Transformer Fault Detection Based on IAHA Optimized BP Neural Network

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Abstract: In view of the shortcomings of artificial hummingbird algorithm (AHA) and BP neural network algorithm in the process of fault detection, this paper improves the AHA by introducing the chaotic sequence of tent map, and proposes an improved AHA (IAHA), which makes the initialization of hummingbird population more uniform. To test the effectiveness of the IAHA, using IAHA to optimize the BP neural network model, and is applied to fault detection together with AHA-BP model, SSA-BP model and GWO-BP model. The results show that the fault detection accuracy of the proposed IAHA-BP model is 97.5%, AHA-BP model is 92.5%, SSA-BP model is 90%, GWO-BP model is 92.5%. It shows that the proposed IAHA-BP model has higher accuracy in the field of transformer fault detection.

Keywords: Improved Artificial Hummingbird Algorithm; BP Neural Network; Tent Mapping; Transformer; Fault Detection

1. Introduction

As a key equipment for converting voltage in the power grid, transformers are prone to failure. If they fail and cannot be detected in a timely manner, it can cause economic losses, power grid failures, and even a series of accidents. Therefore, it is necessary to perform fault detection on its operating status. [1-3].

Although the structure of transformer is complex, the fault forms of transformer are mostly thermal type and electrical type [4-6]. Thermal faults can be divided into low temperature overheating and high temperature overheating. Electrical faults can be divided into low-energy discharge and high-energy discharge. When the transformer is abnormal, some columns of gases will be dissolved in the insulating oil, such as H_2, CO, C_2H_6, etc. Using this information, scholars have proposed a series of transformer fault detection methods, for example, three ratio method, Rogers ratio method, etc. [7-10]. Although the structure of the above transformer fault diagnosis strategy is simple, its shortcomings are that its state coding is incomplete and the coding boundary is fuzzy, which affects the later fault detection accuracy.

Artificial intelligence algorithm is widely used in transformer fault detection. Reference [11] uses artificial neural network algorithm for fault detection. Although this method can autonomous learning and deep mining association, it has the problems of easy to be affected by local extremum and limited adaptability. Literature [12] uses sparrow search algorithm (SSA) for fault detection. Although this method has strong global optimization ability, however, this method cannot escape from local optima. Reference [13] uses deep belief network (DBN) for fault detection. Although this method has the advantages of processing small sample data, it is difficult to solve the problem of data imbalance, which affects the accuracy of fault detection. These literatures focus on using a single algorithm for transformer fault diagnosis, but each has its own shortcomings.

Based on the traditional AHA, this paper puts the chaotic sequence of tent map into the AHA algorithm, improves it, proposes an IAHA method, and uses IAHA to optimize the BP neural network (IAHA-BP). After completing the establishment of IAHA-BP model and parameter optimization, IAHA-BP model is combined with the field of transformer fault diagnosis. The results show that IAHA-BP model has higher fault diagnosis accuracy and accuracy than AHA-BP model, SSA-BP model and GWO-BP model.

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2. Theoretical Basis of Algorithm

2.1 BP Neural Network

It has the ability to transmit forward propagation and error backward propagation [14-18]. The principle of BP algorithm applied to fault detection is based on the learning and classification ability of neural network. Using gas concentration as the characteristic vector and the nonlinear transformation and processing are carried out through the BP algorithm, and finally the fault type of transformer is output. During training, the network parameters are continuously adjusted using backpropagation to minimize the error between the network output and the actual fault type, so as to accurately classify and identify the fault characteristic gas.

2.2 AHA

AHA simulates the flying skills, foraging methods, and memory abilities of hummingbirds using mathematical models, and calculates and implements them in the form of algorithms. It is currently mainly used in function optimization and engineering optimization [19-23].

2.2.1 Tent chaotic sequence

In order to avoid the AHA falling into local optimization, chaotic sequence is introduced in the initialization stage of hummingbird population position [24-28]. Chaos is a common nonlinear phenomenon in nature. Because its chaotic variables have the characteristics of randomness, ergodicity and regularity, it has been applied to intelligent optimization algorithms by many scholars. However, chaotic sequences are divided into different types according to different mappings. The chaotic sequence introduced into the optimization algorithm in the early stage is generally the chaotic sequence generated by the logistic map, but the chaotic sequence generated by it has poor uniformity and is easy to concentrate in a certain interval, so the optimization speed of the algorithm will be affected to some extent. The results show that the uniformity and convergence speed of tent map are better than that of logistic map. The tent mapping is as follows:

$$y_{i+1}=\begin{cases}2y_i, 0\le y_i\le \frac{1}{2}\\ 2(1-y_i), \frac{1}{2}<y_i\le 1\end{cases} \tag{1}$$

The expression of tent map after Bernoulli displacement transformation is:

$$y_{i+1}=(2y_i)\bmod 1 \tag{2}$$

In the population initialization stage, the hummingbird population size is defined as N hummingbirds, corresponding to N food source locations. In the initialization stage of hummingbird food source locations, the chaotic sequence of tent mapping is introduced. The introduction of chaotic sequence has certain randomness and nonlinearity, resulting in a more complex and diverse distribution of individuals in the population searching for space.

