Fault Diagnosis Method of Power Transformer Based on Improved PNN

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Abstract. Power transformer is a core hub of power transmission in power grid, and its operation state will affect the effective operation of power grid. The existing power transformer fault diagnosis methods mainly use the traditional dissolved gas analysis (DGA) method combined with artificial neural network. Probabilistic neural network (PNN) has a wide range of applications in the field of power transformer fault diagnosis because of its good fault tolerance and high training efficiency. In PNN, the smoothing factor has a great influence on the output, but the parameter is lack of efficient selection method, which makes the classification efficiency of PNN not high. Aiming at this problem, a diagnosis method based on improved PNN is proposed for power transformer faults in this paper. Bat algorithm is used to optimize the smoothing factor of PNN to determine the optimal value. Based on the optimal results, the network model is trained to obtain the optimal power transformer fault diagnosis model. The experiment fully proves that the improved PNN has higher diagnosis accuracy than other methods.

1. Introduction

Power transformers (PT) have always been the core component in the operation of the power grid, and their operational status determines the efficiency of the grid. The fault of PT will cause serious harm to the security and stability of power grid, hence, it can be seen as a significant task for the maintenance department of power enterprise that they need to monitor and find out the fault of PT as soon as possible. The fault diagnosis of PT is a key research topic in the field of power equipment condition monitoring in recent years, which has good development and application prospects. At present, it has been greatly developed, but the existing practical application is not universal. At present, the mainstream diagnostic method is gas chromatography in transformer oil, among which the application of the three-ratio method (TRM) is more. However, the TRM has some problems, such as the lack of code quantity and the defects of the criterion of critical value. With the continuous progress of artificial intelligence, a large number of calculation methods of AI are used to improve the PT fault diagnosis technology based on DGA[1-2]. Artificial neural network (ANN) is widely applied to diagnosis PT fault because of its ability to classify complex samples and remarkable self-learning performance. However, the parameters of ANN are normally determined by artificial experience, and the training structure for specific problems needs repeated training, so the efficiency is too low and a has a tendency to fall into the trap of local optimum [3-4].

PNN can be seen as a typical representative of ANN. The network architecture and training principle of PNN is simple. The excellent classification performance of PNN model can form an accurate correlation between samples and labels, form a classification network with high fault tolerance and
adaptive adjustment ability. Although PNN has a good effect in classification, the smoothing factor of PNN determines the final classification accuracy, and the smoothing factor is also assigned by experience, which makes it difficult for PNN to give consideration to both efficiency and accuracy in classification. Therefore, this paper introduces bat algorithm to optimize PNN, mainly to optimize the network smoothing factor, to ensure the classification efficiency of PNN and the classification accuracy at the same time, so that it can be better applied to the fault diagnosis of PT.

2. The basic principle of PNN

PNN can be seen as a kind of feedforward network, which is considered to be developed from probability density estimation and Bayesian maximum a posteriori probability criterion. PNN uses Parzen window to realize probability density estimation, and defines Gaussian function as kernel function [5]. PNN generally has 4 layers, including input layer, mode layer, summation layer as well as output layer. Therefore, the basic framework of PNN is shown in Figure 1.

\[
F(X, \omega_i) = \exp\left(-\frac{(X-\omega_i)^T (X-\omega_i)}{2\delta^2}\right)
\]

In equation (1), $\delta$ represents the smoothing factor, which determines the accuracy of PNN final classification and is the core parameter of the network.

The 1st layer of PNN is the input layer. The number of neurons in this layer corresponds to the dimension of the sample. The difference between the input vector and the sample vector is solved by calculating the difference between the input value and the whole sample, which can be used to represent the spacing between the two.

The 2nd layer of PNN is the mode layer. In this layer, it is necessary to determine the appropriate number of samples, and select the similar samples by comparing the samples with the input. The similarity of samples is taken as the output of the layer.

The 3rd layer of PNN can be defined as the summation layer. The layer can be approximately regarded as an adder, and the similarity from the output of the pattern layer can be added to form a whole. In this paper, the total number of neurons in this layer can be treated as the total number of all types of transformer faults. Because the process of classification is one-to-one correspondence, the neurons in this layer are only link to the corresponding neurons in the 2nd layer.

The 4th layer of PNN is the output layer. The layer can be approximately regarded as a comparator, which compares the probability density belonging to the output of the 3rd layer, and selects the largest quantity as the result output.
The whole probabilistic neural network has good compatibility and anti-interference. When the number of samples fluctuates, it only needs to change the number of neurons in the 2nd layer. When the total amount of fault modes to be diagnosed increases, it only needs to change the number of neurons in the 3rd layer.

