Multi-parameter Overload Capacity Evaluation of Power Transformer Based on Improved Neural Network

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Abstract. Normally, transformer overloading capacity is calculated using method in guide for loading mineral-oil-immersed transformers. However, the method is not so accurate for every transformer. Therefore, a modified BP neural network based on transformer overloading calculation model is proposed. With BP neural network, computers can learn history data of transformer overloading and compute overloading time. This model combines a conditions parameter of cooling devices to make the result more accurate. The calculation data of case study using modified BP neural network model reveal that this model can get reasonable overloading time. Moreover, the overloading time is based on transformer stabilized operation, which is very practical significance.

Introduction

The rapid development of China's economy has not only promoted the people's living standards, but also driven a new round of industrial development. Therefore, besides residential electricity demand, industrial electricity demand is also substantially growing, which results in the ever increasing demand in electricity. Due to the fact that power grid construction is lagging behind while the pressure of energy use is large, and that transformers under maintenance and accidents will encounter the N-1 situation, overload operation at least for a period of time should be required for transformers. This can not only avoid the economic losses caused by load shedding, but also improve the load rate of main transformer, enabling the power network's safe and stable operation. [1]

In the meantime, transformers with high overload capacity can replace the power transformer with large capacity but expensive price. The higher capacity utilization reduces waste, saves investment in substation and optimizes fund distribution. Therefore, the study on transformers' overload capacity has important significance.

Transformers are affected by electrical, thermal, chemical, mechanical and other factors in the operation process, and the insulative part will age over time. Among these factors, temperature is a major reason for the aggravation of insulator aging and the transformer failure. The aging degree of the transformer's insulative part shows exponential increase with the temperature. Specifically, the aging degree will double for every 1 ° C increase in temperature. Thus, the transformer's internal temperature is a main factor to limit the transformer overload. The transformer overload study of domestic and overseas scholars also focuses on temperature. Literature [2] calculated the transformer temperature changes in several cases (especially overload conditions) using the top oil temperature and hot-spot temperature calculation model in IEEE Guide for Loading Mineral-Oil-Immersed Transformers (Std C57.91 -1995), the alternating temperature calculation model in the appendix of IEEE standard, the equivalent thermal furnace model, and the hot-spot temperature calculation model based on oil duct temperature. This study provides a good description of temperature changes under the transformer overload condition, but the hot-spot temperature needs further improvement, as pointed out in its conclusion. In literature [3], the overload test of a power transformer with 400 MVA was carried out. The temperature rise of the transformer under 1.29-times and 1.60-times rated load, and the temperature of the transformer kept at 2.5-times rated load for 20 minutes were detected. The conclusion points out that, the calculation result of hot-spot temperature under the short-term emergency load in IEC354 criteria is relatively low. Literature [4] used the formula in IEC Std 60076-7 [5] to calculate the temperature of the transformer overloaded. The overload conditions were analyzed through the comparison of the economic benefits from transformer overload and the losses caused by transformer aging. Literature [6] used the formula in IEEE/ANSI Guide for Oil-Immersed Transformer to calculate the top oil and hot-spot temperature change following load, and made risk assessment based on transformer aging degree and temperature according to the manual.

With respect to the analysis on transformer overload or load conditions, the articles above use primarily the recommended formulae in IEEE or IEC guides for oil-immersed transformers rule for calculation. It has been pointed out [7] that the hot-spot temperature calculation model in IEEE Guide for Loading Mineral-Oil-Immersed Transformers [8] obtains top oil and hot-spot temperature calculation formulae with the assumption that winding temperature increases linearly along the height and is parallel to the oil temperature which also presents linear increasing. There is a big error when such simplified calculation model is used in practice.

According to the above contents, this paper uses back-propagation (BP) neural network to realize transformer overload capacity calculation[9]. The ideal transformer overload time is obtained by inputting relevant data before overload. In literatures [9, 10], a good effect was obtained in the prediction of hot-spot temperature of transformer oil and top oil temperature with neural network. Although temperature is the main factor, there are other factors that need to be considered. Therefore, compared with the overload capacity judgment based on temperature prediction using neural network, it is more effective to directly use the neural network to learn overload conditions. Moreover, by learning the historical overload information, the model in this paper gives the result which is the recommended overload time in actual operation. It better guarantees the safety and stability of the transformer compared with the judgment using temperature.

BP neural network and its improvement

BP neural network

As entering the era of big data, increasingly more attention is paid to the using and learning of data for assisting decision-making. The neural network has been widely used in artificial intelligence and assistant decision-making. BP neural network is currently one of the most widely used and successful neural networks. The basic idea is two propagation processes, that is, the forward signal transmission process and the reverse error propagation process. The signal is transmitted from the input layer and processed by the hidden layer, and the output layer outputs results, which constitute the forward transmission process. According to sample data, the error generated from the forward output results can be obtained. Then, the error signals in the nodes of each layer are obtained by reverse propagation, followed by weight correction. Thus, a reverse error propagation process is completed. These two processes are continuous and the weight value is constantly adjusted. The training of neural network is over until the error is small enough.

