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Research Paper

Improving thermal model for oil temperature estimation in power distribution transformers

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HIGHLIGHTS

- A method of oil temperature estimation of ONAN distribution transformer is proposed.
- A identification process using Levenberg-Marquardt algorithm improves IEC 60076-7 standard.
- The oil temperature soft sensor can be implemented in a smart meter.
- Experimental results with three distribution transformers show the effectiveness of the approach.

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ABSTRACT

This paper presents a method estimating the oil temperature for ONAN distribution transformers. A Levenberg-Marquardt algorithm improving the reliability of standard IEC 60076-7 thermal model is developed. An oil temperature model, based on standard parameters is compared with that given by the proposed identification procedure. The improvement of temperature estimation is highlighted and validated on three distribution transformers from 160 kVA to 800 kVA.

1. Introduction

Distribution transformers are essential in controlling the service continuity of electrical networks. In order to reduce the number of replacements, it is important to develop monitoring methods [1–3]. Among the most known methods, thermal monitoring is one of the most powerful and provides efficient informations about ageing and overload capacity [4,5]. In this field, the hot spot temperature is a very important parameter in terms of supervision. Many researchers consider the hot-spot temperature as the sum of the top-oil temperature rise in tank, and the hot-spot-to-top-oil (in tank) gradient at rated current [6–8]. In this approach, the differential equations parameters are derived from the standard IEC 60076-7. In [9], an identification procedure based on Levenberg Marquardt algorithm have been used in order to estimate thermal model parameters for a 400 kVA ONAN distribution transformer. Authors show that estimated parameters are different from those given in the standard leading to an improved top-oil temperature estimation. In this paper, another problem is addressed. Indeed, in the standard, a single set of parameter is proposed for a wide power range which results in significant errors in temperature estimation. In the following, thermal model parameters are estimated for three ONAN distribution transformers (160 kVA, 400 kVA and 800 kVA). In Section 2, the thermal model proposed in the standard IEC 60076-7 is reminded. In Section 3, the oil temperature is estimated using the standard IEC 60076-7 showing a lack of precision for large power transformers. Parameters are identified and compared with the standard recommendation in Section 4. The improvement of oil temperature estimation is highlighted for the three transformers.

2. Transformer thermal model

This paragraph describes the use of heat transfer differential equations to estimate the oil temperature of a distribution

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transformer as a function of time with a time-varying load current K and time-varying ambient temperature θ_a.

They are intended to be the basis for the software processing data in order to define oil temperature as a function of time [1]. This method is particularly suitable for on-line monitoring, especially as it does not have any restrictions concerning the load profile.

The standard $IEC60076-7$ defines the parameters of the thermal model shown in Fig. 1 as follows:

- K: Load factor (LV side currents),
- θ_a: The ambient temperature in the transformer substation,
- $\Delta\theta_{or}$: The top-oil (in tank) temperature rise in steady state at rated losses (no-load losses + load losses),
- R: The ratio of load losses at rated current to no-load losses,
- x: The oil exponent,
- k_{11}: The thermal model constant,
- θ_o: The average oil time constant.

The inputs K, θ_a are a function of time and all other parameters are constant.

When heat-transfer principles are applied to the transformer situation, the differential equations are only linear for directed-flow OD cooling. For the other forms of cooling, OF and ON, the cooling medium circulation rate depends on the coolant temperature itself.

In other words, if there are no fans, the airflow rate in the radiator depends on its temperature, whereas if there are fans, it does not.

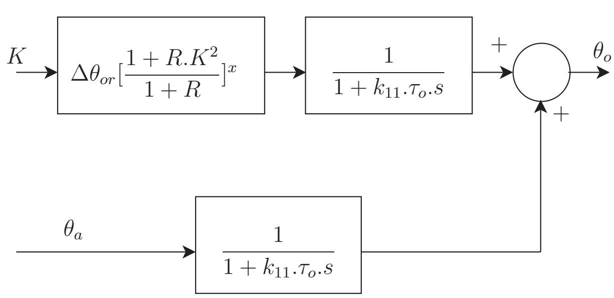

Fig. 1. Thermal model.

The consequence of this is that for ON cooling, the differential equations are nonlinear, implying that the response of the top-oil temperature rise to a change in load current, is not a linear function.

So the model presented in Fig. 1 should take into account the different variations of the thermal resistances presented in Fig. 2.

