu et al. use genetic algorithm (GA) to solve the problem that BPNN is easy to fall into local minimum and slow convergence speed [7]. GA has good parallel computing ability and global search ability [8], but there is a problem of information loss in population iterative updating, and it is prone to slow or stop convergence. The bat algorithm is combined with BPNN for transformer fault diagnosis, and the accuracy is further improved [9]. However, this algorithm has some disadvantages such as prematurity and poor diversity in the later stage. BPNN optimized by PSO is used for transformer fault diagnosis [10]. The recognition accuracy of this method is good, but the training time of BPNN is long and the efficiency of this method is poor. GA is used to optimize BPNN for transformer fault diagnosis to avoid BPNN falling into the problem of local optimum [11].

Whale optimization algorithm (WOA) is a brand new swarm intelligence optimization algorithm discovered by Mirjalili et al. in 2016 [12]. WOA simulates what humpback whales would do in nature to round up their prey, and summarizes the process as searching, attacking, and surrounding. WOA has the characteristics of simple operation, few required parameters and strong searching ability. WOA can solve the problems of large computational load and long training time of neural network in other algorithms mentioned above. This method has been well applied in neural network training [13] and resource allocation [14]. However, WOA still has defects in some areas. For example, after optimizing parameters, it still cannot completely simulate the cetacean search process. In iteration, due to low population diversity, it is easy to fall into local extreme values. The efficiency of solving high-dimensional complex problems is not high. Faced with the above situation, in recent years, researchers have also provided many methods to improve WOA, so as to effectively improve the computing efficiency. Such as, binary version of the WOA [15], tradeoff between exploration and exploitation [16], chaotic WOA, and WOA for optimizing neural networks [17]. Liu et al. improve the performance of the algorithm by optimizing the initial WOA population [18]. Bi et al. introduce chaos theory into WOA optimization process to adjust the main parameters of WOA in the iterative process [19].

Oliva et al. apply the improved chaotic whale optimization algorithm to the parameter estimation of photovoltaic cells [20]. Based on the ergodic and non-repeatability of chaos strategy [21], it is introduced into WOA to improve the convergence speed and global optimization ability of the algorithm. However, there are not many literatures on WOA to solve high-dimensional complex problems. Mafarja and Mirjalili propose WOA based on two binary variants and apply it to feature classification [22].

Aiming at the shortcomings of the above WOA and inspired by the existing papers. This paper proposes an improved whale optimization algorithm (IWOA) combined with BPNN. The accuracy of transformer fault diagnosis is improved. The main work and contributions are as follows:

Chaos mapping (CM) is used to initialize the WOA population, enhance the population diversity, and expand the search scope to obtain the optimal solution.

Adaptive inertia weight (AIW) is introduced into WOA to increase the global optimization ability of the algorithm and avoid falling into local optimum.

IWOA is used to update the BPNN weights and thresholds, and a BPNN diagnosis model with optimized weights and thresholds is obtained, thus further improving the accuracy of transformer fault diagnosis.

The rest of this paper is organized as follows. The related methods are given in Section II and III. The BPNN optimized by IWOA for transformer fault diagnosis is given in Section IV. The algorithm implementation is given in Section V. The experiment results compared with other methods are given in Section VI. The conclusion and future works are given in Section VII.

2. Back Propagation Neural Network

The scientific group led by Rumelhart and McCelland first proposed BPNN in 1986, which is a multi-layer feedforward network based on error inverse transmission calculation, and has become one of the most commonly used neural network models. BPNN can learn and record a large number of mapping relationships between input-output modes without giving a mathematical expression, so it is widely used in fault diagnosis, fault tolerance control and other related fields.

