A method of optimized neural network by L-M algorithm to transformer winding hot spot temperature forecasting

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Abstract. Transformers are essential devices of the power system. The accurate computation of the highest temperature (HST) of a transformer's windings is very significant, as for the HST is a fundamental parameter in controlling the load operation mode and influencing the life time of the insulation. Based on the analysis of the heat transfer processes and the thermal characteristics inside transformers, there is taken into consideration the influence of factors like the sunshine, external wind speed etc. on the oil-immersed transformers. Experimental data and the neural network are used for modeling and protesting of the HST, and furthermore, investigations are conducted on the optimization of the structure and algorithms of neutral network are conducted. Comparison is made between the measured values and calculated values by using the recommended algorithm of IEC60076 and by using the neural network algorithm proposed by the authors; comparison that shows that the value computed with the neural network algorithm approximates better the measured value than the value computed with the algorithm proposed by IEC60076.

1. Introduction

Electric transformers are widely used in all levels of the power grid and play an important role in all processes of the economical transmission, flexible distribution and safe consumption of power [1]. The capacity of transformer continues getting larger with the increasing electricity demand, however, it can't keep getting large correspondently, which will cause excessive heat generated by windings and more eddy loss, and eventually it will lead to the failures [2]. The oil-immersed transformers take a proportion of 75% in all transformers in distribution network. Exposed to high temperature environment, the oil-paper insulation degradation fastened and thus the life expansion of transformers lessened [3]. According to the law of 6℃, when the temperature of hot-spot reaches 98℃, the relative aging rates is 1 [4]. For every 6℃'s increase of the temperature, the life cycle halved, namely the relative aging rate double. Therefore, it has a great meaning to accurately compute the hottest temperature (HST) of windings under different load modes and surrounding temperatures The most accurate method to get the hot-spot temperature is to lay temperature sensor near the conductor and measure directly, it is commonly used in tests despite its high cost and difficult to maintain [5,6]. For transformers in operation, indirect methods are adopted which generally are the temperature rise calculation formulas of the hot-spot recommended in the standard IEEE C57.91 [7] and the IEC 60076

[8]. The recommended formulas are limited since they neglected the influences of top-oil temperature and hot-spot temperature of factors like sunlight, wind speed and etc. In domestic and abroad field, investigations are done to compute the top-oil temperature and hot-spot temperature with new methods. Lesieutre B C, *et al* [9] built the top-oil temperature calculation model which the surrounding temperature are added to it as a variable. The backward Euler discrete equation and the linear regression are used to calculate the top-oil temperature and the identifying parameters of the model; however, the model remains relatively high error. Susa D, *et al* [10] took the variation of oil viscosity and the loss with temperature into consideration, and equaled to the heat transferring process inside the transformer with two thermal lumped-parameter circuits in series. The time constant of top-oil temperature calculated by this model is less than the recommended value in the IEC 60076. However, the model neglected the temperature difference between the oil and the tank, and the complex heat transferring process on the external surface of the tank. Susa D and Nordman H, Zeng H and Zhou X X and Chen W G and Zhao T [11-13] also made much research work about it.

In this paper, firstly, the heat mechanism and the thermal behavior inside transformers were analyzed, the influence on the oil thermal characteristics parameters of surroundings' factors and change of temperature were taken into consideration. And then the parameters that have more influence on the hot-spot temperature were selected through using formulas recommended in guidance. The neural network optimized with L-M algorithm was trained to get proper oil thermal characteristics parameters using data from the cases of the guidance. Finally, the hot-spot temperature was calculated by using the improved equation and the proper oil thermal characteristics parameters obtained with the neural network. Comparison between the measured value and the calculated values that obtained by using the recommended algorithm of IEC60076 and the neural network algorithm showed that the value computed by neural network algorithm approximated more to the measured value.

2. The computational algorithm of winding hot-spot temperature

The computation equation of hot-spot temperature is given in IEC 60076 guideline [8].

$$\theta_h = \theta_a + \Delta\theta_o + \Delta\theta_h \tag{1}$$

When the load coefficient increases,

$$\theta_h(t) = \theta_a + \Delta\theta_{oi} + \{\Delta\theta_{or} \times [\frac{1+R\times K^2}{1+R}]^x - \Delta\theta_{oi}\} \times f_1(t) + \Delta\theta_{hi} + \{Hg_r K^y - \Delta\theta_{hi}\} \times f_2(t) \tag{2}$$

Where,

$$f_1(t) = (1 - e^{(-t)/(k_{11}\times\tau_o)}) \tag{3}$$

$$f_2(t) = k_{21} \times (1 - e^{(-t)/(k_{22}\times\tau_w)}) - (k_{21} - 1) \times (1 - e^{(-t)/(\tau_o/k_{22})}) \tag{4}$$

When the load coefficient decreases,

$$\theta_h(t) = \theta_a + \Delta\theta_{or} \times [\frac{1+R\times K^2}{1+R}]^x + \{\Delta\theta_{oi} - \Delta\theta_{or} \times [\frac{1+R\times K^2}{1+R}]^x\} \times f_3(t) + Hg_r K^y \tag{5}$$

Where,

$$f_3(t) = e^{(-t)/(k_{11}\times\tau_o)} \tag{6}$$

3. Analysis of transformer heating mechanism

Transformers transfer the electromagnetic energy into heat during operation. The core and windings all produce losses and the windings are the main heat source. The heat transfer to the surroundings raises the temperature of transformer.