With:

- $Rth1$: Thermal resistance between MV windings and oil (Cooper losses),
- $Rth2$: Thermal resistance between LV windings and oil (Cooper losses),
- $Rth3$: Thermal resistance magnetic circuit and oil (Iron losses),
- $Rth4$: Thermal resistance between oil and transformer tank (Oil Natural),
- $Rth5$: Thermal resistance between transformer tank and air (Air Natural),

3. Oil temperature estimation using Standard IEC 60076-7 parameters

3.1. Experimental plant for ONAN distribution transformer

Three distribution transformers (primary 20 kV/secondary 400 V) with the following powers 160 kVA, 400 kVA and 800 kVA are used to validate the proposed method. Each transformer is equipped with a PT100 sensor installed 10 cm below the top of the tank which gives the oil temperature. Upstream of the transformer, a motorized auto-transformer is connected in order to adjust the load factor K. The available measurements are the three secondary currents (Iph1, Iph2, Iph3), the three primary composed voltages, the ambient temperature at a distance of two meters from the transformer and the oil temperature inside the transformer given by the PT100 sensor. A computer equipped with Matlab/Simulink is connected to a data acquisition DSpace card. To obtain a nominal secondary current the transformer should be supplied with 15750 V voltages side MV which are not available in our experimental platform. Consequently, low-voltage phases are short-circuited as shown in Fig. 3. Then, low primary voltages can be used and the transformer may be temporary pushed beyond its nominal secondary and primary currents. Because of the very low value of primary side voltages, iron losses are very low and the parameter R in the thermal model is affected (R is the ratio of the total load losses at rated current to no-load losses).

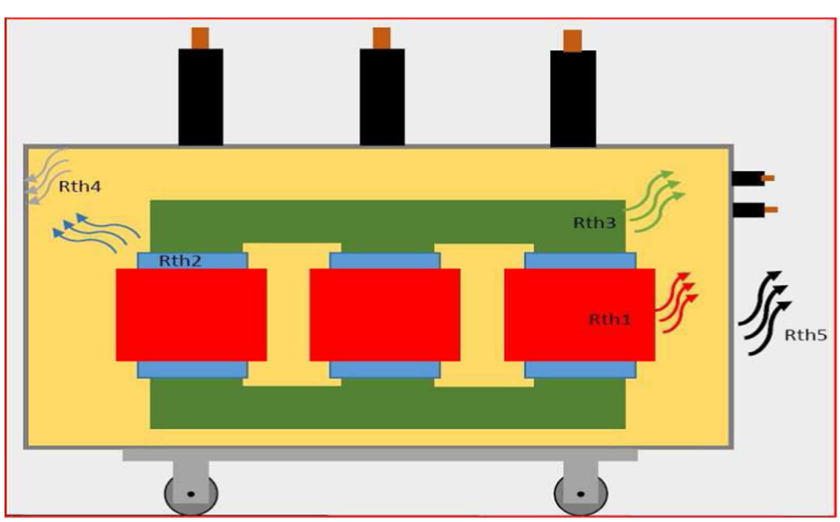

Fig. 2. Heating schematic of ONAN transformer.