2.1. BPNN principle

BPNN includes two processes of signal forward propagation and error reverse propagation. In forward propagation, the training sample is transmitted to the output layer through the hidden layer, and the output sample is generated by nonlinear transformation. If the output value differs greatly from the expected value, the training will be transferred to the error back propagation. At this time, the output sample is transferred from the hidden layer to the input layer in reverse, and in the process, the weights and thresholds of each layer are gradually adjusted, so that the error is smaller and smaller. The BPNN is updated iteratively and repeatedly until it reaches the expected error requirement or the specified maximum training times. To a certain extent, the training process is a process of constantly revising the training model through different error functions, timely adjusting and updating the weights and thresholds through the comparative analysis of the training results and the expected results, and finally achieving the expected training results.

Fig. 1 shows a three-layer neural network architecture. The model consists of input layer, hidden layer and output layer.

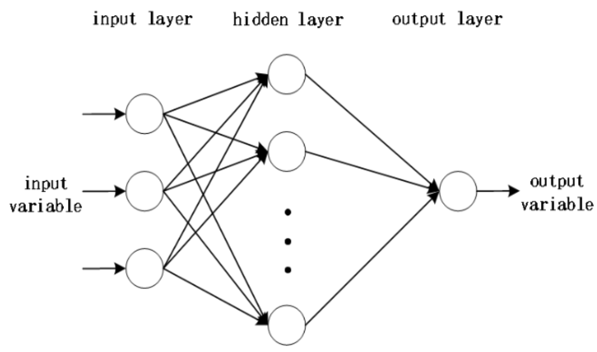

Fig. 1 BPNN model.

2.2. BPNN training process and flow chart

(1) Training process

①Initialize the weights and thresholds of the network;

②Presentation of training samples;

③Forward propagation calculation;

④Error backpropagation calculation and updating weights;

⑤Iteration: Repeat steps 3 and 4 with a new sample until the stop criteria are met.

(2) Flow chart

The flow chart of BPNN is shown in **Fig. 2**.

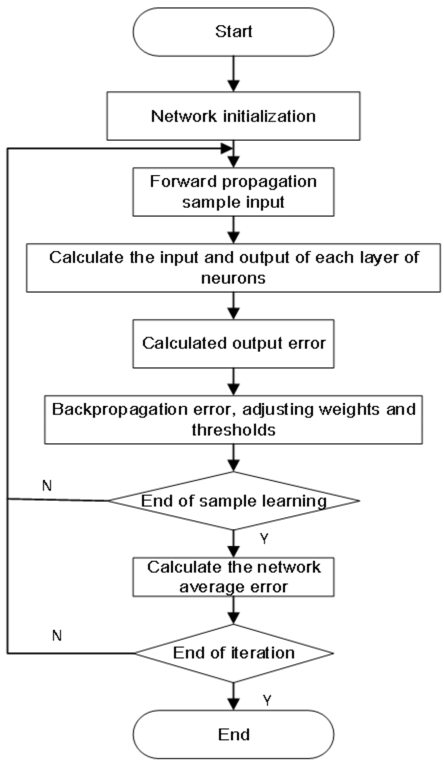

Fig. 2 BPNN training flow chart.

2.3. BPNN disadvantages

The learning process of BPNN is divided into two parts: forward propagation and reverse propagation. If the error generated by forward propagation is very different from the expected result, on this basis, the weight and threshold of each layer of neurons are corrected reversely until the sum of squares of the error reaches the expected precision. It can be seen that BPNN is based on gradient descent method. But gradient descent method is easy to fall into the local minimum and slow convergence rate, and gradient descent method is easy to cause oscillation. To avoid this problem, we used the WOA to optimize the network parameters by searching the global optimal value [23]. Therefore, IWOA is used to optimize the initial weights and thresholds of BPNN, so as to improve the situation that BPNN is prone to falling into local optimum, and increase the accuracy of BPNN applied to transformer fault diagnosis.

3. Whale Optimization Algorithm

WOA is a new heuristic optimization algorithm that can simulate the predation behavior of humpback whales. Humpback whales have a particular type of hunting method called bubble net foraging. WOA mimics humpback whales' unique foraging and trapping mechanism, which consists of three steps: encircling prey, bubble net attack, and search for prey. In the WOA model, the position of each humpback whale is represented as a potential solution, and it is iterated to obtain a global optimal solution.

