Research on Ant Lion Optimization Algorithm for BP Neural Network in Transformer Fault Diagnosis

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Abstract: Aiming at the problem of low accuracy in transformer fault diagnosis, an Ant Lion Optimization (ALO) algorithm is proposed to optimize the BP neural network for transformer fault diagnosis. By using the ant lion optimization algorithm to optimize the weights and thresholds of the BP neural network, the problem of premature convergence of the BP neural network can be avoided, and the accuracy of the transformer fault diagnosis model can be improved. The BP neural network model optimized by the ant lion optimization algorithm was used for transformer fault diagnosis. To verify the effectiveness of the proposed method, it was compared with the genetic algorithm optimized BP neural network (GA-BP) and the artificial bee colony (ABC-BP) algorithm optimized BP neural network methods. The experimental results showed that the proposed method has higher fault diagnosis accuracy.

Keywords: Transformer; Fault Diagnosis; BP Neural Network; Ant Lion Optimization Algorithm; Artificial Bee Colony Algorithm

1. Introduction

The operational status of power transformers has a significant impact on the safe and reliable operation of the power system, and timely and accurate fault diagnosis is of great significance [1-3]. Dissolved Gas Analysis (DGA) is currently one of the most widely used and effective methods for diagnosing transformer faults both domestically and internationally. This method uses mathematical relationships between the amount of fault gas and the type of fault to accurately and reliably diagnose latent faults in transformers, preventing major accidents. Classic applications include the Three Ratio Method and the David's Triangle Method. The three ratio method has simple calculation and clear judgment, and is sensitive to local overheating and partial discharge faults. However, it has problems such as missing coding, overly absolute boundary processing, and difficulty in identifying multiple faults. With the rapid development of artificial intelligence technology and big data technology, scholars at home and abroad have conducted research on DGA in recent years and proposed various fault diagnosis methods combining DGA with intelligent algorithms. Among them, the diagnostic method combining neural networks and DGA has achieved significant results [4-8]. Due to the disadvantages of difficult parameter selection, slow convergence speed, susceptibility to local minima, and poor generalization ability of BP neural networks, some scholars currently use genetic algorithms (GA) to optimize the structure and parameters of BP neural networks, in order to improve the accuracy of fault diagnosis [9-12]. However, the mutation and crossover operations of genetic algorithms can easily trap them in local optima, and achieving high-precision optimal values requires setting a large population and iteration times, leading to a sharp increase in computational complexity [13-15].

In response to the above issues, this article combines DGA to design a BP neural network transformer fault diagnosis model based on ant lion optimization algorithm. ALO, as a recently developed swarm intelligence optimization algorithm, has the advantages of coordinating global and local optimization capabilities and having fewer model parameters. Using ALO to optimize the initial weights and thresholds of BP neural networks can effectively improve the shortcomings of BP neural networks. The simulation results show that the ALO-BP model has strong fault tolerance and structural adaptability, which improves the accuracy of transformer fault diagnosis.

2. Ant Lion Optimization Algorithm

The core idea of the ant lion optimization algorithm is to achieve global optimization through the ant lion hunting mechanism, improve search ability based on ants' random walks, use roulette wheel method to ensure population diversity, and use elite strategy to ensure algorithm optimization performance [16]. The principle of ALO algorithm is as follows.

The mathematical expression for ant random walk is:

$$K(t)=[0,cumsum(2r(t_1)-1,\cdots ,cumsum(2r(t_{T_{\max}})-1] \tag{1}$$

$$r(t)=\begin{cases}1, rand>0.5\\ 0, rand\le 0.5\end{cases} \tag{2}$$

Where, $K(t)$ is the set of ant walk steps, $cumsun(\cdot)$ represents the cumulative sum, t is the number of iterations, $T_{\max}$ is the maximum number of iterations of the algorithm, $r(t)$ is a random number, $rand$ is a random function, and the value range is [0,1]. Ants are limited by boundaries when swimming and need to be normalized. The expression is as follows:

$$k_i^t=\frac{(k_i^t-a_i)(d_i^t-c_i^t)}{b_i-a_i} \tag{3}$$

Where, a_i and b_i are the minimum and maximum values of the boundary of variable i walk, respectively. c_i^t and d_i^t are the minimum and maximum values of variable i at the t-th iteration, respectively.

Ants will encounter traps created by ant lions while wandering along the boundary, and their expression is as follows:

$$\begin{cases}c_i^t=P_{AL,j}^t+c^t\\ d_i^t=P_{AL,j}^t-d^t\end{cases} \tag{4}$$

Where, c^t and d^t are the minimum and maximum values of all variables at the t-th iteration, respectively, and $P_{AL,j}^t$ is the position of Ant Lion j at the t-th iteration.