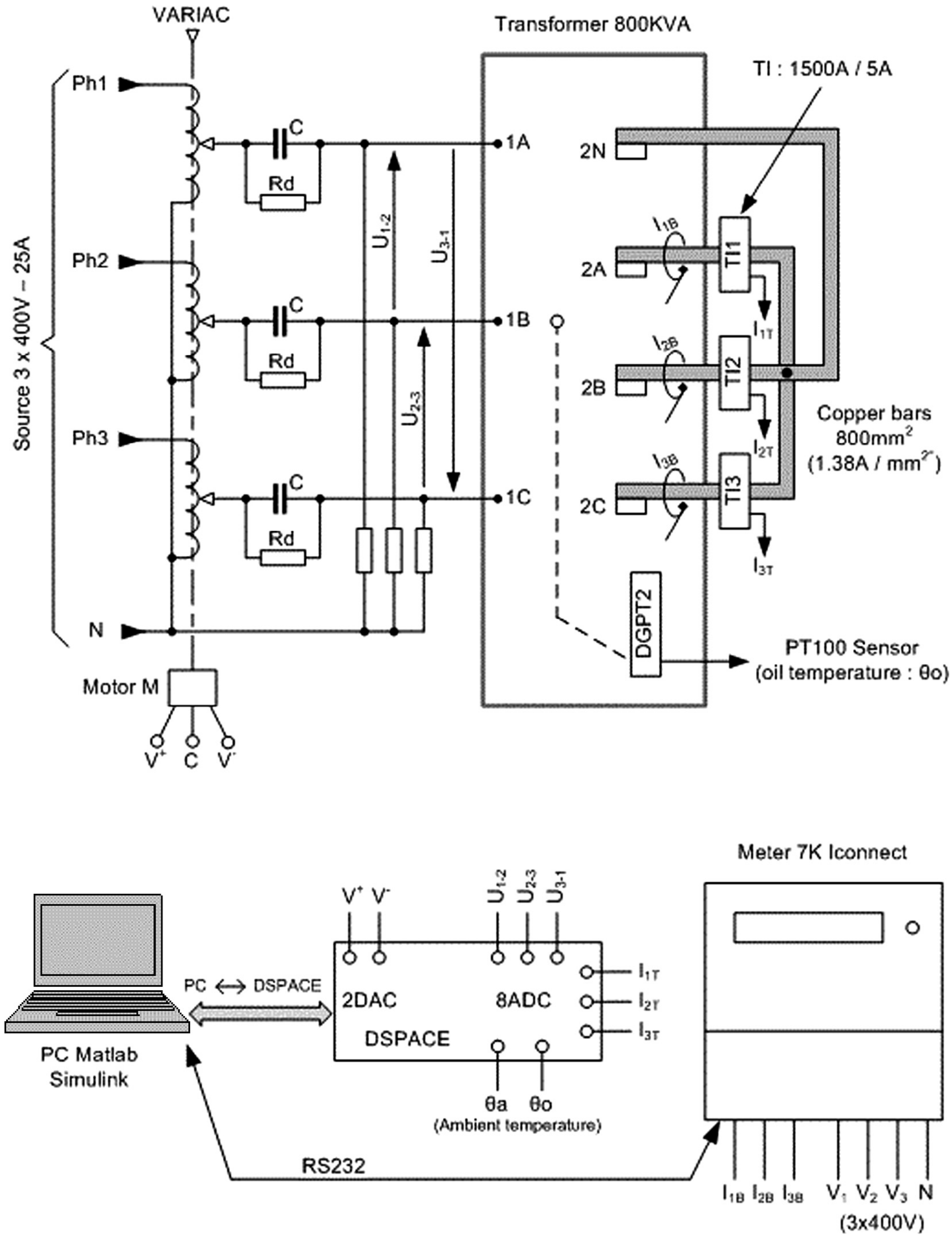

Fig. 3. Test bench for load current adjustment and measurements.

Because the transformer is supplied with reduced voltages, a compensation of the no-load losses is made by using a modified load factor K derived from the following reasoning. Total losses in this configuration are defined by:

$$L_{total} = L_{iron} + L_{Copper} \cdot K_{real}^2, \tag{1}$$

where L_{total} are the total losses, L_{iron} are the no-load losses, L_{Copper} are the load losses and K_{real} is the real load factor. The load losses, L_{pf} in reduced voltages configuration are:

$$L_{pf} = L_{iron} \cdot U_{cc}(\%)^2 + L_{Copper} \cdot K_{pf}^2, \tag{2}$$

With $U_{cc}(\%)$ the short-circuit voltage.

The expression of the real load factor K_{real} according to the platform load factor K_{pf} in short circuit test is:

$$K_{real} = \sqrt{\left(K_{pf}^2 \cdot \left(\frac{L_{iron}}{L_{Copper}} \cdot U_{cc}(\%)^2 + 1\right) - \frac{L_{iron}}{L_{Copper}}\right)} \tag{3}$$

3.2. Model based on the Standard IEC 60076-7

After inputs acquisition (load factor K and ambient temperature) and output (measured oil temperature), a Matlab program computes the estimated oil temperature for the three distributions transformers (160 kVA, 400 kVA and 800 kVA) with parameters

Table 1
Parameters given by the IEC 60076-7.

Parameters	Values
x	0.8
R	5
τ_o (min)	180
$\Delta\theta_{or}$ (K)	55

given by the standard IEC. In this approach, the four parameters are considered to be constant and suitable for ONAN transformers between 50 kVA and 1000 kVA (Table 1).