3.1. Encircling prey

The whale's search range is the global solution space, and it must first find the target before it can round up. However, the specific location of the initial target is not known, so it is assumed that the optimal solution of WOA currently is the target prey for whales. When an optimal search agent is defined, other search agents will try to update their location to the optimal search agent. This act can be expressed as (1) and (2).

$$D = | CX^*(t) - X(t) | \tag{1}$$

$$X(t+1) = X^*(t) - A \cdot D \tag{2}$$

D is the distance between the whale and the target, t is the current iteration number of the algorithm, A and C are coefficient vectors, X^* is the vector of the best position of the whale population, X is the current position vector of the whale, coefficient vectors A and C can be expressed as (3) and (4).

$$A = 2a \cdot r - a \tag{3}$$

$$C = 2 \cdot r \tag{4}$$

Value of a decreases linearly from 2 to 0, and r is a random number between 0 and 1. The descending formula of a can be expressed as (5).

$$a = 2 - 2t / \max gen \tag{5}$$

$\max gen$ is the maximum number of iterations of the algorithm.

3.2. Bubble network attack

In order to simulate the bubble feeding behavior of humpback whales, two mathematical models are designed to express the above-mentioned feeding behavior.

1) Contraction surround. This predation behavior is almost identical to the mathematical model of enveloping prey behavior in Section III, part A, with the difference of the range of values of A. Because the implication of shrinking is to bring the whale at the current position closer to the whale at the current optimal position, the range of A is adjusted from [- a , a] to [-1,1].

2) Spiral position update. The current individual whale moves in a spiral towards the current best whale. This act is shown in the (6).

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) \tag{6}$$

b is the parameter that defines the shape of the spiral curve (1 here), l is the random number between [-1,1], and D' is the location of the prey from the best whale. D' can be expressed as (7).

$$D' = | X^*(t) - X(t) | \tag{7}$$

Assuming a humpback whale catches its target prey, there is a 50% chance that it will choose to change position using either a retraction encircle or a spiral renewal mechanism. Choosing p to represent the probability, choosing (6) to update the position when p <0.5, choosing (7) to update the whale position when $p \geq 0.5$.

3.3. Search for prey

In order to ensure that all whales can fully search in the solution space, WOA updates the position according to the distance between whales, so as to achieve the purpose of random search. Therefore, when $|A| \geq 1$, the search individual would swim to a random location. Random search can be expressed as (8) and (9).

$$D = | C \cdot X_{rand} - X | \tag{8}$$

$$X(t+1) = X_{rand} - A \cdot D \tag{9}$$

X_{rand} is a random whale position vector.

The flow chart is shown in **Fig. 3**.

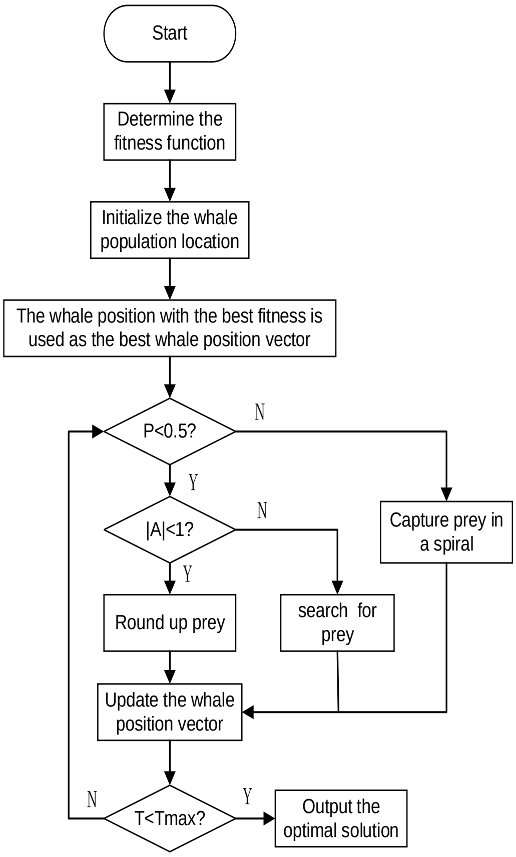

Fig. 3 Flow chart of WOA.