The initialization phase is responsible for the initiation of the hummingbird population food source location and access table,

$$\begin{cases}x_i=Low+r*(Up-Low)\\ vt_{i,j}=\begin{cases}0 & i\ne j\\ null & i=j\end{cases}\end{cases} \tag{3}$$

2.2.2 Guide foraging

Hummingbirds always want to get more nectar and the food source should have the characteristics of high nectar supplement rate and not being visited by hummingbirds for a long time. In the algorithm, the hummingbird determines the nectar content of the food source by accessing the table. The highest level of access means more nectar. The mathematical expression of its axial flight is:

$$D^i=\begin{cases}1 & if\ i=randi([1,d])\\ 0 & else\end{cases} \tag{4}$$

The mathematical expression of diagonal flight is:

$$D^i=\begin{cases}1 & if\ i=P(j), j\in[1,k],\\ & P=randperm(k),\\ & k\in[2,[r_1*(d-2)+1]\\ 0 & else\end{cases} \tag{5}$$

The mathematical expression of omnidirectional flight is:

$$D^i=1, i=1,\cdots,d \tag{6}$$

In formula (4), $randi\ ([1,d])$, and in formula (5), $randperm\ (k)$ means to create a random arrangement of integers between 1 and k . With the aid of these flight capabilities, hummingbirds will get the location of the candidate food source. Therefore, the food source should be updated from the old source according to the target food source in the existing food source. Specifically, as shown in equation (7) and equation (8).

$$V_i(t+1)=x_{i,tar}(t)+a*D*(x_i(t)-x_{i,tar}(t)) \quad (7)$$

$$a \sim N(0,1) \quad (8)$$

According to the fitness value of the updated food location, the corresponding food source location will be updated, as shown in equation (9):

$$x_i(t+1)=\begin{cases} x_i(t) & f(x_i(t)) \le f(v_i(t+1)) \\ v_i(t+1) & f(x_i(t)) > f(v_i(t+1)) \end{cases} \quad (9)$$

Where, $f(\cdot)$ is the fitness value, which is related to the updated food source location in equation (8).

2.2.3 Regional foraging

After hummingbirds visit the target food source, new food sources in other locations may also be explored as better food sources. The formulas for simulating hummingbird's foraging and alternative food sources are shown in equation (10) and equation (11):

$$v_i(t+1)=x_i(t)+b*D*x_i(t) \quad (10)$$

$$b \sim N(0,1) \quad (11)$$

In equation (10), b is the regional factor. Equation (10) means that hummingbirds are allowed to obtain new food sources at nearby locations with the help of flight skills. After hummingbirds foraging in the execution area, the data will also be updated.

2.2.4 Migration for food

If the hummingbird is short of food in its own activity area and nearby areas, the hummingbird may migrate to other areas in order to survive. At this time, the hummingbird will find a new food source, abandon the old source. The equation for modeling the hummingbird position update is:

$$x_{wor}(t+1)=Low+r*(Up-Low) \quad (12)$$

3. Experimental Analysis

3.1 Establishment of Prediction Model

Transformer fault will cause insulation oil cracking to produce H_2, CO, C_2H_6 and other mixed gases. The concentration of these characteristic gases varies with the type of transformer fault. Therefore, the concentration of these characteristic gases is selected as the input quantity in this paper. Considering that the concentration difference of some fault characteristic gases is not small, in order to reduce the simulation deviation, pretreatment must be carried out before importing the program. The pretreatment equation is:

$$x' = \frac{x_i}{\sum_{j=1}^{5} x_j} \quad (13)$$

Where, x_i is the concentration of a certain gas.

Set the corresponding codes for the four different fault types as the output of the neural network. The fault type and its corresponding code are: 1 corresponds to low energy discharge, 2 corresponds to high energy discharge, 3 corresponds to medium and low temperature overheating, and 4 corresponds to high temperature overheating. From the transformer historical fault data and relevant references, selecting 120 sets of sample data containing the above four operating states are selected. These data can fully reflect the diversity and representativeness of transformer operation status in the complex environment on site. 80 sets of sample as the training set, and another 40 sets of sample as the test set, so as to ensure that the model is sufficient to learn the data pattern and accurately evaluate the performance of the model.

3.2 Result Analysis

After the IAOA model is established, the simulation training and result analysis are carried out. The convergence function is used to test the convergence speed of IAOA-BP. Figure 1 shows the IAOA-BP fitness curve. In Figure 1, the minimum fitness value of IAOA-BP model is 0.001 after five iterations, indicating that the algorithm has obtained a set of optimal weight thresholds for BP neural network after five iterations, which can be considered that the IAOA algorithm has good convergence. To verify the advancement of the proposed method, the proposed method, AOA-BP model, SSA-BP model and GWO-BP model are applied to transformer fault detection. Figure 2-5 shows the results of the above methods.