During the hunting process, an ant lion can only capture one ant. The higher the fitness value of an ant lion, the greater the possibility of capturing ants. The roulette wheel method determines which ant a particular ant lion will capture. In order to prevent ants from escaping, ant lions use the method of throwing sand to force ants to quickly shrink their range of movement. The mathematical expression of this process is as follows:

$$\begin{cases}c^t=\dfrac{c^t}{I}\\ d^t=\dfrac{d^t}{I}\end{cases} \tag{5}$$

$$I=\begin{cases}1, t\le 0.1T\\ 10^v\cdot\dfrac{t}{T_{\max}}, t>0.1T\end{cases} \tag{6}$$

Where, I is the proportionality coefficient, and v is the variable that increases with the number of iterations. According to the elite strategy, after each iteration, the individual with the best fitness value among the ant lions is identified. Under the combined effect of roulette wheel and elite strategy, the expression of ant position is as follows:

$$P_{Ant,q}^{t+1}=\frac{R_A^t(l)+R_E^t(l)}{2} \tag{7}$$

Where, $R_A^t(l)$ represents the position where ant q swims one step around the ant lion according to the roulette wheel method at the t-th iteration, and $R_E^t(l)$ represents the position where ant q swims one step around the ant lion according to the elite strategy at the t-th iteration.

Ultimately, when the fitness value of the ant lion exceeds that of the ant, the ant lion captures the ant.

$$P_{AL,j}^t=P_{Ant,q}^t \tag{8}$$

Where, $P_{Ant,q}^t$ represents the position of ant q at the t-th iteration.

3. BP Neural Network

The standard BP neural network is a three-layer network structure consisting of an input layer, a hidden layer, and an output layer, with fully connected neurons between different layers. The training of BP neural network includes two steps: forward propagation and error back propagation. The forward propagation process takes the training samples as the input of the neural network, and calculates the corresponding output through the hidden layer in the output layer. The forward propagation calculation formula is as follows:

$$\begin{cases}H_j=f(\sum_{i=1}^{n}\omega_{ij}x_i+b_j)\\ O_k=\sum_{j=1}^{n}\omega_{ij}H_j+b_k\end{cases} \tag{9}$$

Where, H_j is the output of the hidden layer, $f(\cdot)$ is the activation function, ω is the connection weight between adjacent layers of neurons, b is the bias, and O_k is the output of the neural network. The error between the output of the neural network and the actual value is defined as E, and its calculation formula is as follows:

$$E=\frac{1}{2}\sum_{k=1}^{n}(Y_k-O_k)^2 \tag{10}$$

Where, Y_k is the expected output of the network. Calculate the gradient information of the network based on the error, update the weights of the network, set the learning rate to η, and set the error $e=Y_k-O_k$.

Update weights from the hidden layer to the output layer and from the hidden layer to the input layer using the error backpropagation algorithm. When the error meets the preset accuracy or reaches the preset learning times, the training of the BP neural network is completed. Otherwise, the above steps will continue to be repeated until the requirements are met.

4. ALO Optimization of BP Neural Network Algorithm

In the construction process of a standard BP neural network, the initial weights and threshold matrices are usually initialized randomly to generate a random array with initial values limited to a certain range and following a uniform or normal distribution. Based on this, the error backpropagation algorithm is used to correct the connection weights and thresholds of each layer. However, this method has a high degree of randomness, which can easily lead to gradient vanishing and exploding problems during the training process of BP neural networks, resulting in unstable updates of weights and thresholds, thereby affecting the training time, convergence ability, and the possibility of the model falling into local optima of BP neural networks. This article uses ALO to select the optimal initial weights and thresholds for BP neural networks. The basic steps for optimizing BP with ALO are as follows:

1) Divide the fault data into a training set and a testing set, and use the training set to train a BP neural network.

2) The error between the actual output fault type encoding and the expected output fault type encoding in the BP neural network is taken as the optimization objective of the ALO algorithm. The objective function is as follows:

$$fittness(i)=\frac{\sum_{j=1}^{6}(p_j-q_j)}{\sum_{j=1}^{6}p_j}\times 100\% \tag{11}$$

Where, $fitness(i)$ comprehensive failure rate, p_j is the number of j-type faults, and q_j is the number of misdiagnosis cases in j-type faults.

3) Continuously optimize the weights and thresholds of the BP neural network using the ALO algorithm until the iteration conditions are met.

4) The BP neural network uses ALO to obtain the optimal weights and thresholds for training the network.

Use ALO-BP model to diagnose test set data.