Tests during several days are presented for each transformer. The load factor K increase and decrease with a step of 10% at nominal load (Fig. 4). This load profile allows to have a signal rich in information particularly suitable for the identification procedure used in Section 4.1.

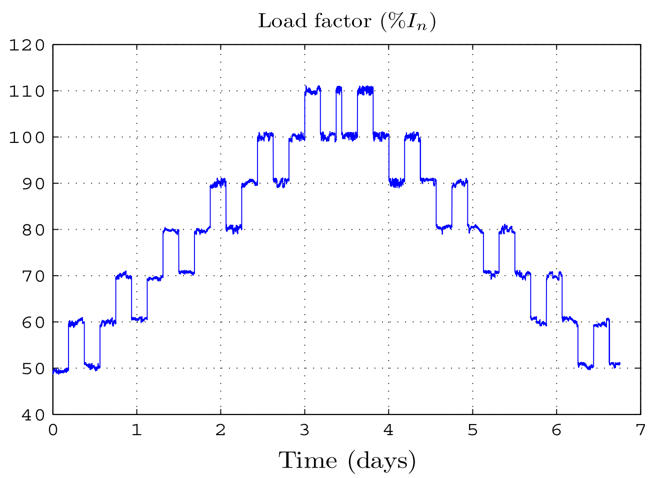

Fig. 4. Load factor for experimental tests.

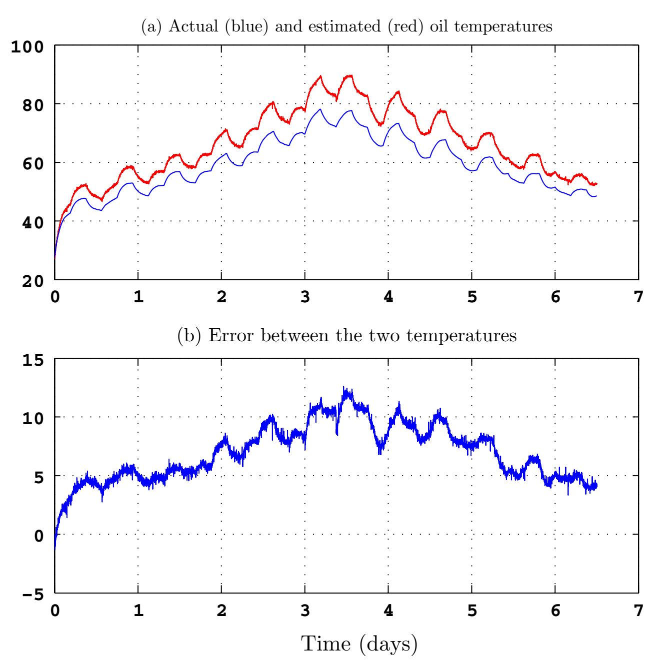

Fig. 5. IEC 60076-7 parameters for the 160 kVA transformer. (a) Comparison between measured (blue) and estimated (red) temperatures. (b) Error between temperatures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Results are shown in Figs. 5–7. A significant error between the two temperatures (around ±10 °C) is highlighted. This error is due to the fact that the IEC standard gives parameters according to a huge range of power transformers.

In order to reduce this error, parameters must be estimated for each transformer using an identification algorithm.

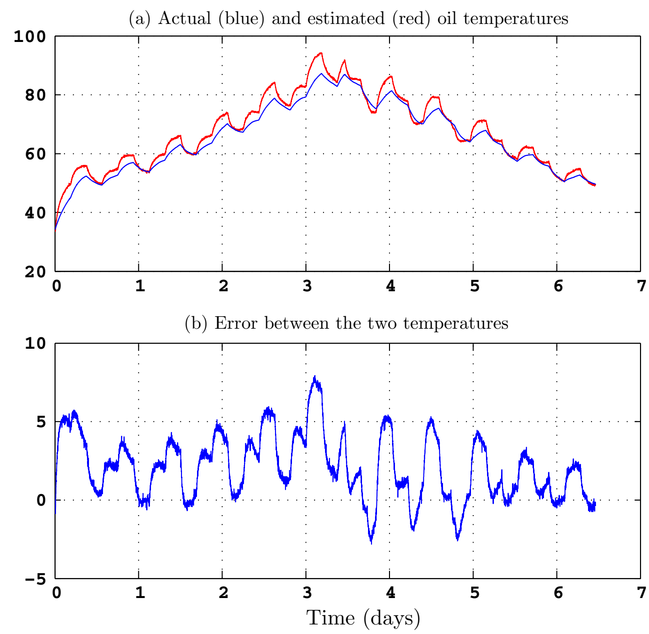

Fig. 6. IEC 60076-7 parameters for the 400 kVA transformer. (a) Comparison between measured (blue) and estimated (red) temperatures. (b) Error between temperatures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

