Research on transformer fault diagnosis based on genetic algorithm optimized neural network

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Abstract. Aiming at the problem of transformer fault diagnosis in power system, a fault diagnosis method based on genetic algorithm optimization BP neural network is proposed. The BP neural network structure was established based on the traditional three-ratio fault diagnosis method. The concentration of dissolved gas in transformer oil was taken as the input value of the neural network, and the fault working state of transformer was taken as the output value. The established neural network is used to diagnose transformer faults. In order to avoid BP neural network falling into the problem of local optimal value, the weights and thresholds of the neural network are optimized by genetic algorithm. By using the genetic algorithm toolbox in Matlab to establish the genetic algorithm network structure, the transformer fault data as input for the performance of the neural network test. The results show that the neural network optimized by genetic algorithm has a high classification effect on transformer fault types, and the neural network optimized by genetic algorithm has a higher diagnostic efficiency and accuracy than BP neural network.

1. Introduction
With the rapid development of intelligent power grid construction and the rapid growth of power equipment, the load of power system also increases sharply. The increase of power system capacity will inevitably lead to the expansion of power system scale, more complex structure, ensure the stable and healthy operation of the power grid is facing greater challenges. Transformer is one of the basic equipment of power system, and the running state of transformer directly affects the health state of power grid[1]. Therefore, it is very important for the stable operation of the power system to accurately judge the running state of the transformer and ensure that the transformer is always running in a healthy state[2].

The traditional fault diagnosis method uses the ratio of methane (CH₄), ethane (C₂H₆), acetylene (C₂H₂), ethylene (C₂H₄) and hydrogen (H₂) dissolved in oil to establish the ratio coding method to correspond to different fault types[3]. In this paper, the three ratio method for the prototype of the traditional BP neural network model is set up, using genetic algorithm to optimize neural network weights and threshold, get the global optimal value, can improve the convergence speed of the network, to overcome the neural network for gradient descent easily trapped in local minimum problem, effectively improve the identification precision of the neural network to fault types[4].
2. BP neural network fault diagnosis

2.1. Determination of input vector
Power transformer faults have latent overheating or discharge faults. These faults do not directly cause the equipment to not work, but will accelerate the generation rate of dissolved gas in the oil[5]. When the gas produced in the oil is enough, the gas alarm device can be triggered, at this time, irreparable losses have been generated. Selection of \( \text{H}_2, \text{CH}_4 \) and \( \text{C}_2\text{H}_2 \) dissolved in transformer oil characteristics, \( \text{C}_2\text{H}_4 \), and \( \text{C}_2\text{H}_6 \) gas concentration as input vector of the network, the network input layer node number is 5, the input vector of the network structure is as follows:

\[
X_i = [x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}]^T
\]  

(1)

In the formula, \( X_i \) represents the \( i \)-th input sample and \( x_{i1} \sim x_{i5} \) represent the numerical results of normalized gas concentrations of \( \text{H}_2, \text{CH}_4, \text{C}_2\text{H}_2, \text{C}_2\text{H}_4 \) and \( \text{C}_2\text{H}_6 \), respectively. Data normalization is carried out through the formula as follows:

\[
y = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]  

(2)

In the formula, \( y \) represents the result after input parameter normalization, \( x \) represents the value of input sample, and \( x_{\text{max}} \) and \( x_{\text{min}} \) are the maximum and minimum values of input sample respectively.

2.2. Determination of output vector
The output of the neural network corresponds to the fault types of the transformer. The main fault types of the transformer include low temperature overheating, high temperature overheating, low energy discharge and high energy discharge. The normal working state and fault type of the transformer are binary coded. Five-digit binary is used to represent the five different working states of the transformer. The expected output table corresponding to the fault type of the transformer is shown in Table 1. Since the output is composed of normal state and four types of fault, the number of output neurons is 5[6].

| The fault types                 | The desired output of the output neuron |
|---------------------------------|----------------------------------------|
| normal                         | 0 0 0 0 1                               |
| Low temperature overheat       | 0 0 0 1 0                               |
| High temperature overheating   | 0 0 1 0 0                               |
| Low energy discharge           | 0 1 0 0 0                               |
| High energy discharge          | 1 0 0 0 0                               |

2.3. Establishment of neural network model
According to the number of existing input and output neurons, the neural network fault diagnosis network structure is established, as shown in Figure 1:

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Fig 1. BP neural network fault diagnosis model.
BP neural network is a kind of multi-layer feedforward neural network. The main characteristic of this network is signal forward transmission and error reverse transmission. If the output layer can't get the expected output, it turns into back propagation and adjusts the network weights and thresholds according to the prediction errors. Thus, the predicted output of BP neural network is constantly approaching the expected output[7].