4. Improved Whale Optimization Algorithm

The intelligent optimization algorithm generates the optimal solution during the population iteration process, and the performance of the algorithm is largely affected by the initial population. Increasing the diversity of the initial population plays a great role in improving the performance of the algorithm. In addition, inertia weight has an important impact on the global search performance of WOA, and appropriate inertia weight value is conducive to increasing the global search ability of the algorithm. Therefore, this paper proposes to construct IWOA using CM and AIW factors.

4.1. Chaotic mapping

At present, the initial population of most intelligent optimization algorithms is randomly generated, and the quality of the initial population is directly related to the performance of the optimization algorithm. The uniform distribution of population can broaden the search area, thus improving the convergence rate and accuracy of the algorithm.

Like other methods, WOA is easier to achieve local optimum in the process of simplifying complex problems because the individual complexity of the population is reduced in the late iteration. In order to increase the population complexity, considering that chaos operator has the characteristics of both randomness and regularity, it can not traverse all states repeatedly in a certain region, so it is proposed to optimize the initial population through chaos operator.

In this paper, Cubic CM is used to initialize the population of WOA, and the calculation formula of Cubic CM is shown as (10).

$$X_2 = \rho \cdot (1 - X_1^2) \tag{10}$$

ρ is the control parameter with the value of 1, $X_1 \in (0,1)$.

The pseudo-code of CM is given in **Algorithm 1**.

Algorithm 1 Chaotic mapping of WOA

Generate a random initial matrix leader_pos1.
Initialize rho=1.
leader_pos=rho*(1-leader_pos1.^2)
Initialize fitness value leader_score.
Randomly generate the initial population location Position(:,i)
for i=1 to size(Position,1) do
  Check to see if each individual in the population has crossed the line.
  Calculated the population fitness value fit(i).
   if fit(i)< leader_score
      leader_score= fit(i);
      leader_pos= Position(:,i);
   end if
end for

4.2. Adaptive inertia weight

Inertia weight is a key parameter in WOA, and a fixed weight value will lead to a decrease in computing efficiency, which is not conducive to global optimization. The larger the inertia weight is, the easier it is to obtain the global optimal solution. The ideal trend of inertia weight change should be: in the initial stage of iteration, the weight value should be large to ensure that it has good global optimization ability. In the iteration process, the weights should be small to ensure the enhancement of its local optimization ability. Therefore, selecting the appropriate inertia weight can take into account the local mining ability while searching the whole world.

Introducing the adaptive inertia weight (AIW) as (11).

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) * mm * \exp(-t / \max gen) \tag{11}$$

The minimum inertia coefficient $\omega_{\min}$ is 0, the maximum inertia coefficient $\omega_{\max}$ is 1, the adjustment coefficient mm is 1, and t is the current iteration frequency of the algorithm. $\max gen$ indicates the maximum number of iterations of the algorithm. The position of the new whale is influenced by the dynamic nonlinear feature of ω. At this time, the position update formula is modified from the original (2) and (6) to (12) and (13).

$$X(t+1) = \omega \cdot X^*(t) - A \cdot D \tag{12}$$

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + \omega \cdot X^*(t) \tag{13}$$

Based on the above discussion, the pseudo-code of AIW is given in **Algorithm 2**.

