Thermal circuit model parameters identification of oil-immersed transformer based on PSO algorithm

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Abstract. The thermal circuit model of oil-immersed transformer needs to improve its accuracy in predicting the winding hottest-spot temperature, especially in the case of overload and different cooling modes. In the case of overload condition, the estimate values obtained from most existing models are smaller than the actual measurement values, which increase the potential of transformer overheating fault because of the estimate shortage. These limitations are mainly due to the thermal circuit parameters which are deviating when overloaded or having different cooling modes. In order to overcome these limitations, a parameter identification and correction approach based on PSO algorithm is proposed. The approach works on daily load pattern, permits better accuracy and improves the estimation security margin of thermal circuit in the presence of overload condition and different cooling modes.

Introduction

In order to increase system operation margins, a transformer may load beyond its nameplate rating. What's worse, some transformers operate beyond nameplate ratings in peak load period in order to avoid load shedding. The hottest-spot temperature of the winding is a basic criterion which can indicate the dynamic load margin and insulation life loss and detect latent overheat faults [1-4]. Hence, it is important to evaluate the winding hot-spot temperature accurately so that transformers can operate safely and economically. The researches of the winding hot-spot temperature evaluation have been taken for many years and a number of methods and models have been proposed [5-15].

Among the methods, the direct measurement based on the optical fiber is supposed to be the most accurate method [16-18]. However, it isn't suitable for hot-spot temperature predicting and the optical fiber's service life is shorter than the transformers'. The thermal model based on the heating equations and thermal circuits has a better transient accuracy so that it is widely adopted [1][5-8].

The accuracy of thermal circuit models decays in the case of overload and different cooling modes [7][8]. Some model parameters could lead to negative estimate errors which will increase the operation risk when overloaded [1-3][7][8]. These limitations result from the situation that the computation of thermal circuit parameters is based on nameplate data and not suitable for overload condition or different cooling modes.

For those reasons, a parameter identification approach based on PSO algorithm is proposed. It works on daily load pattern and could improve the accuracy and estimation security margin of thermal circuit when overloaded or in different cooling modes. It has been tested and verified by three sets of data furnished by a substation.

Mathematical Model of Thermal Circuit

Thermal circuit model based on the thermal-electrical analogy, heat transfer theory and lumped parameters was first established by G. Swift [5]. This model focuses on the nonlinear thermal resistances and has been developed to estimate the hot-spot temperature [6-8]. D. Susan improved the thermal circuit model by taking oil viscosity changes and temperature loss variations into account [8]. The model is based on an assumption that the hot-spot temperature is the sum of the

top oil temperature rise $\Delta\theta_{oil}$, and the hot spot temperature rise above top oil temperature $\Delta\theta_{hs}$. The model is depicted in Figure1 and as the detailed report in reference [8].

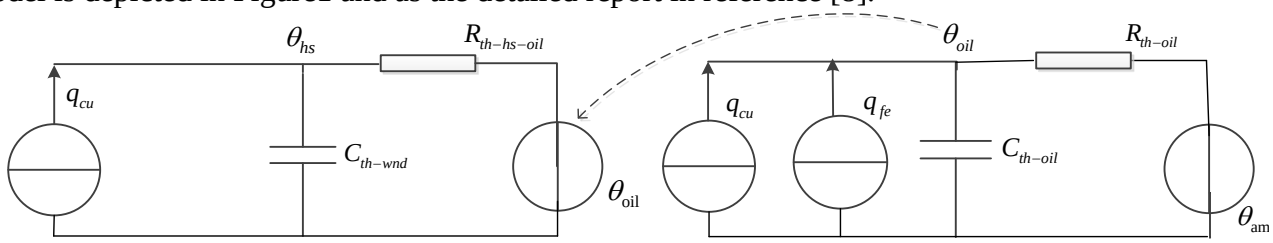


Fig.1. Thermal circuit model

The corresponding mathematical model is expressed as follows:

$$\begin{cases} \dfrac{1+R\cdot K^2}{1+R}\cdot\mu_{pu}^{n}\cdot\Delta\theta_{oil,rated}=\mu_{pu}^{n}\cdot\tau_{oil,rated}\cdot\dfrac{d\theta_{oil}}{dt}+\dfrac{\left(\theta_{oil}-\theta_{amb}\right)^{1+n}}{\Delta\theta_{oil,rated}^{n}} \\ \left[K^2\cdot P_{cu,pu}(\theta_{hs})\right]\cdot\mu_{pu}^{n}\cdot\Delta\theta_{hs,rated}=\mu_{pu}^{n}\cdot\tau_{wdg,rated}\cdot\dfrac{d\theta_{hs}}{dt}+\dfrac{\left(\theta_{hs}-\theta_{oil}\right)^{1+n}}{\Delta\theta_{hs,rated}^{n}} \end{cases} \tag{1}$$