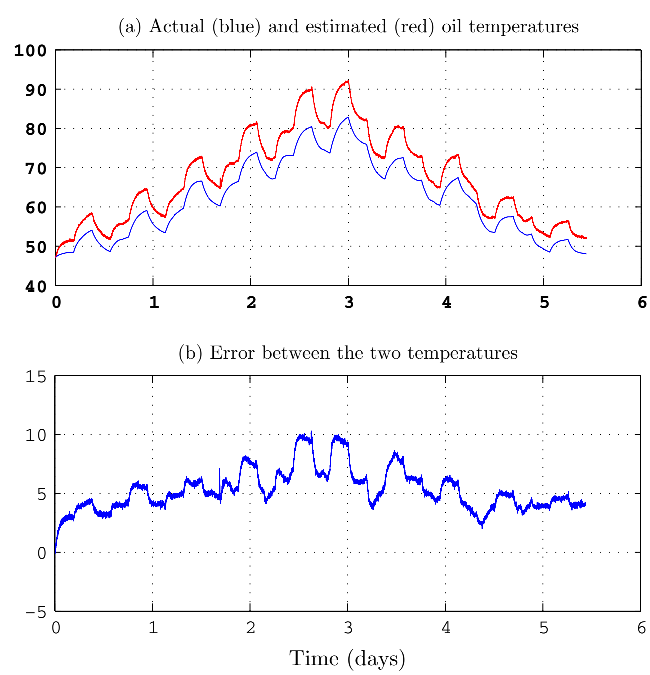

Fig. 7. IEC 60076-7 parameters for the 800 kVA transformer. (a) Comparison between measured (blue) and estimated (red) temperatures. (b) Error between temperatures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Parameters identification

4.1. Levenberg-Marquardt algorithm

The Levenberg-Marquardt (LM) algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions [10,11]. It has become a standard technique for non-linear least-squares problems [12], widely adopted in a broad spectrum of disciplines. In this study, the LM algorithm is used to adjust parameters in order to minimize the error between the real and estimated temperatures [13]. The thermal model (Fig. 8) has two inputs with the same transfer function. As the first bloc diagram depends on the inputs of the model (the load factor K), the system is non-linear with 4 parameters to be identified.

The MISO (Multi Input Single Output) system is defined by:

$$z = f(u, \theta) \tag{4}$$

where u and z are respectively the system inputs (load factor K and the ambient temperature θ_a) and output (transformer oil temperature θ_o).

The predicted output $\hat{z}$ is given by:

$$\hat{z} = f(u, \hat{\theta}) \tag{5}$$

where $\hat{\theta} = [\hat{x} \quad \hat{R} \quad \Delta\hat{\theta}_{or} \quad \hat{\tau}_o]$ is the parameters vector to be estimated.

The output prediction error is:

$$\varepsilon = z(n, \theta) - \hat{z}(n, \hat{\theta}) \tag{6}$$

The minimization of the quadratic criterion J can give us the optimal value of $\hat{\theta}$, where z represents the measured output.

$$J = \sum_{k=1}^{N} \varepsilon(k)^2 = \sum_{k=1}^{N} \left(z(n, \theta) - \hat{z}(n, \hat{\theta})\right)^2 \tag{7}$$

L.M algorithm can be seen as a combination of steepest descent and the Gauss-Newton method. When the current solution is far from the correct one, the algorithm behaves like a steepest descent method: it is not fast, but guaranteed to converge. When the current solution is close to the correct solution, it becomes a Gauss-Newton method.