The losses of transformers can be expressed as follows:

$$P_T = P_C + P_L \tag{7}$$

In the equation (7), P_T means the total loss, W; P_C means no-load loss, W; P_L means load loss, W.

No-load losses are the active power transformer absorption when the rated voltage is applied on one winding while the other windings are open. The no-load losses include eddy current loss and hysteresis losses. The on-load loss includes resistant loss caused by windings, eddy current loss and the stray loss caused by components like holdings and tank. There are sleeves outside the iron core in order to separate the oil-duct of core from the oil duct of windings inside the transformer, so on-load loss is the main cause of temperature rise.

No-load loss can be expressed as follows:

$$P_C = P_1 + P_2 = \delta_h f B_m{}^2 + \delta_e f^2 B_m{}^2 \tag{8}$$

In the equation (8), P_1 means the hysteresis loss of core; P_2 means the eddy current loss of core; δ_h means the hysteresis loss coefficient; δ_e means the eddy current loss coefficient; B_m means the amplitude of magnetic flux density, Wb/m^2. According to the equation (8), load loss is directly proportional to the square of B_m. The value B_m of transformers is designed to be nearing saturation zone of magnetization curve for the saturation characteristic of the magnetization curve. The B_m will not increase a lot with the increasing load current.

On-load loss can be expressed as follows:

$$P_L = I^2 R + P_E + P_S \tag{9}$$

In equation (9), I^2R means the direct-current loss of resistance; P_E means the eddy current loss of winding; P_S means the stray loss of metal components.

There are some parameters have tiny impact on hot-spot temperature that can be ignored, such as $\Delta\theta_{oi}$, R and $\Delta\theta_{hi}$. The parameters which have large impact on hot-spot temperature are related with the oil and windings, for example x, τ_o, y and τ_ω. Recommended values of the transformer thermal characteristic parameters are according to empirical constant [8]. However, the thermal characteristic parameters especially the exponent of oil and winding (x and y) will change a lot with the changing temperature. So it is important to get the actual dynamic parameters to predict the hot-spot temperature.

4. The determination of hot-spot temperature parameter

There is an example of 250MVA ONAF transformer in IEC 60076. According to the example and equations (1)-(6), the variation of the hot-spot temperature based on one parameter changing are calculated, the relationship between the single parameter and hot-spot temperature are shown in table 1:

Table 1. Relationship between change of parameters and hot-spot temperature.

Parameter name	Relationship expression
Ambient temperature θ_a	$\Delta T = \Delta\theta_a$
Top-oil temperature rise $\Delta\theta_{or}$	$\Delta T = 1.1(d\Delta\theta_{or})$
Top-oil temperature rise at start $\Delta\theta_{oi}$	$\Delta T \approx 0$
Average time constant of oil τ_0	$\Delta T = 2.79e^{(-\Delta\tau_0/44.62)} - 2.764$
Ratio (R) of on-load loss to no-load losses at rated current	$\Delta T \approx 0$
Time constant of winding τ_ω	$\Delta T = 1.43 + 19.4197 * \sin(\pi(\Delta\tau_\omega - 14.68)/14.28 * 180 \div \pi)$
Exponent of oil x	$\Delta T = 21.12e^{(\Delta x/0.48)} - 20.954$
Exponent winding y	$\Delta T = 87.02e^{(\Delta y/1.52)} - 87$

Temperature gradient from hot-spot to top-oil at start $\Delta\theta_{hi}$	$\Delta T \approx 0$

Parameters like ambient temperature, top-oil temperature rise at start, ratio of on-load loss to no-load loss at rated current and top-oil temperature can be directly acquired. These parameters are necessary to obtain accurate thermal characteristic parameters. In equation (1), $\theta_a + \Delta\theta_o$ is the sum of environmental temperature and top-oil temperature rise, namely the top-oil temperature θ_o. In this way, we use the more accurately measured value θ_o and the part related to hot-spot and top-oil temperature in equations (2) and (5) are ignored. It is helpful to get more accurate oil thermal characteristic parameters.