According to the neural structure of the brain, the neural network unit as shown below is established. The neuron has the function of processing the input data and then mapping it to the output. The sample data input to the neuron is processed by the weight and threshold of the neuron, and then mapped to the output y by the activation function. The activation functions used in this chapter are as follows:

$$f(x) = \frac{1}{1 + e^{-x}}$$  (3)

In the formula, x represents the value of the input sample processed by the weight threshold. The function f(*) represents the mapping of input values to output values.

Output calculation of hidden layer: the neural network calculates the output from output layer to output layer according to the data of input samples, the connection weights and thresholds of input layer and hidden layer.

$$Y_j = f(\sum_i^m \omega_{ij}x_i + a_j)$$  (4)

In the formula, x is the value of the input sample, \(\omega_{ij}\) and \(a_i\) are the connection weight and threshold of the input and output respectively, and the output \(Y_j\) of the hidden layer. Where, j is the number of neurons in the hidden layer, and f is the excitation function of the hidden layer.

Output calculation of the output layer: according to the output of the hidden layer, connect the weight \(\omega_{jk}\) and the threshold \(b_j\) to calculate the pre-output of the BP neural network \(O_k\):

$$O_k = \sum_{j=1}^n H_j \omega_{jk} + b_k$$  (5)

Calculate the error between the predicted value and the actual value: Calculate the network prediction error \(\delta\) by comparing the neural network forecast output \(O_k\) with the actual expected output value \(Z\).

$$\delta = Z - O_k$$  (6)

Update of weight threshold: the error value calculated by the neural network is compared with the set error value. If the error is less than the set error value, the iteration will end. Otherwise, the weights and thresholds of the neural network are updated and a new iteration is carried out.

Updation of weights:

$$\omega_{ij} = \omega_{ij} + \eta (1 - H_j)x(i) \sum_{k=1}^m \omega_{jk} e_k$$  (7)

$$\omega_{jk} = \omega_{jk} + \eta (1 - H_j)x(i)$$  (8)

Threshold update:

$$a_j = a_j + \eta (1 - H_j)x(i) \sum_{k=1}^m \omega_{jk} e_k$$  (9)

$$b_k = b_k + e_k$$  (10)

2.4. Fault identification of neural network
Transformer fault diagnosis is an important part of transformer research, and it is an important research direction to apply neural network to transformer fault diagnosis. The identification process of fault diagnosis is as follows: As shown in Figure2:
2.5. Selection of training samples
The fault data of the same oil-immersed transformer was collected, and 200 sets of data determined by the transformer fault type after inspection were selected as training samples. Meanwhile, the concentration of five gases in the transformer corresponding to the fault was measured as input data. The fault type is encoded as the expected output.

3. Genetic algorithm optimization BP neural network fault diagnosis

3.1. Principle of genetic algorithm
Genetic algorithm (GA) was proposed by Professor Holland from University of Michigan in the United States in 1962 to simulate the genetic mechanism of nature and biological evolution and become a parallel random search optimization method[8]. It the "evolution, survival of the fittest" nature of biological evolution principles in optimizing parameters of coding series[9], according to the selected in the fitness function and genetic selection, crossover, and mutation of individual screening, make good individual fitness value is retained, poor fitness of individuals are eliminated, the new group inherits the generation of information, and is better than the last generation[10].

3.2. Optimization of BP neural network by genetic algorithm
The neural network uses gradient descent method to find the optimal solution when training data. Gradient descent method is easy because the local extreme point is trapped in the local optimal solution, so it is impossible to find the optimal solution of the whole system. Genetic algorithm (GA) is a kind of adaptive heuristic global search algorithm, which has good global optimization performance and high search efficiency. Genetic algorithm can iterate the initial weights and thresholds of neural network, evolve the value of minimum system error, and optimize the system.

Genetic algorithm optimization neural network can be divided into three parts: neural network structure determination, genetic algorithm optimization and neural network prediction. The neural network structure can be determined, and then the weights and thresholds of the neural network can be calculated:

$$S = R \times N + N \times M + N + M$$ \hspace{1cm} (11)

In the formula, $R$ is the number of input neurons, and $N$ is the number of hidden layer neurons. $M$ is the number of neurons in the output layer.

