Application of Double-Hidden Layer BP Neural Network in Transformer Fault Alarm

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Abstract. The traditional power transformer fault judgment is through the oil chromatography online monitoring data set a threshold to determine whether the transformer is faulty, so there is a problem of the correct rate of fault alarm. This paper adopts the data analysis method, based on the Fuzhou transformer oil chromatography and its repair order data, selects effective characterization of influence the characteristics of transformer running state as evaluation indexes. A double-hidden layer BP neural network models were constructed and applied into transformer fault alarm, and evaluation accuracy is higher than the common fault alarm model.

Keywords: Power transformer · Fault diagnosis · Double-hidden layer BP neural network

1 Introduction

Since the types and contents of dissolved gas in oil are different when an oil immersed power transformer operates in the different state, dissolved gas in oil analysis (DGA) has long been an effective means of judging the state of a transformer. With the development of artificial intelligence technology, domestic and foreign scholars proposed a variety of classification algorithms based on DGA, such as probabilistic neural network [1], limit learning machine [2], random forest [3], support vector machine [4] and so on. However, the above methods belong to the single-layer neural network learning method, the learning ability is limited, the model accuracy is unstable, and when the accuracy of the alarm reaches a certain height, it is difficult to improve greatly.

At present, the evaluation system of transformer state concentrated on the certain indicators exceeds the standard warning by the artificial experience sets the corresponding threshold. On the one hand, because of the uncertainty of

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human experience, the power transformer has false alarm problems, and the on-site identification of the fault situation requires a lot of manpower and material resources; on the other hand, excessive warning only reflects some parts of the transformer and fails to combine use of multi-source information to comprehensive evaluation the power transformer. So that the transformer operation and status information scattered in a number of relatively independent information platform, which is not conducive to the multidimensional of information and the analysis and display of multi data. Therefore, a new type of alarm method is needed in order to improve the correct rate of transformer fault alarm.

From the view of combining genetic algorithm [5], the training speed is accelerated and the precision of the training is improved by introducing the mutation operator, the inertia weight factor and the Gaussian weighted global extreme in the genetic algorithm. From the view of clustering algorithm [6], which is suitable for the overheating fault diagnosis of the transformer and the performance is better than the three ratio method, but it is not good when dealing with mixed electric fault. From the research of fuzzy control [7], which avoids the traditional algorithm using the three ratio method in the border to determine the shortcomings of inaccurate.

BP (Back-Propagation) neural network was proposed by scientists Rumelhart and McClelland in 1986 which is a kind of multilayer feedforward neural network trained by error back propagation algorithm. In 2006, the University of Toronto professor, the field of machine learning Geoffrey Hinton [8] and his students put forward a view that the multi-hidden layer of artificial neural network with excellent feature learning ability. The characteristics of the study have a more fundamental characterization of the data, which is conducive to visualization or classification. Literature [9] proposed the transformer discharge pattern recognition based on convolution neural network. According to the segmentation of the discharge signal visual attention mechanism, and take the gray image and bilinear interpolation normalization as the convolution of the input of the neural network the correct rate of which is about 94% in transformer fault diagnosis. Literature [10] put forward based on the deep learning neural network (DLNN), build a number of hidden layer neural network, through the characteristics of transformation or data feature extraction to discover intrinsic properties, classification accuracy is superior to the traditional support vector machine (SVM) method.

In order to overcome the influence of the fault alarm results of the uncertainty of human experience, in this paper, a new method of fault alarm for the power transformer is constructed based on double-hidden layer BP neural network. First, the Fuzhou transformer oil chromatography and its repair order data were cleaned, fusion matched and generated a typical training data set for training and testing. Then by adjusting the number of hidden layer neurons and the number of hidden layers and the hidden layer activation function to select the appropriate construction of double-hidden layer BP neural network simulation model. Finally, the correctness and effectiveness of the method proposed in this article is verified through calculation examples and statistical result. Compared with the conventional method that applied to the fault alarm of power transformer, the method proposed in this article has a higher rate of positive judgment.

2 Implementation of Double-Layers BP Neural Network

2.1 Double-Hidden Layer BP Neural Network Principle and Implementation Steps

The BP neural network composed of nonlinear transformation units has good nonlinear mapping ability, which is widely used in power transformer fault prediction, alarm, classification and other fields. According to the number of hidden layer BP network can be divided into a single hidden layer and hidden multi-layer network. The results show that compared with the single hidden layer, the double-hidden layer BP neural network has superior generalization ability and high prediction accuracy. The number of hidden layers is considered from the network accuracy and training time. When the mapping relation is simple, choose a single hidden layer in order to improve the network speed. When the mapping relation is complex, choose a double-hidden layer in order to acquire higher the network accuracy. In this paper, the double hidden layer BP neural network is chosen, because the fault data format of the power transformer is various, the structure is complex, and it needs higher prediction accuracy. Specific BP neural network implementation steps are as follows:

(1) Randomly initialize weights.
(2) Implement forward propagation.
(3) Implement code to compute cost function.
(4) Implement back propagation to compute partial derivatives.
(5) Use gradient descent or advanced optimization method with back propagation to try to minimize cost function.