The results of BP neural network are shown in Figure 1.

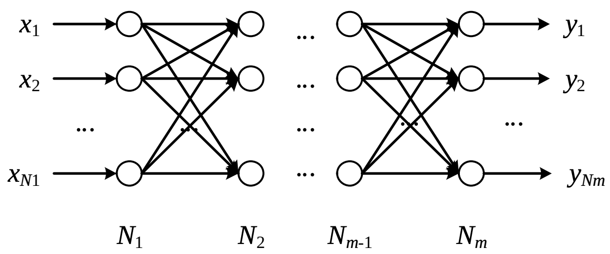

Fig. 1 BP neural network structure diagram

where
x_i - the i-th input quantity in neural-network input layer;
y_j - the j-th output quantity in neural-network output layer;
W^p_{ij} - the weight of connection between the i-th neuron in the p-th layer and the j-th neuron in the (p+1)-th layer.
O^p_j - the output of the j-th neuron in the p-th layer.
U^p_i - the input of the i-th neuron in the p-th layer.
q_i^p - the threshold of the i-th neuron in the p-th layer.
N_p - number of neurons in the p-th layer.
m - number of neuron layers.

As shown in Fig. 1, in forward propagation process,

$$U_i^{p+1} = \sum_{k=1}^{N_p} W_{ki}^p O_k^p \tag{1}$$

$$O_j^{p+1} = f\left(U_j^{p+1} - q_j\right) \tag{2}$$

where $f(x)$ is a nonlinear function.

In back propagation, the expected result is output, that is, the sample value is set as dj, and the output layer outputs the value yj in the j-th node. Then the error is represented as

$$e_j = d_j - y_j \tag{3}$$

The output error's quadratic sum is

$$E = \frac{1}{2}\sum_{j=1}^{N_m} e_j^2 \tag{4}$$

So, the weight updating formula is

$$\Delta W = -h\frac{\partial E}{\partial W} \tag{5}$$

where W is the weight value, h is the learning rate ($h > 0$), and ΔW is the weight correction.

Analysis shows that if the error of BP neural network during the training process tends to be flat, the convergence will become slow, resulting in the increase of iterations. In addition, if the error has a minimum, the error may be easily convergent to this minimum locally, while the convergence at a small error value expected cannot be achieved. Thus, this paper uses the improved BP neural network algorithm.

Improved BP neural network with adaptive learning rate adjustment

The error function values of the multilayer network vary with the parameters. Therefore, the error function is improved by adjusting the learning rate, so as to accelerate the learning rate. When the error does not change significantly, the learning rate is so small that training times will increase. When the error changes drastically, the learning rate is too large, easily leading to difficult convergence to the desired value. So the learning rate in the training process should be adjusted according to the change of sum of the squared errors (E).

x is set as the reference for the change of E. If the updated E (n + 1) and the last E (n) satisfy the following relation:

$$\frac{E^{(n+1)} - E^{(n)}}{E^{(n)}} > x \tag{6}$$

then $h = rh$, where FIG-URE15#15_38_55_48.jpg is the coefficient and $0 < r < 1$; the weight value is the value before update.

If

$$0 < \frac{E^{(n+1)} - E^{(n)}}{E^{(n)}} < x \tag{1}$$

then h does not change.

If

$$E^{(n+1)} - E^{(n)} < 0 \tag{8}$$

then $h = uh$, where u is the coefficient and $u > 1$.

Application of transformer overload based on improved BP neural network

Input selection

Top oil temperature

The top oil temperature as an important indicator reflecting the temperature when the transformer runs under overload state should be taken into account in the calculation. Since the hot-spot temperature of the transformer is not easy to obtain, and literature [6] points out the inaccuracy of prediction by many relevant algorithms, hot-spot temperature is not included in our neural network. Moreover, the recording data of the transformer under overload in actual production are selected, and the important recording data such as hot-spot temperature before and after overload and the overload time are the data under safe overload running condition. Therefore the neural network using these data for training can get the result including this situation that hot-spot temperature does not exceed the rated temperature.

Overload multiple

The higher the overload multiple of the transformer is, the faster the internal temperature rises, and the shorter the overload duration is. When the overload multiple is less than 1, the transformer can run continuously. Thus overload multiple is also an important indicator for overloaded transformer.