In the type, $R_{th\text{-}hs\text{-}oil}$ is the winding to oil thermal resistance; $R_{th\text{-}oil}$ is the oil to ambient thermal resistance; $C_{th\text{-}wnd}$ is the winding thermal capacitance; $C_{th\text{-}oil}$ is the oil thermal capacitance; θ_{hs} is the hot-spot temperature; θ_{oil} is the top-oil temperature; θ_{amb} is the ambient temperature; R is the ratio of load losses at rated current to no-load losses; K is the ratio of load current to rated current; μ_{pu} is the ratio of oil viscosity to oil viscosity at rated oil temperature rise; $\tau_{oil,rated}$ is the top-oil time constant at rated oil temperature rise, product of rated oil thermal resistance and oil thermal capacitance; $\tau_{wdg,rated}$ is the winding time constant at rated hot-spot temperature rise and is the product of rated winding to top oil thermal resistance and winding thermal capacitance; n is the empirical constant.

The parameters such as rated load losses q_{cu} and rated no-load losses q_{fe} are based on nameplate data or the manufacture tests while n is an empirical constant. However, according to the tests in previous literature [7][8], the accuracy decays obviously under different working condition, especially when overloaded or in different cooling modes. Considering the security margin, the estimate values should be larger than the measured values when overloaded, but no reference takes it into account.

The main reason of accuracy degradation is the parameters deviation under different working conditions and it is necessary to identify the parameters to achieve a satisfactory accuracy. Hence, a novel technique based on PSO algorithm considering the estimation security margin is developed.

Problem Formulation of Parameters Identification

It is primary to determine two sets of thermal circuit parameters X respectively for ONAN and ONAF cooling modes to minimize the global error between the estimated values Θ_i^e and the measured values Θ_i^m of hot-spot temperature samples. In particular, the negative error and the positive error are processed differently when overloaded. In order to increase the estimation security margin, the positive error (the estimated value is larger) is processed with a little larger tolerance while the negative error is processed with a very small tolerance.

For transformers working in such two kinds of cooling modes, Θ_i^e and Θ_i^m are respectively divided into two groups to identify two sets of parameters. Hence, the problem is divided into two optimization problems with the same form of objective function as follows:

$$\begin{cases} \min f(X) \\ f(X)=\sum_i \omega_i[\Theta_i^e-\Theta_i^m]^2 \end{cases} \tag{2}$$

Noticing that the weighting factor ω_i is very important and the larger value of ω_i means the error

is processed with less tolerance. Therefore, ω_i can be used to evaluate the relevance of the estimated errors and the load rates, especially under overload conditions. ω_i is defined as follows:

$$\omega_i = \begin{cases} \dfrac{I_i^m}{I_{rated}} & \text{normal load condition} \\ \dfrac{I_i^m}{I_{rated}} \cdot \alpha^{\left(\theta_i^m - \theta_i^e\right)} & \text{overload condition} \end{cases} \tag{3}$$

The positive error (θ_i^e-θ_i^m>0) is more inclination to be accepted considering estimation security margin. So we proposed a novel thermal circuit parameters identification and correction approach with positive error preference strategy. Figure 2 shows evolution of ω_i with estimation error under overload condition.

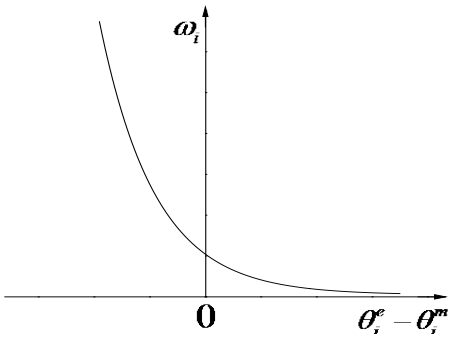


Fig.2. Evolution of weighting factors with estimation error under overload condition

With measured hot-spot temperature samples of transformers working in ONAN and ONAF cooling modes and adopting the thermal circuit model expressed in Eq. (1), two sets of thermal circuit parameters X corresponding to two sets of cooling modes can be respectively identified via optimization algorithm in the next section.