The iterative estimation of $\hat{\theta}$ ensures the convergence of the parameters by minimizing J:

$$\hat{\theta}_{i+1} = \hat{\theta}_i - \left\{ \left[J''_{\hat{\theta}\hat{\theta}} + \lambda \cdot I \right]^{-1} J'_{\hat{\theta}} \right\} \Big|_{\hat{\theta}_i}, \tag{8}$$

where

$$\begin{aligned} J'_{\hat{\theta}} &= -2 \sum_{k=1}^{N} \varepsilon_k \cdot \sigma_{k,\hat{\theta}_i} : \text{Gradient} \\ J''_{\hat{\theta}\hat{\theta}} &\approx 2 \sum_{k=1}^{N} \sigma_{k,\hat{\theta}_i} \cdot \sigma^T_{k,\hat{\theta}_i} : \text{Hessien} \\ \sigma_{k,\hat{\theta}_i} &= \frac{\partial \hat{x}_k}{\partial \theta_i} . : \text{Sensitivityfunction} \end{aligned} \tag{9}$$

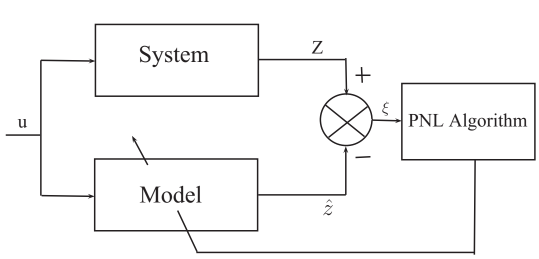

Fig. 8. Algorithm L.M applied to our system.

Table 2
Distribution transformer parameters given by the L.M algorithm.

Power	Parameters			
	IEC 60076-7	160 kVA	400 kVA	800 kVA
x	0.8	0.8	0.76	0.71
R	5	9.15	12.71	15
τ_o (min)	180	199	141	129
$\Delta\theta_{or}$ (K)	55	54.87	57.56	62.5

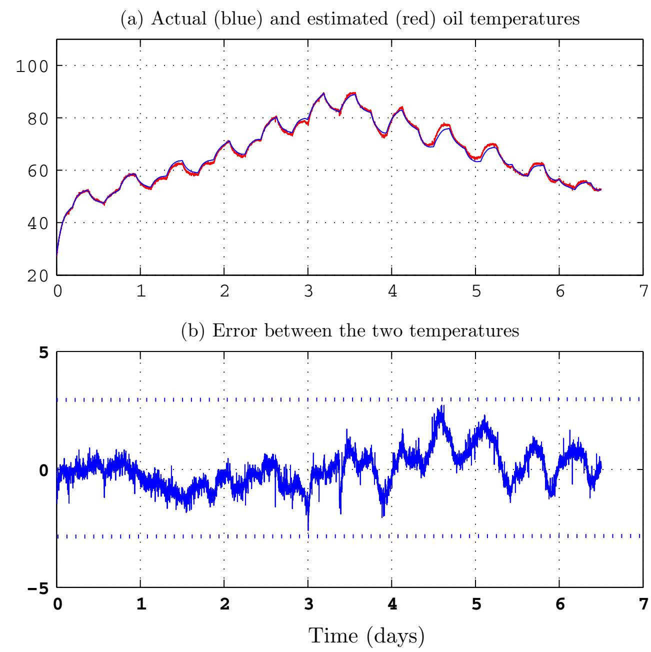

Fig. 9. IEC 60076-7 parameters for the 160 kVA transformer. (a) Comparison between measured (blue) and estimated (red) temperatures. (b) Error between temperatures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

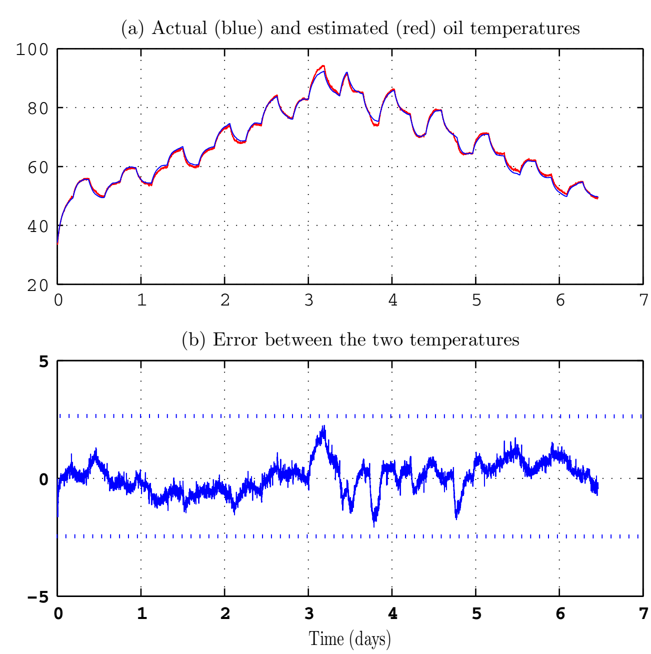

Fig. 10. IEC 60076-7 parameters for the 400 kVA transformer. (a) Comparison between measured (blue) and estimated (red) temperatures. (b) Error between temperatures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