Figure 2 is the classification results of the IAOA-BP model proposed in this paper, there is one sample classification error in forty test samples, and its comprehensive fault detection accuracy rate is 97.5%, while in the classification results of the AOA-BP model,

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there are three sample classification errors in forty test samples, and its comprehensive fault detection accuracy rate is 92.5%, while in the classification results of SSA-BP, there are four sample classification errors in forty test samples, and its comprehensive fault detection accuracy rate is 90%, while in the classification results of the GWO-BP model, there are three sample classification errors in forty test samples, and its comprehensive fault detection accuracy rate is 92.5%. According to the above analysis and experimental results, the proposed IAOA-BP model has good fault detection performance.

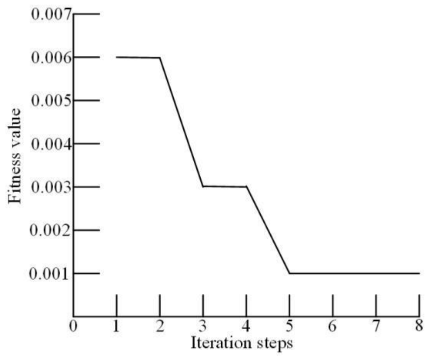

Figure 1. IAOA-BP Fitness Curve

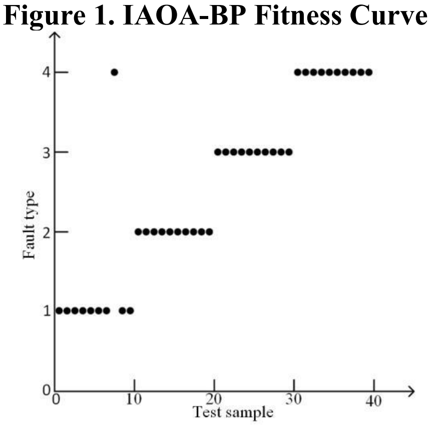

Figure 2. IAOA-BP Model Test Sample Classification Results

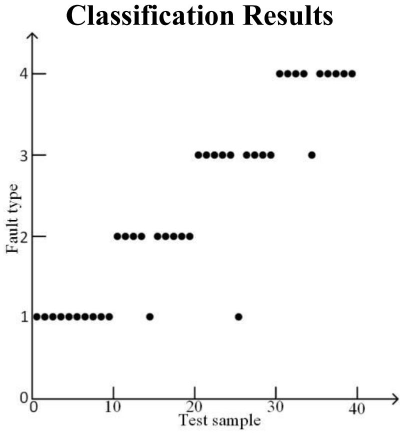

Figure 3. AOA-BP Model Test Sample Classification Results

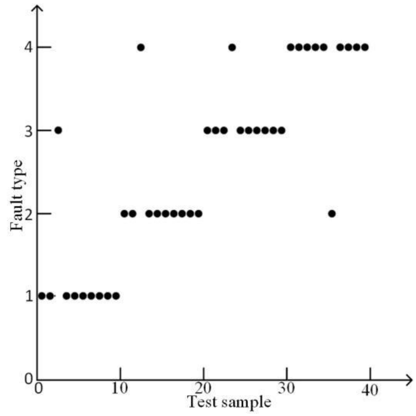

Figure 4. SSA-BP Model Test Sample Classification Results

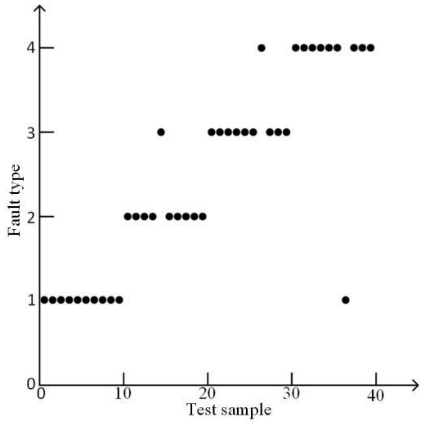

Figure 5. GWO-BP Model Test Sample Classification Results

4. Conclusion

Aiming at the problem of slow convergence of BP neural network and traditional AOA, the IAOA algorithm is proposed to determine the artificial hummingbird algorithm using Tent chaotic sequences. The BP neural network model is optimized using the IAOA and the IAOA-BP model is used to realize the transformer fault detection. To verify the advancement of IAOA-BP, it is applied to fault detection together with AOA-BP, SSA-BP and GWO-BP. Finally, the fault detection accuracy of IAOA-BP is 97.5%, which is significantly higher than the other three methods, which verifies the advancement of the method.

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