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Transformer evaluation strategy based on improved machine learning

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Transformer evaluation strategy based on improved machine learning

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Abstract. A transformer state assessment method based on an improved extreme learning machine is proposed in this paper, which introduces an adaptive evolution algorithm into the extreme learning machine. This method is used in the evaluation model to evaluate the state of the transformer. The algorithm is trained and tested through sample sets. Furthermore, the test results are analyzed to prove the feasibility of the proposed control strategy.

1. Introduction

As the "transition station" of the power transmission and distribution system, power transformers undertake the conversion function of power from high voltage to low voltage. Power transformers affect important power customers, such as government agencies, large steel companies, scientific research institutions, military industries, etc.. If the power transformer cannot guarantee reliable operation, it will inevitably bring about huge hidden dangers in production. Therefore, power transformers are very important in the production field [1-2]. According to the relevant operation and maintenance experience of the operation and maintenance department, if the maintenance strategy can be adjusted in time according to the actual operation of the power transformer, the failure of the power transformer can be effectively avoided. Furthermore, the economic, political, and social risks caused by transformer aging or failure are reduced.

A large amount of research data has shown that many reasons cause power transformers to malfunction or abnormal working conditions, such as severe internal insulation aging of power transformers, long-term overload operation under extreme weather, and excessive short-circuit current leading to excessive short-circuit electromotive force [3]. With the continuous changes of working conditions and environments, the working status of power transformers is also constantly changing. It is impossible to determine the working status of transformers only by relying on a single index or very few operating parameters. Therefore, it is necessary to integrate a series of data to make a comprehensive judgment for the judgment of the operating state of the transformer.

Accurate evaluation of the operation status of power transformers is conducive to the maintenance of transformer status, and only then can a reasonable maintenance strategy be formulated. With the in-depth development of research work and the initial maturity of condition maintenance theory, transformer condition assessment technology has also received key attention [4]. At present, many researchers have proposed many research methods in the evaluation of power transformer status, and there have been mathematical methods such as Bayesian network, fuzzy theory and information fusion.

The intelligent method described above establishes a good evaluation model between the state of the transformer and the actual operating state of the transformer. This is of great significance to the evaluation of the state of the transformer. However, in practice, it is difficult to collect or collect data from many indicators [5-6]. The actual operating state is very different. The problems of the classification of transformer grades, the selection of membership functions, and the weighting of evaluation indexes proposed by these methods can only be solved theoretically, and there is inevitable subjectivity. The above evaluation methods lack the judgment of transformer equipment with operating years, regions, manufacturers, voltage levels, geographic locations, and operating conditions. Therefore, it is urgent to explore a transformer condition evaluation method that is closer to the actual operating condition of the transformer, which can comprehensively consider the factors that may affect the operating condition of the transformer, so that it can play an important role in the transformer condition maintenance. In this paper, a comprehensive state assessment strategy based on machine learning of temperature, load, current, and three-phase unbalance data is proposed, which can accurately estimate the transformer.

2. Machine learning theory

The extreme learning machine is a single hidden layer feedforward neural network (SLFN) learning algorithm proposed by G.B. Huang et al. Compared with the traditional neural network model, the extreme learning machine effectively overcomes the main shortcomings that the network model is difficult to determine and easy to cause over-learning. Its advantages are good generalization performance, small training error, fast learning speed, etc. As shown in Figure 1, the structure is composed of input layer, hidden layer, and output layer. The neurons in the hidden layer are connected with the neurons in the input layer and the output layer.