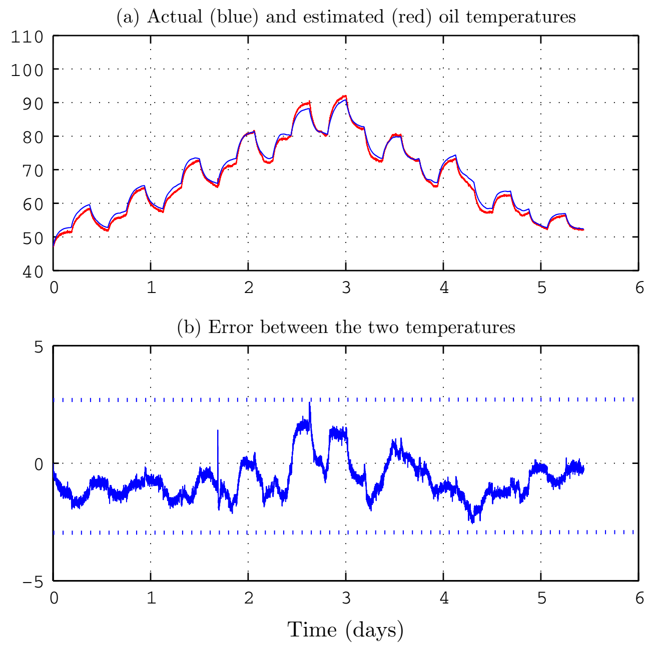

Fig. 11. IEC 60076-7 parameters for the 800 kVA transformer. (a) Comparison between measured (blue) and estimated (red) temperatures. (b) Error between temperatures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

N represents the number of measurement points and λ is a monitoring parameter which adjusts the search direction of the optimum at each iteration:

- if $\lambda \to 0$, we find the algorithm of Gauss-Newton,
- if $\lambda \to \infty$, we find the algorithm of Gradient.

Let us define the sensitivity functions corresponding to the four parameters:

$$\begin{aligned}
\sigma_{\tau_o} &= \frac{\partial z}{\partial \tau_o} = \frac{-s}{(1+s\tau_o)^2}\left[\theta_a + \Delta\theta_{or}\left(\frac{1+RK^2}{1+R}\right)^x\right] \\
\sigma_{\Delta\theta_{or}} &= \frac{\partial z}{\partial \Delta\theta_{or}} = \frac{1}{(1+s\tau_o)}\left(\frac{1+RK^2}{1+R}\right)^x \\
\sigma_x &= \frac{\partial z}{\partial x} = \frac{\Delta\theta_{or}}{(1+s\tau_o)}\left(\frac{1+RK^2}{1+R}\right)^x \log\left(\frac{1+RK^2}{1+R}\right) \\
\sigma_R &= \frac{\partial z}{\partial R} = \frac{\Delta\theta_{or}}{(1+s\tau_o)}\frac{x\left(K^2-1\right)\left(1+RK^2\right)^{(x-1)}}{(1+R)^{(x+1)}}
\end{aligned} \tag{10}$$

4.2. Experimental results

Table 2 shows parameters obtained with L.M algorithm for each transformer. Errors between measured oil temperatures and the estimated ones are shown in Figs. 9–11. These errors are reduced from $\pm 10\,^{\circ}\mathrm{C}$ to $\pm 3\,^{\circ}\mathrm{C}$. The parametric identification algorithm is very fast and provides accurate parameters. About 40 different heating tests have been performed in the platform validating the proposed method.

5. Conclusion

This paper presents a model which provide an accurate estimation of oil temperature for power transformers. Thermal model parameters are identified using a Levenberg-Marquardt algorithm. The comparison with parameters derived from IEC 60076-7 leads shows that these parameters must be adapted according to the transformer power. In the future, this temperature monitoring will be integrated in an industrial energy meters and will complete larger system including tracking losses in power transformers.

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