2.2 Double-Hidden Layer BP Neural Network Pseudo Code:

a means neurons, superscript l means number of layers, j represents a layer of j neurons.

Activation function:

$$g(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

Cost function:

$$J(\Theta) = \frac{1}{2m} \sum_{i=1}^{m} (Y(\Theta)^{(i)} - y^{(i)})^2 \tag{2}$$

$\triangle_{ij}^{(l)}$ is the ith neuron in the weight matrix of the l layer influences the weight of the next layer of the jth neuron.

Algorithm 1. Double-layer BP neural network

Input: Training set A; learning rate α; Number of training sets m; Network Structure N; Number of layers L; $g(x)$: activation function; $J(\Theta)$: cost function;
Output: DBP's parameters ω, b;

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initial network parameters ω, b randomly;
Set △^l_ij=0(for all l,i,j);//use to compute the derivative of J(Θ)
for each i ∈ [1, m] do
    set a^(1) = x^(i)
    for each l ∈ [1, L] do//perform forward propagation to compute a^(l)
        a^(l+1) = g(a^(l) Θ^(l))(add a_0^(l+1))
    end for
    σ^(4) = a^(4) − y^(i); //compute all previous layer error vector
    σ^(3) = (θ^(3))^T θ^4. ∗ g'(θ^(2) a^(2));
    σ^(2) = (θ^(2))^T θ^3. ∗ g'(θ^(1) a^(1));
    for each i ∈ [1, L] do // compute weight matrix
        △^(l)_ij = △^(l)_ij + a^(l)_j δ^(l+1)_i
    end for
    if j = 0 then
        D^(l)_ij = (1/m) △^(l)_ij;
    else
        D^(l)_ij = (1/m) △^(l)_ij + α Θ^(l)_ij;
    end if
end for
```

3 Double-Hidden Layer BP Neural Network Model Performance Debugging

The double-hidden layer BP neural network model is composed of the input layer, hidden layer, and output layer. The output layer classifier uses SVM, which is suitable for the two class problem, which can give the results of each classification in probability and combine with the neural network will get better classification performance. Applying Matlab explore and optimize the experimental conditions, such as the layer number, the number of layer neurons and the activation function of the layer, which markedly influenced the performance of the BP neural network.

3.1 Performance Analysis of Different Layers

As shown in Fig. 1, the neuron network has better performance when it is on the first floor and the two layers and the standard deviation is the lowest at the two levels, and the highest accuracy mean meets the engineering requirement. When the hidden layer increases, the mean precision does not improve significantly, and when the hidden layer is greater than four layers, the training time will increase exponentially. Therefore, it is suitable to choose double hidden layer BP neural network.

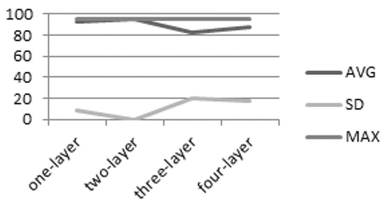

Fig. 1. Performance analysis of different layers

3.2 Performance Analysis of Different Neuron Numbers

As shown in Fig. 2, the neuron network has better performance when the number of neurons is 10 or 20. As the number of neurons increases, the training time will be increased. Therefore, it is appropriate to select the neural network structure with a smaller number of neurons to meet the requirements of accuracy.

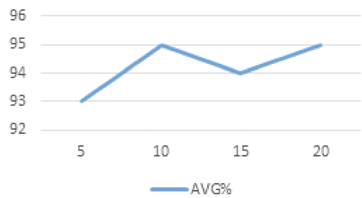

Fig. 2. Performance analysis of different neuron numbers

3.3 Performance Analysis of Different Activation Functions

As shown in Fig. 3, the neuron network has better performance when the activation function is logsig, purelin and tansig and purelin, the precision is higher and the standard deviation is lower. When the activation function is purelin and tansig, the precision is lower and the standard deviation is higher. Therefore, it is appropriate to choose the activation function of the combination of logsig and purelin.

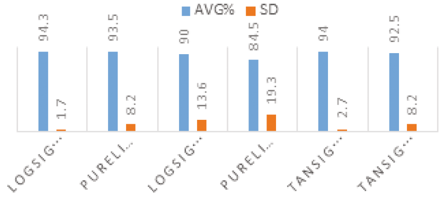

Fig. 3. Performance analysis of different activation functions

Finally, the selected BP neural network structure is double-layer, the number of neurons is 10, and the activation function is logsig and purelin. The constructed double-hidden layer BP neural network is shown in Fig. 4.

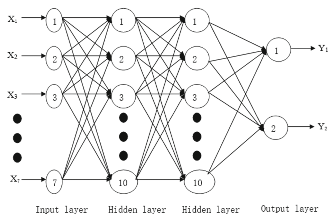

Fig. 4. Structure of double-layer BP neural network

In conclusion, the selected BP neural network structure is double-layer, the number of neurons is 10, and the activation function is logsig and purelin. The constructed double-layer BP neural network is shown in Fig. 4.

4 Experimental Results and Analysis