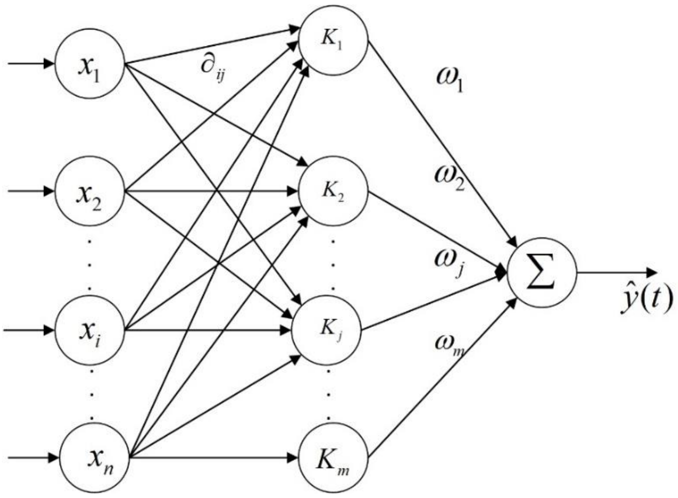

Figure 1 Single hidden layer feedforward network structure

Figure 1 shows the structure of the neural network, its principle is

$$K_j = \chi_j\left(\sum_{i=1}^{n}\partial_{ij}x_i\right), \tag{1}$$

$$\chi_j(l) = \frac{2}{1+e^{-2l}} - 1, \tag{2}$$

$$\hat{y}(t) = \sum_{j=1}^{m}\omega_j K_m \tag{3}$$

where $i=1,2,3\cdots n$, $j=1,2,3\cdots m$. x_i represents the element of the input layer neuron. K_j represents the activation function, which is the Sigmoid function. The network output $\hat{y}(t)$ is an estimate of the disturbance. The weights of and are randomly selected at [-1, 1].

The weight vector is updated through the Back-Propagation Algorithm (BPA). $y(t)$ is the error between the actual value and the observed value.

$$D(t)=y(t)-\hat{y}(t) \tag{4}$$

The goal of BPA is to ensure the smallest $e(t)$, that is

$$e(t)=\frac{1}{2}D^2(t). \tag{5}$$

where $e(t)<a$, a is a normal number. According to the chain rule, we can update the weight based on $e(t)$.

$$\dot{\partial}_{ij}(t)=-\eta\frac{\partial e(t)}{\partial\hat{y}(t)}\frac{\partial\hat{y}(t)}{\partial\chi_j(t)}\frac{\partial\chi_j(t)}{\partial_{ij}(t)} \tag{6}$$

$$\dot{\omega}_j(t)=-\eta\frac{\partial e(t)}{\partial\hat{y}(t)}\frac{\partial\hat{y}(t)}{\partial\omega_j(t)}=\eta D(t)K_j \tag{7}$$

where η is the learning rate. Combining equations (4) and (5), the neural network output is calculated as follows

$$\hat{y}(t)=\sum_{j=1}^{m}\omega_j(t)\beta_j\left(\sum_{i=1}^{n}\partial_{ij}x_i\right). \tag{8}$$

As mentioned above, the two parameters of the hidden layer input weight and hidden layer node bias in the traditional neural network are randomly selected, and they remain unchanged during the training phase, so there are non-optimized hidden layer nodes. The parameter appears in the matrix, which has a certain influence on the output function. In view of this, in the improved extreme learning, the adaptive evolution algorithm optimizes the hidden layer parameter input weights and node offsets, and calculates the hidden layer output weights through the extreme learning machine.

Given a set of hidden layer nodes of training data as x_i and novel activation function as $G(a_i,b_i,x)$. The improved algorithm is as follows:

Step 1: initialization

Initialize the first-generation parameters including hidden layer input weights and node offsets, and generate vector groups of corresponding dimensions (NP) as follows:

$$\theta_{k,g}=\left[a_{1,(k,g)}^T,\cdots,a_{\mathrm{m},(k,g)}^T,b_{1,(k,g)},\cdots,b_{\mathrm{m},(k,g)}\right] \tag{9}$$

where a_i and $b_i(i=1,2,3,\cdots,\mathrm{m})$ are randomly generated; $k=1,2,3,\cdots,\mathrm{NP}$; g represents evolutionary algebra.