Algorithm 2 Adaptive inertial weight of WOA

Initialize the adjustment coefficient mm, the minimum inertia coefficient $\omega_{\min}$, the maximum inertia coefficient $\omega_{\max}$.
By (11), generate adaptive inertial weight.
for j=1:size(Position,2) do
  if(p<0.5)
    if(|A|>=1)
      Position(:,i)=ω*X_{rand}(j)-A*D;
    elseif(|A|<1)
      By (12), update the position for population.

```
        endif
    elseif p>=0.5
            By (13), update the position for population.
    endif
end for
```

The flow chart of IWOA for introducing CM and AIW is shown in **Fig. 4**.

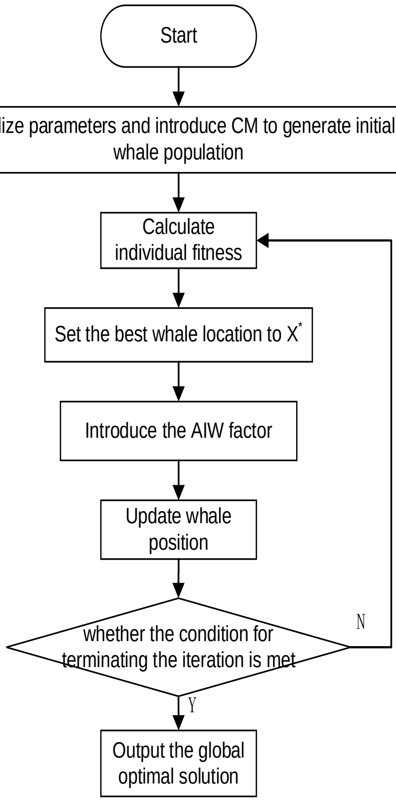

Fig. 4 Flow chart of IWOA.

5. Transformer Fault Diagnosis Based on IWOA-BPNN

At present, most of large power transformers are oil-immersed, and the internal transformer oil plays the role of insulation and heat dissipation. The main component of transformer oil is alkane and other compounds. With the aging of power transformer and insulation failure, transformer oil crack under high temperature and high pressure conditions, generating gas dissolved in the oil, mainly hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2) and so on. When the transformer fails, the volume fraction of dissolved gas in the oil will also change. Therefore, the volume fraction of dissolved gas in the oil can reflect the operation of the transformer.

5.1. Fault feature selection

According to the dissolved gas in the oil to analyze whether the transformer failure, called dissolved gas analysis (DGA) [24]. It is the main means of transformer monitoring [25]. DGA can be free from external interference, and the collected fault data is completer and more convenient for processing and analysis, and is widely used in transformer fault diagnosis.

At present, there are several methods for power transformer fault diagnosis using DGA data, such as the ratio method [26], key gas method [27], triangle method [28] and pentagon method [29]. However, several existing algorithms have their own defects, even the same set of DGA, due to the using of different methods, the results are not the same. In addition, due to the complex structure of transformer, fault cause, fault phenomenon and mechanism are characterized by diversity, randomness and fuzziness, which brings great difficulty to fault diagnosis. Therefore, fault diagnosis of power transformer has always been one of the important directions of power equipment safety.

In this paper, the ratio of dissolved gas in oil (CH_4/H_2, C_2H_2/C_2H_4, C_2H_4/C_2H_6) is taken as the input of the network model, and the fault types (normal, medium and low temperature overheating, high temperature overheating, low energy discharge, high energy discharge) are taken as the output of the network model. The above five fault types are coded. The encoding results are shown in **TABLE I**.

TABLE I. Fault Type Codes

Fault type	Fault code
Normal	1
Medium and low temperature overheating	2
High temperature overheating	3
Low energy discharge	4
High energy discharge	5

5.2. Network training

By establishing BPNN model, BPNN model is applied to transformer fault classification, and the mapping between the input (CH_4/H_2, C_2H_2/C_2H_4, C_2H_4/C_2H_6) gas ratio and the output (fault type) is learned, so as to predict the internal fault of transformer.