PNN network structure can be said to be simple, without adjusting too many parameters, and because there is no hidden layer, the network training speed is faster, and can realize nonlinear discrimination under various conditions. PNN classification follows the Bayes minimum risk criterion. When the samples are sufficient, an optimal solution can be obtained. Even if there are some errors in the selected data samples or the samples need to be modified due to engineering requirements, the original network can be used for classification directly, which has strong anti-interference performance [6].

Although the classification performance of PNN is remarkable, in the process of network work, the smoothing factor always carries a big weight in the final classification results. However, the smoothing factor is usually assigned manually. In the past, it was mainly determined based on experience. It can be seen a hard task to seek the best smoothing factor quickly, so that the efficiency of PNN is low. Therefore, it is of great significance to seek an outstanding optimization method to improve the classification effect of PNN and enhance the diagnosis accuracy of PT fault.

3. Improvement of PNN and Establishment of Fault Diagnosis Model

3.1. Bat algorithm

Bat algorithm (BA) is an intelligent algorithm inspired by predation behaviour of bats. The basic principle of BA is: when the bat starts to search for prey, the pulse emissivity is small and the loudness is the largest. In the process of bats flying to their prey, the correlation coefficient can be used to control the gradual increase of pulse emissivity and the gradual decrease of loudness. The algorithm includes global search and local search. The adjustment of pulse frequency is mainly used to update the global search part, and the adjustment of pulse emissivity and loudness is mainly used to update the local search part [7-8].

In the process of searching, bats update their position and velocity according to the pulse frequency

\[ \eta_i = \eta_{\text{min}} + (\eta_{\text{max}} - \eta_{\text{min}}) \beta \]  
\[ v_i' = v_{i-1}' + (v_{i-1}' - v_s) \eta_i \]  
\[ P_i' = P_{i-1}' + v_i' \]  

In equation (2), \( \eta_i \) represents the pulse frequency. \( \eta_{\text{max}} \) represents the maximum pulse frequency and \( \eta_{\text{min}} \) represents the minimum pulse frequency. \( \beta \) can be seen as a random constant in the range of 0–1. \( P_i' \) represents the position of bat \( i \) that born in generation \( t \), \( v_i' \) represents the speed of bat \( i \) that born in generation \( t \), and \( P_i \) represents the optimal position of all bats.

The location update formula of local search is

\[ P_{\text{new}} = P_i + \lambda \overline{L} \]  
\[ P_{\text{new}} = P_i' + \lambda \overline{L} \]  

Where, \( P_{\text{new}} \) represents the new position after updating, \( \lambda \) represents a random number in the range of [-1,1] and \( \overline{L} \) represents the average loudness of a bat in generation \( t \).

The updated formula of pulse emissivity is as follows:

\[ R_i^{t+1} = R_i^t (1 - e^{-\alpha}) \]
The updated formula of pulse loudness is as follows:

\[ L_{t+1}^i = aL_t^i \]  

(8)

Where, \( a \) is a constant belonging to \((0,1)\), \( c \) can be seen as a random constant and \( c > 0 \). \( R_i^t \) can be defined as the maximum value of the pulse emissivity. \( L_i^t \) represents the pulse loudness of bat \( i \) in the generation \( t \). \( R_i^t \) represents the pulse emissivity of bat \( i \) in the generation \( t \).

The specific process of BA is as follows:

Step 1: Initializing parameters of BA and setting the initial threshold.

Step 2: Under consideration of the fitness function, the optimal position of bats will be calculated, and the speed and position of bats are updated according to the formula (2) - (4).

Step 3: Generating a random constant in the range of \([0,1]\). When the pulse emissivity of a bat is greater than the random number, the bat's position is updated according to equation (4). Otherwise, the optimal bat individual is selected and a local solution is solved around the individual by using formula (5).

Step 4: Generating a random constant in the range of \([0,1]\) again. If the impulse loudness of a bat is greater than the constant and the fitness value is better than the optimal value, the bat updates its position, increases the impulse emissivity according to the increase coefficient of the impulse emissivity, and decreases the loudness according to the loudness attenuation coefficient.

Step 5: If the termination condition is met, the operation result will be output. Otherwise, go to step 2.