5. Transformer Fault Diagnosis based on ALO-BP

5.1 Data Preprocessing

By collecting transformer fault types and their DGA data, a total of 300 sets of sample data were obtained. The fault types include high temperature overheating, medium temperature overheating, low temperature overheating, partial discharge, high-energy discharge, and low-energy discharge, with 50 sets of data for each fault type. Partial sample data is shown in Table 1, with the training sample set consisting of the first 250 sets of data and the testing sample set consisting of the last 50 sets of data.

5.2 Experimental Verification

Set the number of hidden layer neurons in the BP neural network to 15 and establish a 5-15-5 network structure to determine the size of the ALO algorithm solution space. Setting the spatial dimension to 2, the number of ant lions to 70, and the maximum iteration count to 200, the ALO-BP model was used to diagnose faults in the test sample set data. The diagnostic results are shown in Figure 1. From Figure 1, it can be seen that there were two errors in the diagnostic results, which diagnosed the medium temperature overheating fault as a low temperature overheating fault. This may be due to the similarity of DGA data between medium temperature overheating and low temperature overheating.

Table 1. Transformer Fault Codes

Number	Fault category	Fault code
1	High temperature overheating	000001
2	Medium temperature overheating	000010
3	Low temperature overheating	000100
4	partial discharge	001000
5	High-energy discharge	010000
6	Low-energy discharge	100000

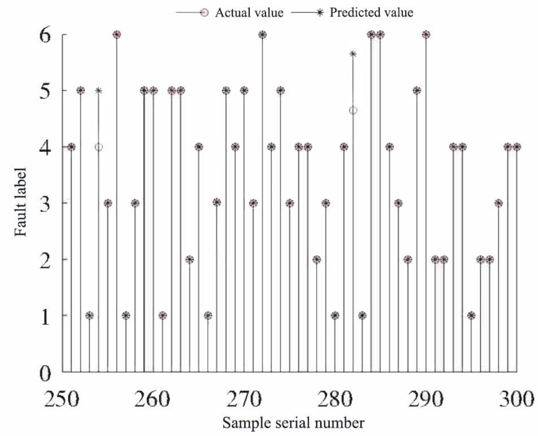

Figure 1. Fault Diagnosis Results of ALO-BP Model

In order to verify the correctness and effectiveness of the proposed transformer fault diagnosis method, a genetic algorithm optimized BP neural network (GA-BP) and an artificial bee colony algorithm optimized BP neural network (ABC-BP) transformer fault diagnosis model were established using simulation data. Two models were used to diagnose faults in the test sample set, and the diagnosis results are shown in Figures 2 and Figure 3.

From Figures 2 and 3, it can be seen that there were 4 errors in the diagnostic results of the IGA-SVM model, and 8 errors in the ABC-BP model. Comparing the diagnostic results of the three models, it can be seen that the proposed ALO-BP model has the best fault diagnosis effect. Table 2 presents the comprehensive accuracy of the diagnostic results of each model on the test set. According to Table 2, the comprehensive accuracy of the transformer fault diagnosis method based on ALO-BP is higher than other fault diagnosis methods, which improves the accuracy of transformer fault diagnosis.