Cooling type

The cooling type of large power transformer is generally divided as below:

(1) Oil-immersed self-cooling

(2) Oil-immersed air cooling

(3) Forced oil circulation and air cooling

(4) Forced oil circulation and water cooling
(5) Forced oriented oil circulation and air cooling
(6) Forced oriented oil circulation and water cooling

The transformer temperature fall changes with the selected cooling type. In general, the cooling type selection is related to the load condition.

Fan state

In air cooling process, the temperature change also has an important relationship with the normal operation of transformer fan or not. Therefore, the construction of the neural network also needs considering the fan running state. The different positions of the fan may cause different fan cooling effect. However, in order to simplify the operation, this paper assumes that the cooling capacity of all fans is the same, regardless of the position.

Air temperature

There is important relationship between air temperature and the internal temperature of transformer. The transformer's top oil and hot-spot temperature rated operation state will be lower in winter than in summer because of low air temperature.

Transformer parameters

Time constant of transformer oil, winding time constant, and temperature limit have some effect on the overload capability. The parameters of different transformer are different. In order to improve the accuracy of the calculation results, the specific transformer needs separate analysis and hence these parameters are employed.

Selection of output layer

Overload time

Overload time is the main output result which reflects the overload capacity of transformers in the corresponding state and under the request. This overload time may be shorter than the actually endurable overload time by transformer. This is determined by the sample selection. Sample data are the transformer operation data before and after safe overload, so the overload time output by our neural network is more reliable and closer to the overload time in actual operation.

Top oil temperature

Because the raw data of neural network training are the historical data in safe overload operation, the result is recommended time for safe overload running. In this overload time, the top oil and hot-spot temperature may have a gap to the limit value. Thus, in actual operation the overload time can be adjusted according to the output data of top oil temperature.

3.2.3 Determination of node number in hidden layer

According to Kolmogorov's theorem, the number of nodes selected for the hidden layer in the three-layer forward neural network can be determined by the following formula:

$$N_2 = \sqrt{N_1 + N_3 + 1} + a \tag{9}$$

where N2 is the number of nodes in the hidden layer; N1 is the number of input layers; N3 is the number of output layers; a is the adjustment constant, and $a = 1 \sim 10$.

Neural network training and application11

In the process of training the neural network, minimum error is not the only criterion of convergence, because over-fitting phenomenon will occur inevitably in the training process, which can affect the generalization ability of neural network, as shown in Figure 2.

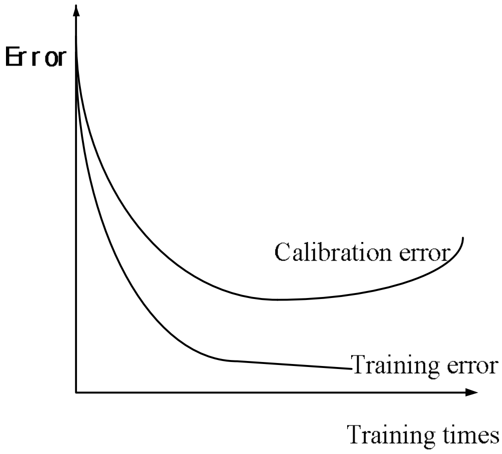

Fig. 2 Error curve

In the training of neural network data, the judgment method is introduced. During the training, the sample data are input into the neural network for verification and thus the errors of sample data are obtained. With the set standard step number d , the change of the error after continuous d inspections is judged. If the error does not decline or even rise, it shows that the error of neural network will no longer decline in subsequent training. So there is no necessary to continue training, and the training should be stopped to avoid over-fitting phenomenon. The method is convenient to use and can obtain good results. Based on the above method, the transformer overload behavior records (including hot- spot temperature, overload time, etc.) from Shandong power grid as the neural network learning data are used to train the neural network in this article.

As mentioned above, the neural network totally has seven input parameters. Transformer parameters include oil time constant and winding time constant, which are specially set according to different transformer. There are two output parameters. According to equation (9) calculation, when $a=10$, the number of nodes in the hidden layer is 13 Therefore the improved BP neural network has seven nodes in input layer, thirteen nodes in hidden layer nodes and two nodes in output layer.

The improved neural network is used for data prediction. The predicted data and the raw data for neural network learning are compared, as seen in Figure 3.