3.2. The process of PNN optimized by bat algorithm

![Figure 2. The overall flow of BA-PNN](image)
Since the smoothing factor of PNN determines the accuracy of the final classification, in order to effectively increase the operation speed and reduce the smoothing factors of manual value, the combination of BA and PNN is applied to the fault diagnosis of PT to further promote the accuracy. The BA-PNN still uses three-ratio method to process fault data.

Using MATLAB 2018b to establish BA-PNN model, the bat population size is 20, The maximum number of iterations of the algorithm is 100, the bat position belongs to [-5,5], the bat speed belongs to [-1,1], the initial pulse emissivity is 0.5, the pulse emissivity enhancement coefficient is 0.8, the initial pulse loudness is 0.9, the loudness attenuation coefficient is 0.9, and the pulse frequency is 10. Input the training samples of PT fault data into BA-PNN model to obtain the optimal smoothing factor. The overall flow of BA-PNN can be seen in Figure 2.

4. Experimental Result

The sample data has been processed into a 33×4-dimensional matrix, in which the first 3 columns are the values processed by the TRM, and the fourth column is the classification label. The first 23 samples are defined as the training set and the last 10 samples are defined as the test set, PNN and BA-PNN are respectively applied for fault diagnosis. The comparison of the calculation results is shown in Figure 3 and Figure 4. The “○” in the figure represents the predicted value, meanwhile the “*” represents the actual fault situation.

![Figure 3. Experimental result of PNN](image1)

![Figure 4. Experimental result of BA-PNN](image2)
It can be seen from Figure 3 that the predicted value and the actual value have errors in the training process PNN, and the training set classification accuracy is 91.3%. The accuracy of test set classification is 80%. As can be seen from Figure 4, when PNN improved by bat algorithm is applied to diagnosis power transformer fault, the predicted value is consistent with the actual value in both training set and test set, and the classification accuracy is 100%. This shows that the bat algorithm can improve the classification accuracy and diagnosis accuracy.

5. Conclusion
The existing power transformer fault diagnosis method mainly combines DGA with artificial neural network. Usually, the three ratio method is used to process the original fault information data, and then the processed data is input into the artificial neural network for classification. PNN has strong classification function, which can accurately divide the samples into corresponding fault types according to the fault characteristics, and can effectively resist the interference caused by data changes. However, the smoothing factor of PNN carries a wide weight in the process of classification. In the past, it was mostly determined by artificial experience, which makes the accuracy of PNN unsatisfactory. Aiming at the shortcomings of the existing PNN, this paper introduces BA to optimize the PNN, which reduces the interference of human factors and effectively improves the classification accuracy of PNN. Compared with a single PNN, it has better classification effect and is helpful to further expand the research of PT fault diagnosis.

References
[1] Dai, J., Song, H., Sheng, G. and Jiang, X. (2017) Dissolved gas analysis of insulating oil for power transformer fault diagnosis with deep belief network. IEEE Transactions on Dielectrics and Electrical Insulation., 24: 2828-2835.
[2] Abed, N.Y. and Mohammed, O. A. Modeling and Characterization of Transformers Internal Faults Using Finite Element and Discrete Wavelet Transforms. IEEE Transactions on Magnetics. 43: 1425-1428.
[3] Xiong, H. and Sun, C. (2007) Artificial Immune Network Classification Algorithm for Fault Diagnosis of Power Transformer. IEEE Transactions on Power Delivery., 22: 930-935.
[4] Castro, A. R. G. and Miranda, V. Knowledge discovery in neural networks with application to transformer failure diagnosis. IEEE Transactions on Power Systems., 20 :717-724.
[5] Shanbehzadeh, J. and Ogunbona, P. O. (1997) On the computational complexity of the LBG and PNN algorithms. IEEE Transactions on Image Processing., 6: 614-616.
[6] Tian, B. and Azimi-Sadjadi, M. R. (2001) Comparison of two different PNN training approaches for satellite cloud data classification. IEEE Transactions on Neural Networks., 12: 164-168.
[7] Song, W. and Huang, C. (2018) Mining High Utility Itemsets Using Bio-Inspired Algorithms: A Diverse Optimal Value Framework. IEEE Access., 6: 19568-19582.
[8] Damasceno, N. C. and Filho, O. G. (2017) PI controller optimization for a heat exchanger through metaheuristic Bat Algorithm, Particle Swarm Optimization, Flower Pollination Algorithm and Cuckoo Search Algorithm. IEEE Latin America Transactions., 15: 1801-1807.