3.3. Implementation of genetic algorithm
Optimization of BP neural network by genetic algorithm is to use genetic algorithm to optimize the weight and threshold of neural network, so that the optimized neural network structure can better predict the output.

1 Population initialization
   Genetic algorithm population individual contains the input layer to the hidden layer and hidden layer to the output layer of the weight and threshold, each individual is encoded. Set the number of the initial population. The number of the population set in this paper is 50.

2 Fitness function
   According to the principle of genetic algorithm, it is necessary to calculate the fitness of each population to determine the existence of the individual.
3 choices
The selection process of genetic algorithm is to keep the excellent genes and eliminate the bad genes in order to get better results. In this paper, the method of roulette to select and judge the individual population, population individual accounted for the overall fitness ratio as the probability, random selection and elimination of the individual population. The probability calculation formula for each individual is as follows:

\[ P_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \]  

(12)

In the formula, \( f_i \) is the fitness value of individual \( i \). \( N \) is the population individual.

4 cross
The crossing process of genetic algorithm is to cross and interchange multiple individuals to ensure a variety of individual possibilities. Individuals exist in the genetic algorithm in the way of encoding, so it is only necessary to exchange the same position of the coding of cross individuals. The crossing operation of the \( n \) chromosome \( a_n \) and the \( m \) chromosome \( a_m \) at the \( j \) position is as follows:

\[ a_{nj} = a_n(1 - b) + a_mb \]  

(13)

\[ a_{mj} = a_m(1 - b) + a_nb \]  

(14)

In the formula, \( b \) is a random number between \([0, 1]\).

5 the variation
Variation is the result of selecting the random coding position of the individual to carry out variation, which helps to calculate the multiple possibilities of the individual. The \( j \)-th gene \( a_{ij} \) of the \( i \)-th individual was mutated, and the mutation operation method was as follows:

\[ a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\text{max}}) \times f(g) & r > 0.5 \\ a_{ij} + (a_{\text{min}} - a_{ij}) \times f(g) & r \leq 0.5 \end{cases} \]  

(15)

In the formula, \( a_{\text{max}} \) is the upper bound of individual \( a_{ij} \); \( a_{\text{min}} \) is the lower bound of the individual. \( f(g) = r^2 (1-g/G_{\text{max}}) \) 2; \( r \) is a random number; \( g \) is the number of current iterations; \( G_{\text{max}} \) is the maximum number of evolutionary times; \( r \) is a random number \([0, 1]\).

4. Simulation Test
In this paper, MATLAB software is used to establish a neural network model, using the established neural network to judge the type of fault. 150 samples were randomly selected from the existing training samples as training samples, and the remaining samples were selected as verification samples. BP neural network was used to train the data first, and then the test set was used to validate the data, so as to test the verification accuracy of the system. The diagnostic structure is shown below.

![Fig 3. Fault diagnosis accuracy ratediagram.](image1)

![Fig 4. Fault diagnosis identification error.](image2)

In this simulation, there are 150 samples as input samples and 20 samples as output samples. In the test, 13 samples were accurately classified.
Genetic algorithm was used to optimize the weight threshold of the neural network, and the same data were simulated again. Simulation results are shown in the figure below:

![Fig 5. fault diagnosis accuracy rate.](image1)

![Fig 6. Fault diagnosis identification error.](image2)

According to the experimental results in the figure above, it can be seen that the BP neural network optimized by genetic algorithm has a higher diagnostic accuracy for fault diagnosis. There were 20 samples as test samples, 17 samples were correctly identified.

5. Conclusions

Due to the small amount of transformer fault data and the complexity of diagnosis data, the use of simple neural network for transformer fault diagnosis has the disadvantages of low accuracy, long convergence time and easy to fall into local optimal value. In this paper, a diagnosis model combining genetic algorithm and neural network is proposed. The weight and threshold of neural network are optimized by genetic algorithm to improve the fault diagnosis of transformer. Through the comparison of different diagnosis models, the transformer fault diagnosis results show that:

1. BP neural network optimized by genetic algorithm has a higher accuracy, which can overcome the shortcomings of traditional neural network that it is easy to fall into local values and improve the convergence speed of the whole network structure.

2. Better practical performance. It overcomes the problem of unstable accuracy in diagnosis by using BP network alone.

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