5. The structure design of the neural network

The neural network consists of three layers which are the input layer, the hidden layer and the output layer. These three layers connect to each other but the nodes of the same layer don't connect. As shown in figure 1, the input of network is $X = [x_1, x_2, ..., x_n]^T$, the output of network is $Y = [y_1, y_2, ..., y_m]^T$. Supposing the number of learning samples is P and the desired output are respectively $d^1, d^2, ..., d^p$, through adjusting the weights of error correction, the purpose of neural network is to minimize the errors between y^p and d^p. To simplify the process of computation, we added the thresholds of each nodes into the weight vectors. That is to assume that: $\theta'_l = \omega'_{n_2 l}$, $\theta'_k = \omega'_{n_1 k}$, $\theta_j = \omega_{nj}$, $x'_{n_1} = x'_n = -1$.

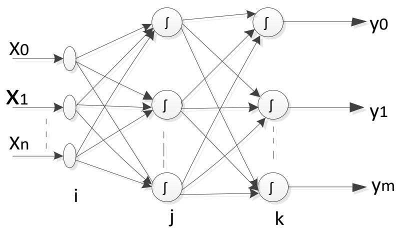

Figure 1. Topological graph of BP neural network.

The learning rule is derived from the principle of Least-Mean-Square (LMS). When a sample is input into the network and an output is generated, the mean-square-error is the sum of the square of each output unit error as shown in equation (10).

$$E^{(p)} = \frac{1}{2}\sum_{k=0}^{m-1}(\mathrm{d}_k{}^{(p)} - \mathrm{y}_k{}^{(p)})^2 \tag{10}$$

Then the total error is:

$$E_A = \sum_{p=1}^{p} E^{(p)} = \frac{1}{2}\sum_{p=1}^{p}\sum_{k=0}^{m-1}(\mathrm{d}_k{}^{(p)} - \mathrm{y}_k{}^{(p)})^2 \tag{11}$$

Assuming the ω_{sp} is a connecting weight, based on the gradient descent algorithm, the weight correction is:

$$\Delta\omega_{sp} = -\eta\frac{\partial E_A}{\partial \omega_{sp}} \tag{12}$$

Since the neural network adapt the steepest descent method which is based on the gradient, problems like that the low convergence speed and the existence of local minimum occurred. Improvements can be made by adapting Lenvenberg-Marquardt (L-M) method. This method is the combination of gradient descent method and gauss-newton method, the new weight adjustment equation is:

$$\omega(k+1)=\omega(k)-[J^T J+\mu \mathrm{I}]^{-1} J^T e \tag{13}$$

Where, J means Jacobian matrix namely the network error' derivative of weight; e means error vector; I means unit matrix; μ means scalar quantity which is self-adaptive in the process of calculation. When μ is large, the equation is approximate to the gradient method; when μ is small, the equation gets close gauss-newton method [14].

According to Kolmogorov principle, any continuous function can be realized by a three layers neural network. So the three layers BP neural network is selected to predict the oil thermal characteristic parameters in this paper.

To use the examples given in the IEC guidance which only include six groups of data at six time points, we selected one hundred groups of data by changing the exponent of oil x and the average oil time constant τ_o in a reasonable range ($\pm 10\%$), and the six groups of data in guidance are not included in the one hundred groups of data. According to the equation $\theta_o=\theta_a+\Delta\theta_o$, and with the other parameters in guidance are adapted into the calculation, we obtained the hot-spot temperature, then the database includes 100 groups of data was obtained.

As the variables of input and output were determined by the real situation, we designated the ambient temperature θ_a, top-oil temperature rise at start $\Delta\theta_{oi}$, load factor K and top-oil temperature θ_o as variables of input; and the exponent of oil x and average oil time constant τ_o as variables of output. In order to turn the BP neural network, which is a static network into a memory system, the delay unit is used to save the state value of input at previous moment as the input of the next moment. The initial oil temperature of every time step is the calculated top-oil temperature of its previous moment, consequently the static network was turned into a dynamic network.

The selection of hidden layer directly matters the training of neural network. Thus many empirical equations are referenced to determine the nodes number of the hidden layer by using the heuristics [15]. The nodes values of hidden layer adapted in BP networks are shown in table 2.

$$l=\sqrt{n+m}+\alpha \tag{14}$$

Where, l means the number of hidden unit; n means the number of input unit, m means the number of output unit, α means a constant ranges between 1 to10.

Table 2. The node number of hidden layer of neural network.

Number	1	2	3	4	5	6	7	8	9	10
Node number of the hidden layer	4	5	6	7	8	9	10	11	12	13

The networks were trained for 10 times at each situation, at each time the node number of the hidden layer are different. The node number that corresponded to the minimum average training error was selected as the optimal node number, thus we determined the optimal node number was 10.