5.3. BPNN parameter optimization

When BPNN is used directly for transformer fault diagnosis, the accuracy of the diagnosis result is not good enough because the weights and thresholds are generated randomly. Therefore, the weight and threshold of BPNN are optimized by intelligent optimization algorithm to obtain higher accuracy of fault diagnosis.

Considering that WOA has few parameters and strong optimization ability, WOA is selected to optimize the weight and threshold of BPNN. Firstly, the weight, the dimension of threshold matrix and the size of WOA solution space are determined according to the number of neurons in input layer, hidden layer and output layer of BPNN. Secondly, fitness evaluation function is set as the evaluation index of the optimal solution of WOA. Finally, the weight and threshold information are extracted from the optimal solution and sent to BPNN for network training.

To further increase the accuracy of fault diagnosis, the following improvements are made to WOA. CM was used to optimize the initial population, which increased the diversity of the population. By introducing AIW coefficient, the algorithm can effectively prevent the problem of local extreme value, and improve the global optimization ability of the algorithm. The specific process of combining the improved IWOA with BPNN is shown in **Fig. 5**.

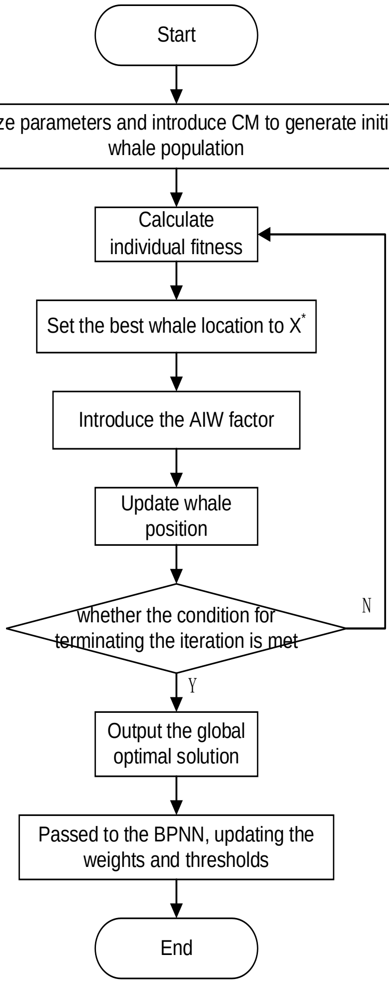

Fig. 5 Flow chart of IWOA-BPNN.

6. Experimental Result

350 sets of data are selected as fault samples, of which 300 are training fault samples and the remaining 50 are test fault samples. The experimental environment is Windows11 operating system, the system memory is 16GB, and the CPU is AMDRyzen processor.

In order to verify the validity of the proposed diagnosis method, transformer fault samples were trained and tested in MatLab. The initial population parameter popsize=30 and the maximum number of evolution iterations maxgen=50 were set as algorithm parameters. IWOA-BPNN model is used to diagnose transformer faults, and the results are compared with those of BPNN and WOA-BPNN.

The convergence curves of WOA and IWOA are shown in **Fig. 6**. In IWOA, the convergence curve tends to be stable at the 20th iteration. In WOA, it becomes stable towards the 30th iteration, indicating that IWOA converges faster and has shorter training time than WOA.

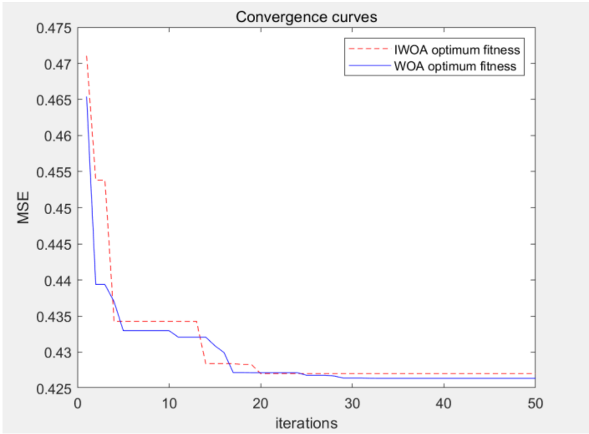

Fig. 6 Convergence curves of WOA and IWOA.