Step 2 Calculation of output weight and root mean square error

Calculate the output weight matrix of hidden layer nodes. The formula is as follows

$$H_{k,g}=\begin{bmatrix} G\left(\mathrm{a}_{1,(k,g)},\mathrm{b}_{1,(k,g)},\mathrm{x}_1\right) & \cdots & G\left(\mathrm{a}_{m,(k,g)},\mathrm{b}_{m,(k,k)},\mathrm{x}_1\right) \\ \vdots & \ddots & \vdots \\ G\left(\mathrm{a}_{1,(k,g)},\mathrm{b}_{1,(k,g)},\mathrm{x}_n\right) & \cdots & G\left(\mathrm{a}_{m,(k,g)},\mathrm{b}_{m,(k,g)},\mathrm{x}_n\right) \end{bmatrix}_{n\times m} \tag{10}$$

$$\beta_{k,g}=H_{k,g}^{+}\hat{y}(t) \tag{11}$$

where $h(x_i)=\left[G\left(a_1,b_1,x\right),\cdots G\left(a_m,b_m,x\right)\right]$, $H=\left[h\left(x_1\right),\cdots,h\left(x_n\right)\right]^T$. $H_{k,g}^{+}$ is called the Moore-Penrose generalized matrix of the hidden layer output matrix $H_{k,g}$.

Step 3 Crossover and mutation

To obtain the contemporary target vector, according to the adaptive possibility, the test vector can be obtained by the following mutation strategy. The crossover probability CR and the control parameter F are randomly selected and generated and obey the normal distributions N (0.5, 0.1) and N (0.5, 0.3) respectively.

Step 4 Evaluation

The output weight standard is added as a standard for the selection of test vectors. Repeat steps 3 and 4 until the desired effect is achieved or the maximum number of iterations is reached.

3. Experiment analysis

In this paper, a total of 300 sets of data are obtained by screening the historical data of the transformer. The data is normalized and divided into levels. These sample sets are randomly divided based on 2:1. Among them, 200 sets of samples are generated as the training sample set, and the remaining 100 sets of samples are used as the test sample set. Perform multiple tests as required and analyze the test results.

3.1. Data set classification

It is necessary to combine these data with the operating status of the transformer into a sample set. The state evaluation model is trained through the sample set, and then the best mathematical model is obtained. Based on the characteristic parameters that can be used for comprehensive evaluation of transformers, the basic parameters, operating parameters and parameters of bad conditions are combined for evaluation.

Table 1 Data classification

Health index	Transformer operating status	Number of samples	Percentage(%)
P1	Excellent	50	16.67%
P2	Good	123	41.00%
P3	General	100	33.33%
P4	Fault	27	9.00%

Table 1 shows the transformer health status classification based on temperature, load, current, and three-phase unbalanced data. These sample sets are used for the test set, training set, and validation set of the state evaluation algorithm. Next, these data are used to evaluate the operating state of the transformer.

3.2. Test result analysis

To better improve the power transformer operating state evaluation index system, this paper considers the temperature, load, current, three-phase unbalanced data and other indicators. The effects of these factors on the accuracy of the transformer operating state evaluation are as follows:

Table 2 Evaluation result

Health index	Number of test samples	The exact number of tests	Correct rate (%)
P1	40	34	85%
P2	100	95	95%
P3	80	74	92.5%
P4	20	17	85%

It can be seen from the data in Table 2 that the temperature, load, current, and three-phase unbalanced data have an impact on the operating state of the transformer. Using it as an evaluation index for the operating state of the transformer can improve the accuracy of the evaluation of the operating state of the transformer.

4. Conclusion

This paper proposes a transformer operating state evaluation model based on an improved machine learning algorithm. To improve the accuracy of transformer state evaluation, temperature, load, current, and three-phase unbalance data are considered as evaluation indicators for transformer operating state. The test results show that considering these factors can improve the accuracy of the transformer condition assessment.

Acknowledgments

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