In order to make accurate predict, the sample data should be pre-processed. For the standard function, the range of input and output were both limited between [0,1], so the data were normalized as the following equation (15):

$$y=0.1+\frac{x_i-x_{\min}}{x_{\max}-x_{\min}}\times 0.9 \tag{15}$$

Where, y_i is the normalized input value, x_j is the actual input value, $x_{\max}$, $x_{\min}$ is the maximum and minimum of actual input. The output of neural network ranges between [0.1, 0.9], and the hot-spot temperature can be acquired after the inverse transformation of output.

These data is divided into two groups, one group was named by training set, which is used to train neural network and another group named test set is used to test the trained network. The training set includes 80 groups of data while the test set includes 20 groups of data. After the network being properly trained, the thermal characteristic parameters were calculated as shown equation (1), and based on the improved algorithm in reference [10], the comparison are done between the hot-spot temperature predicted and the temperature in guidance.

In order to make the prediction more accurate, the L-M algorithm was used to optimize the traditional BP neural network. The train target was 0.001, the train step was 50. The output layer adopted the logarithmic function, and the logarithmic function was also used in hidden layer to maintain the nonlinear characteristic of the hidden layer.

The results of neural network training are shown in figures 2 and 3. Figure 2 is the performance Figure which indicates the process of network training. The final error is only 0.00188, which shows that the good training result. Figure 3 is the regression figure which reflects the fitting ability of the network. Since the value of R is 0.99449, which is very close to one, it shows the network matches the sample well.

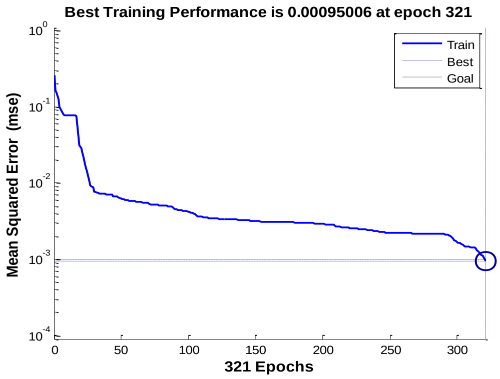

Figure 2. Performance of network.

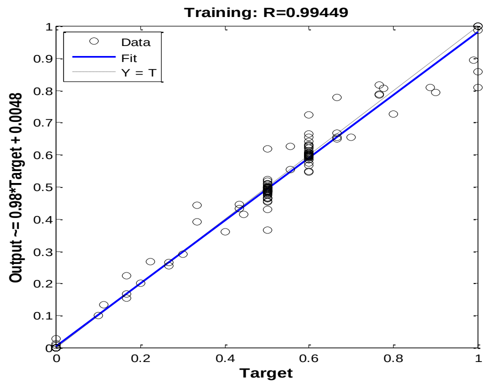

Figure 3. Regression of network.

Predicting the six groups of data given by guideline with the trained network, the results are shown in figure 4 and table 3:

Figure 4 shows the changes bring by the load and time's variation of the measured value and calculation values using the recommended algorithm of IEC60076 and the neural network algorithm. The value computed with network algorithm approximates better to the measured value than the value computed with algorithm of the guidance. Table 3 is the hot-spot temperature at the end of each load level; it also shows that the results of optimized neural network matched the measured results better.

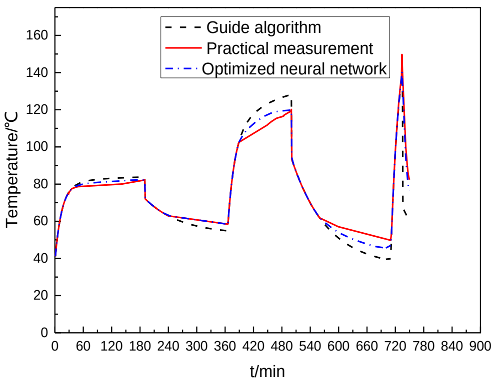

Figure 4. The temperature variation.

Table 3. The hot-spot temperature at the end of each load level.

Time (min)/Load factor	Hot-spot temperature/℃		
	Guide algorithm	Optimized neural network	Practical measurement
190/1.0	83.8	82.2187	82.2
365/0.6	54.9	58.5822	58.6
500/1.5	127.5	119.3922	119.2
710/0.3	39.5	46.2803	49.8
735/2.1	138.2	140.5979	140.7
750/0.0	59.5	75.5228	82.4

6. Conclusions

According to the heat mechanism of transformers, the influence of the oil thermal characteristics parameters of surroundings' factors and change of temperature are taken into consideration. Based on the improved temperature calculation algorithm recommended in guidance, and combined the optimized neural network with L-M algorithm， the temperature of hot-spot are calculated by adopting proper functions and parameters and training the neural network. Comparison between the calculation values using the recommended algorithm of IEC60076 and the neural network algorithm was made, it shows that the value computed by network algorithm approximates more to the measured value.

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