Proposed Solution via PSO Algorithm

The afore-mentioned problem is divided into two optimization problems with the same form of objective function (Eq. (2)). The PSO algorithm is a swarm intelligence heuristic algorithm optimization method and has been widely used in engineering optimization. The particle swarm algorithm is very suitable for solving this problem.

The process of implementing PSO for thermal circuit parameters identification is as follows:

Step 1: Choose the set of thermal circuit parameters (Eq. (4)) as particle arrays and randomly generate primary population. 40 particles are generated.

$$X = \left[\tau_{oil,rated}, \tau_{wdg,rated}, \Delta\theta_{oil,rated}, \Delta\theta_{hs,rated}, R, n\right] \tag{4}$$

Step2: Evaluate the fitness function (Eq. (2)) values and compare the fitness value of each particle with its own best location P_{best} (the best location means the particle array elements can lead to the best fitness value). If current value is better than best P_{best}, update P_{best} with the current location. Besides, if current value is better than global best location G_{best}, then reset best G_{best} to the current index in the particle array.

Step3: Update the velocity and location of each particle according to Eq. (5).

$$\begin{cases} v_{i,j}(\mathrm{n}+1) = w \cdot v_{i,j}(\mathrm{n}) + \mathrm{c}_1 r_1[\mathrm{P}_{best(\mathrm{i,j})} - x_{i,j}(\mathrm{n})] + \mathrm{c}_2 r_2[G_{best(\mathrm{i,j})} - x_{i,j}(\mathrm{n})] \\ x_{i,j}(\mathrm{n}+1) = x_{i,j}(\mathrm{n}) + v_{i,j}(\mathrm{n}+1) \end{cases} \tag{5}$$

Step4: Loop to step2 until meeting the stop criterion (a predefined maximum number of iterations or a sufficiently good fitness value).

Numerical Example

In order to verify the validity of the method, we have a test on a 220kV-75MVA dual winding transformer. The transformer is equipped with optical fiber temperature sensors and was tested in

three typical daily load patterns. When the transformer load rate less than 70%, cooling mode is ONAN. When the transformer load rate more than 70%, cooling mode is ONAF. The load current, winding hot-spot temperature and ambient temperature are measured and recorded at 15-min intervals. Thus we get N=96 sample points. The transformer overloading time lengths and different cooling modes time lengths as shown in table1. Transformer load curves for 3 consecutive days as shown in Figure3 and the measured windings hot spot temperature of day1 as shown in Figure4.

Table.1.Overloading time lengths and cooling modes time lengths

	Over load time(hour)		ONAN (hour)		ONAF(hour)	
day	a.m.	p.m.	a.m.	p.m.	a.m.	p.m.
day1	1.50	3.00	6.75	0.75	5.25	11.25
day2	1.75	3.25	6.75	0.75	5.25	11.25
day3	2.00	4.00	6.75	0.75	5.25	11.25

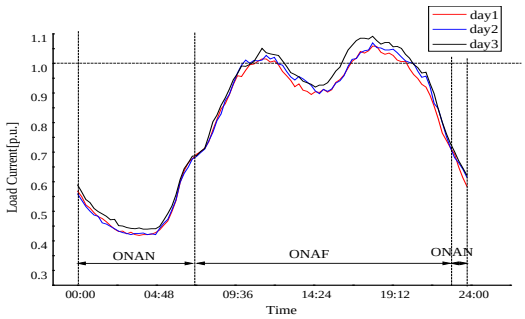


Fig.3. Load curves against time

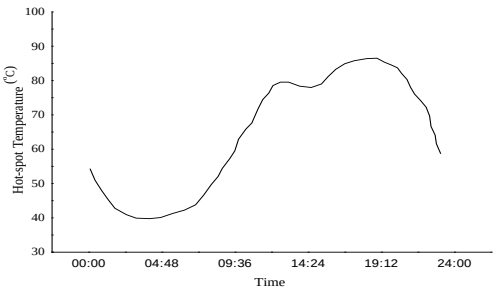


Fig.4. Measured winding HST of day1

Validation tests

The identification method identifies the corrected thermal parameters (Eq. (4)) by using the data of day1. According to the cooling modes, the data of day1 is divided into two sets to identify two sets of thermal parameters respectively. As depicted in table1 and Figure3, sample data in ONAN cooling modes is used to identify thermal parameters for ONAN cooling modes, so as the ONAF cooling modes. Implement steps in section 4 and the corrected parameters reported in table2.