The diagnostic results of BPNN are shown in **Fig. 7**, and the accuracy rate of its diagnostic model is 48%.

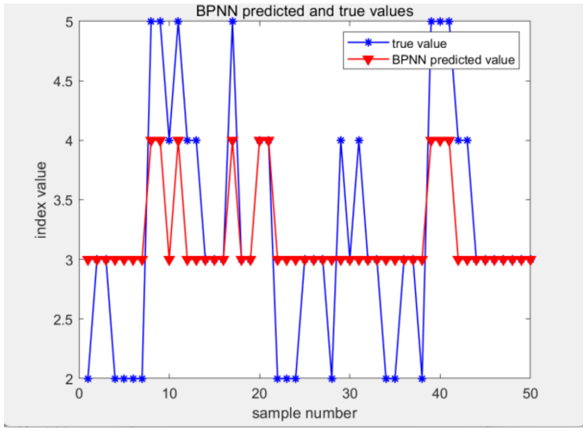

Fig. 7 Results of BPNN diagnostic model.

The diagnostic results of WOA-BPNN are shown in **Fig. 8**, and the accuracy of its diagnostic model is 86%.

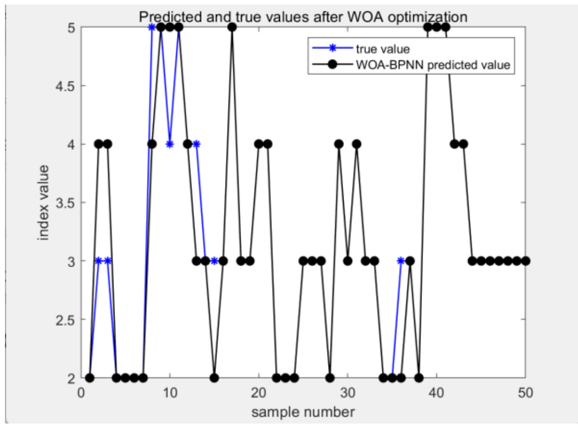

Fig. 8 Results of WOA-BPNN diagnostic model.

The diagnostic results of IWOA-BPNN are shown in **Fig. 9**, and the accuracy of its diagnostic model is 94%.

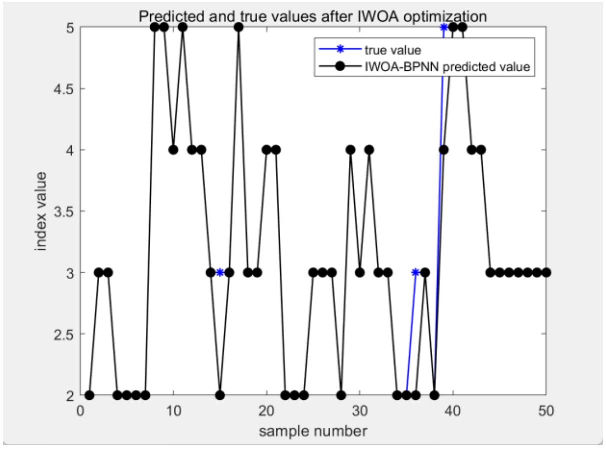

Fig. 9 Results of IWOA-BPNN diagnostic model.

The results of transformer fault diagnosis under different models are shown in **TABLE II.** .

TABLE II. Diagnostic Results of Different Models

Model name	Correct samples	Error samples	Sample count	Accuracy rate
BPNN	24	26	50	48%
WOA-BPNN	43	7	50	86%
IWOA-BPNN	47	3	50	94%

Compared with the accuracy of BPNN, the accuracy of both WOA-BPNN and IWOA-BPNN is greatly improved, and the accuracy of IWOA-BPNN is up to 94%. Compared to BPNN and WOA-BPNN, the improvement is 46% and 8% respectively. The diagnostic errors of WOA-BPNN and IWOA-BPNN are shown in **Fig. 10** and **Fig. 11** respectively, and the diagnostic errors are 14% and 6% respectively. It shows that the fault diagnosis method proposed in this paper has better diagnosis effect.