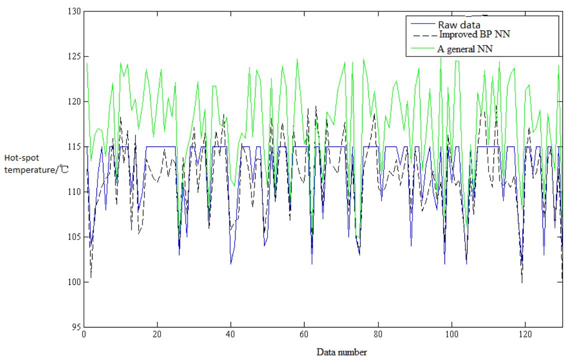

Fig. 3 Comparison between predicted data and raw data of hot-spot temperature

In Fig. 3, 130 groups of actual overload data are input into the improved BP neural network model and a general neural network model for simulation. The hot-spot temperature of the transformer after overload is calculated by the neural network. The comparison results show that the prediction by BP neural network is closer to the actual data, while the calculation result of the general neural network represented by green line in the figure is not accurate. Obviously, the model in this paper more accurately predicts the hot-spot temperature of the transformer after overload.

Fig. 4 shows comparison of overload time prediction results

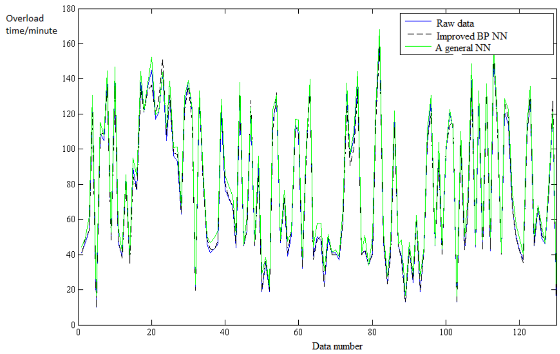

Fig. 4 Comparison of overload time prediction results

Fig. 4 shows the comparison of overload time calculated by different models based on the same data. It can be visually seen in the figure that the improved BP neural network model has more performance in the learning of transformer overload time. The predicted results are closer to the overload time given by the sample. It reflects the effectiveness of the algorithm improvement.

Fig. 5 shows the errors between the predicted data of overload time and top oil temperature and their raw data.

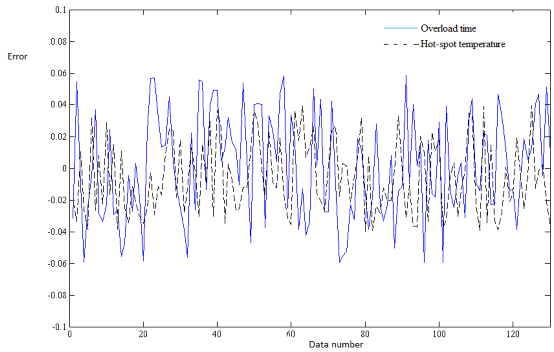

Fig. 5 Errors of predicted data

Fig. 5 shows that the error of overload time predicted by the improved BP neural network model is less than 6%, and the hot-spot temperature prediction error is smaller. It indicates that the prediction accuracy of the model is higher.

For short-term emergency loading, the temperature limit is 115 °C. Table 1 shows the comparison between the raw data and the simulation data after neural network training.

Table 1 Data comparison

Serial number	Sample data		Simulation data		Result comparison	
	Top oil temperature	Overload time	Top oil temperature	Overload time	Top oil temperature	Overload time
1	101	31	102.7209	31.37675	1.70%	1.22%
2	102	26	102.6413	25.78156	0.63%	0.84%
3	104	26	103.1887	26.34399	0.78%	1.32%
4	100	30	102.9779	29.75772	2.98%	0.81%
5	103	84	102.0146	84.08137	0.96%	0.10%
6	97	143	98.16785	145.6953	1.20%	1.88%
7	101	34	102.6836	33.72272	1.67%	0.82%
8	102	35	102.5006	35.41627	0.49%	1.19%
9	103	10	104.7525	10.14822	1.70%	1.48%
10	97	46	101.5783	47.04758	4.72%	2.28%

As seen in Table 1, the neural network in this paper can well predict the transformer overload time in certain conditions and the top oil temperature after overload. As other parameters in Table 1 such as overload multiple and environment temperature are not necessarily the same, so there is no relationship between the top oil temperature and overload time in sample data. However, after using the neural network algorithm for data learning, the calculation error through algorithm simulation is within 6%, which falls into the acceptable error range. Thus, the improved BP neural network model in this paper can understand the overload capacity of transformer more accurately, and can predict the transformer overload time well and evaluate its overload capacity.

Conclusion

In this paper, the improved BP neural network algorithm is used to analyze and calculate the transformer overload capacity. A reasonable BP neural network structure is constructed, and the over-fitting phenomenon in the training process is avoided effectively. The example analysis shows that the neural network can predict accurately about the raw data learned.

The neural network of this paper can learn the transformer overload mode in actual production. The trained neural network can make a decision about reasonable overload time and reasonably evaluate the transformer overload capacity according to the historical overload data. Neural network application in this article has important significance for actual production because it achieves the rational evaluation of transformer overload capacity in safe operation based on empirical data.

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