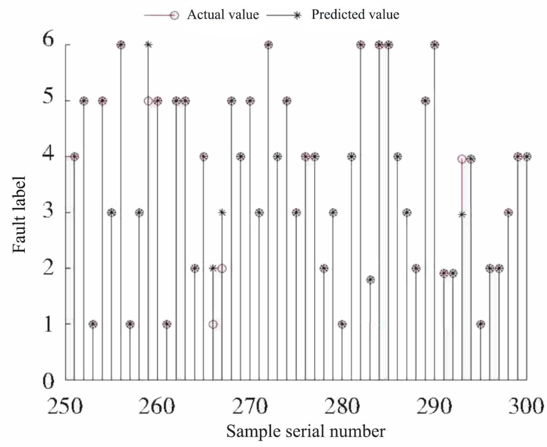

Figure 2. Fault Diagnosis Results of IGA-BP Model

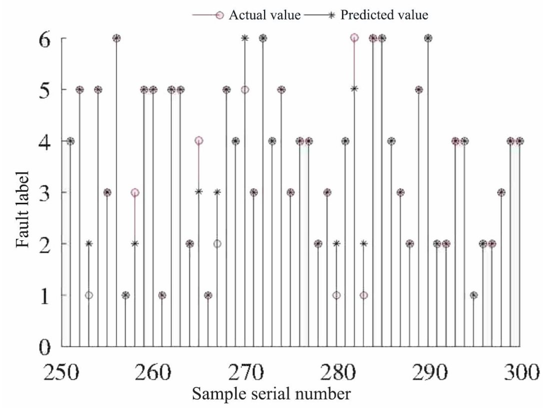

Figure 3. Fault Diagnosis Results of ABC-BP Model

Table 2. Comprehensive Accuracy of Diagnostic Results for Each Model

Method	ALO-BP	IGA-BP	ABC-BP
Accuracy (%)	96	92	84

6. Conclusion

The ant lion optimization algorithm was used to optimize the weights and thresholds of the BP algorithm, and a transformer fault diagnosis model based on ALO-BP was established. Transformer fault data was simulated and analyzed, and the ALO-BP model was used to diagnose faults in the training sample set. The results were compared with other fault diagnosis methods, and the comprehensive accuracy of the ALO-BP model diagnosis results was 96%, which was higher than other fault diagnosis methods, verifying the correctness and effectiveness of the transformer fault diagnosis method proposed in this paper.

References

[1] Abbasi A R, Mahmoudi M R, Avazzadeh Z.

Diagnosis and clustering of power transformer winding fault types by cross-correlation and clustering analysis of FRA results. IET Generation, Transmission & Distribution, 2018, 12(19): 4301-4309.
[2] Wang T, He Y, Li B, et al. Fault diagnosis of transformer based on self-powered RFID sensor tag and improved HHT. Journal of Electrical Engineering and Technology, 2018, 13(5): 2134-2143.
[3] Lv G, Cheng H, Zhai H, et al. Fault diagnosis of power transformer based on multi-layer SVM classifier. Electric Power Systems Research, 2005, 75(1): 9-15.
[4] Khan S A, Equbal M D, Islam T. A comprehensive comparative study of DGA based transformer fault diagnosis using fuzzy logic and ANFIS models. IEEE Transactions on Dielectrics & Electrical Insulation, 2015, 22(1): 590-596.
[5] Alghamdi A S, Muhamad N A, Suleiman A A. DGA Interpretation of Oil Filled Transformer Condition Diagnosis. Transactions on Electrical and Electronic Materials, 2012, 13(5): 229-232.
[6] Jingmin, Fan, Feng, et al. Hybrid RVM–ANFIS algorithm for transformer fault diagnosis. IET Generation, Transmission & Distribution, 2017, 11(14): 3637-3643.
[7] Khan, Shakeb, A, et al. A Comprehensive Comparative Study of DGA Based Transformer Fault Diagnosis Using Fuzzy Logic and ANFIS Models. IEEE transactions on dielectrics and electrical insulation: A publication of the IEEE Dielectrics and Electrical Insulation Society, 2015, 22(1): 590-596.
[8] Dong M, Zhao W, Yan Z. Improved method for transformer fault diagnosis based on DGA. High Voltage Engineering, 2002, 28(4): 6-8.
[9] Duraisamy P, Santhanakrishnan M N, Amirtharajan R. Genetic Algorithm Optimized Grey-Box Modelling and Fuzzy Logic Controller for Tail-Actuated Robotic Fish. Neural processing letters, 2023, 55(8): 11577-11594.
[10] Mansouri M, Bey M, Hassaine S, et al. Genetic algorithm optimized robust nonlinear observer for a wind turbine system based on permanent magnet synchronous generator. ISA transactions, 2022, 129(Pt B):230-242.
[11] Shao R, Zhang G, Gong X. Generalized robust training scheme using genetic algorithm for optical neural networks with imprecise components. Photonics Research, 2022(8): 1868-1876.
[12] Esfe M H, Hajmohammad H, Toghraie M D. Cost and Efficiency Optimizations of ZnO/EG Nanofluids Using Non-dominated Sorting Genetic Algorithm Coupled with a Statistical Method. The Korean journal of chemical engineering, 2024, 41(1): 175-186.
[13] Pan Y, Yang Y, Li L W. UAVs and Mobile Sensors Trajectories Optimization with Deep Learning Trained by Genetic Algorithm towards Data Collection Scenario. Mobile networks & applications, 2023, 28(2): 808-823.
[14] Chen H, Tang Q, Li X, et al. Optimization of five-axis tool grinder structure based on BP neural network and genetic algorithm. The International Journal of Advanced Manufacturing Technology, 2024, 133(5-6): 2565-2582.
[15] Mpuang A P, Shibutani T. Improvements in the genetic algorithm inversion of receiver functions using extinction and a new selection approach. Computational Geosciences, 2024, 28(3): 573-585.
[16] Ali E S, Abd Elazim S M, Abdelaziz A Y. Ant Lion Optimization Algorithm for Renewable Distributed Generations. Energy, 2016, 116(pt.1): 445-458.