Selection of 2011 to 2016 Fuzhou 8 areas of the main transformer oil chromatography online monitoring data and the State Grid of Fuzhou transformer failure work order data. The work order data consists of "time of failure", "fault location", "alarm situation", "processing situation" and other components. Chromatographic online monitoring data consists of "transformer type" and "transformer position", "monitoring data acquisition time" "a device", "two equipment", "oil dissolved gas value" and other components. Applying Matlab match online monitoring data of Fuzhou City with the transformer fault data according to definite fault time matching transformer.

4.1 Data Cleaning

Cleaning data mainly follow the following principles:

(1) Selection: select Fuzhou oil chromatogram data and supporting the work list, a total of more than 200.
(2) Removal: oil chromatographic data due to the detection device did not upload the missing data.
(3) Interpolation value: Select the nearest day data to compliment when the alarm on the day of the oil chromatographic data is missing.
(4) Classification: different types of transformers, oil chromatography data types are different.

According to the engineering field of on-line monitoring data, taking into account the double-layer BP neural network has the characteristics of strong sample conversion and feature extraction ability, select $H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, Co$ of the 6 characteristic variables of gas. In order to reduce the difference of gas content value and reduce the calculation error, formula (3) is used to standardize the gas content value.

x_{new} is the content of gas after standardization; x is the original value of gas; x_{mean} is the mean value of the gas content in the training set or test set x; x_{std} is the standard difference of the gas content in x.

$$x_{new} = \frac{x - x_{mean}}{x_{std}} \tag{3}$$

On the basis of actual engineering requirements, the input variables are $H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, Co$ which are the 6 characteristic variables of gas. The output variable is the correct alarm and error alarm bar shown in the State Grid Fuzhou transformer fault list.

4.2 Experimental Verification

In order to verify the alarm capability of the algorithm, the interception of the national grid from 2011 to 2016 Fuzhou oil chromatography and corresponding work orders of which 192 fault data as a data set. Randomly selected 100 as a training sample, the remaining 92 as a test sample and repeat the test 300 times. Comparing the performance of the double hidden layer BP neural network with support vector machine algorithm, random forest algorithm, limit learning machine algorithm and probabilistic neural network algorithm .The performance of the five algorithms is shown in Table 1.

Table 1. Performance Comparison.

Method	Experimental mean		
	Precision	Recall	F1-measure
Random forest	0.9324	0.7388	0.7301
Support vector machine	0.8821	0.7385	0.7323
Probabilistic neural network	0.9021	0.7222	0.7311
Limit learning machine	0.8654	0.7716	0.7699
Double-layer BP neural network	**0.9589**	**0.8139**	**0.8146**

As can be seen from Table 1, the alert accuracy rate of the double hidden layer BP neural network algorithm is the highest among the 5 algorithms. The classification accuracy of random forest algorithm and the probabilistic neural network is close to that of double-hidden layer BP neural network. Among them, random forest and probabilistic neural network have higher diagnostic accuracy, but there is an important misjudgment which let the correct alarm judge into a false alarm. However, the double-hidden layer BP neural network misjudgment is to correct the false alarm to correct alarm, which is an admissible error in engineering practice. Therefore, the performance of the double-hidden layer BP neural network is better than the other 4 algorithms, either from the engineering practice or from the diagnosis performance.

5 Conclusion

Put forward a method of transformer fault alarm algorithm based on double-hidden layer neural network. The algorithm can analyze and judge the information of power grid fault and get the correct alarm information by setting up a double-hidden layer BP neural network structure. Compared with the conventional algorithms such as random forest algorithm, SVM algorithm, probabilistic neural network algorithm, and extreme learning machine algorithm, the method proposed in this article has a higher rate of positive judgment.

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