Table.2. Identification results

Parameter	Values based on nameplate data	Identified values	Identified values
	ONAN/ONAF	ONAN	ONAF
$\tau_{oil,rated}$(min)	161.8	142.4	130.7
$\tau_{wdg,rated}$(min)	8.7	11.2	9.9
$\Delta\theta_{oil,rated}$(^{o}C)	30.3	32.4	29.1
$\Delta\theta_{hs,rated}$(^{o}C)	42.2	41.9	40.3
R	6.18	5.89	6.93
n	0.25	0.31	0.27

In order to further conduct quantitative analysis, defining the mean squared estimation error MSE and the maximum absolute error value ME during overload period as follows:

$$MSE = \frac{\sum_{i=1}^{i=N}[\Theta_i^e - \Theta_i^m]^2}{N} \tag{6}$$

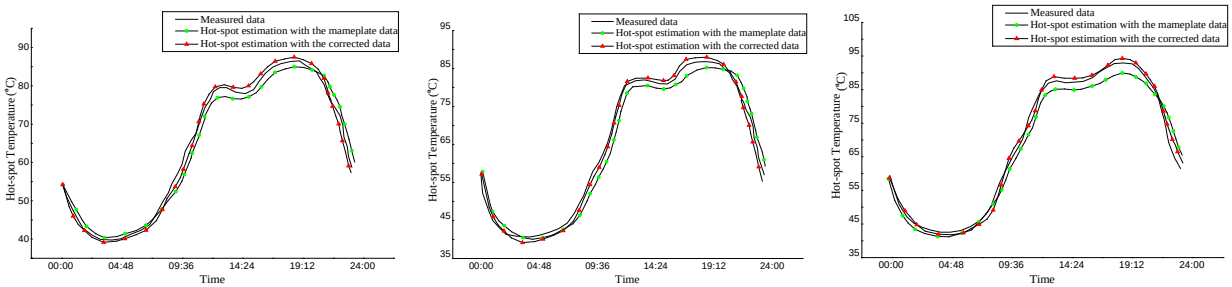
$$ME = \begin{cases} \max(\left|\Theta_i^e - \Theta_i^m\right|) & \text{maximum error is positive} \\ -\max(\left|\Theta_i^e - \Theta_i^m\right|) & \text{maximum error is negative} \end{cases} \tag{7}$$

MSE represents the deviation of the estimation value from the measured value and ME represents

the estimation security margin.

The results of the calibrated model adopting the corrected parameters, the measured winding hot-spot temperatures and the results of the model adopting parameters based on nameplate data are shown in Figure5 (a).By comparing the hot-spot temperature profiles in Figure5 (a), we find that the model with the corrected parameters has a better estimation accuracy than the model with parameters based on nameplate data. In particular, the model with the corrected parameters lead to a positive error (the estimated value is larger) when overloaded. The increase in winding hot-spot temperature estimation accuracy and estimation security margin is of great importance in dynamically full exploitation of transformer load capacity under the precondition of ensuring transformer safe operation.

In order to further prove the validity of the corrected thermal parameters, we estimate the transformer hot-spot temperature values of the next two days according to the load curves. The winding hot-spot temperature curves show in Figure5 (b) and (c). The performance comparison is reported in table3.



(a) Winding HST of day1 (b) Winding HST of day2 (c) Winding HST of day3

Fig.5. The experimental results of windings HST

Table.3. Comparison results

	MSE		ME	
	with nameplate parameters	With identified parameters	With nameplate parameters	With identified parameters
day2	10.93	3.66	-4.15	2.51
day3	13.24	4.17	-4.83	2.73

The comparison shows the model with identified parameters has better estimation accuracy and positive estimation error when overloaded, which means the increase of estimation security margin.

Conclusion

In this paper, a thermal circuit parameters of oil-immersed transformer identification approach based on PSO algorithm was proposed and the thermal circuit model based on the identified parameters was tested and verified by comparing the actual measured data with theoretical data one by one. The results show an increase in the estimation accuracy, especially when transformer works in overload condition and in different cooling modes. In particular, the model with identified parameters leads to positive estimation errors, which reduce the risk of transformer overheating fault caused by estimation shortage and guarantee the estimation security margin. The research in this paper could provide a more reasonable and effective approach for electric power utility to predict transformers' hot spot temperatures.

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