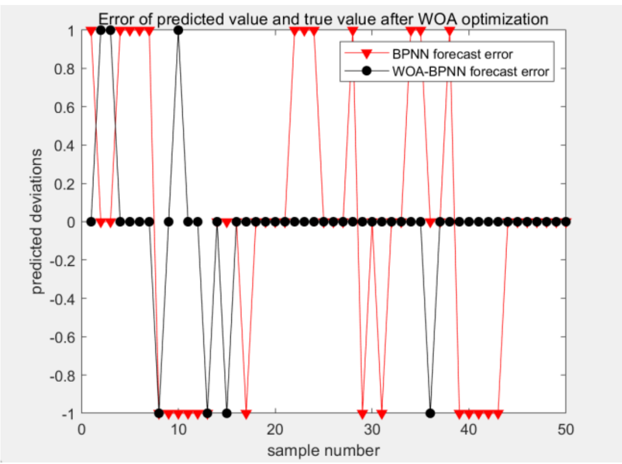

Fig. 10 Errors of WOA-BPNN diagnosis results.

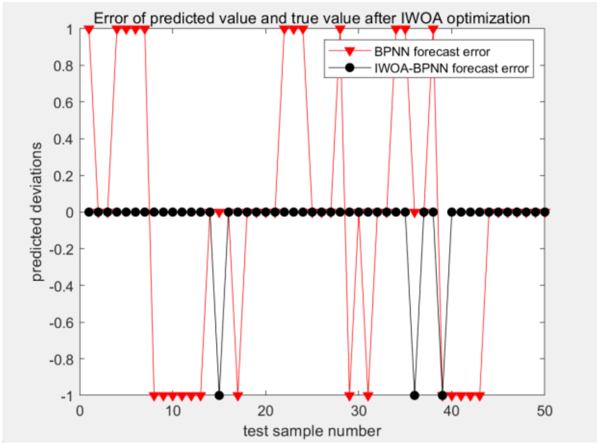

Fig. 11 Errors of IWOA-BPNN diagnosis results.

Compared with other similar models, the accuracy and training time are also greatly improved, as shown in **TABLE III**.

TABLE III. Accuracy and Training Time of Different Models

Model	accuracy rate	training time(s)
BPNN	48%	989
GA-BPNN	52%	955.02
PSO-BPNN	62%	113.34
WOA-BPNN	86%	606.43
IWOA-BPNN	94%	306.08

As can be seen from Table III, compared with BPNN, GA-BPNN and PSO-BPNN, the accuracy of WOA-BPNN and IWOA-BPNN have been greatly improved, and the accuracy of IWOA-BPNN is the highest. In terms of network training time, PSO-BPNN takes the shortest time, while IWOA-BPNN takes longer time. IWOA-BPNN model has great advantages when the accuracy rate is required.

7. Conclusion and Future Works

In this paper, WOA is further improved by introducing CM and AIW, and BPNN weights and thresholds are optimized for transformer fault diagnosis. Specific conclusions are as follows:

1)Using CM to initialize WOA population increases the diversity of the initial population.

2)At the same time, AIW is introduced to update the best whale position vector, so that the algorithm has better global search ability.

3)In terms of transformer fault diagnosis accuracy, the improved IWOA-BPNN model has a better effect than other similar models, which verifies the effectiveness of the IWOA-BPNN model.

In summary, the fault diagnosis method proposed in this paper has good diagnostic performance, can diagnose transformer faults quickly and accurately, and has high reference value. However, the study of DGA data in this paper is not comprehensive. In the future, we will conduct in-depth analysis and research on DGA data to further improve the accuracy and stability of transformer fault diagnosis.

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