NEW SOFT SENSORS FOR DISTRIBUTION TRANSFORMER MONITORING

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ABSTRACT

This paper deals with the thermal and electrical monitoring of distribution transformers; these transformers are one of the most expensive components in the distribution grid. Monitoring these transformers is a good solution to check the availability of the network, increase transformer operational efficiency and minimize the probability of unexpected outage. This paper will present a solution for the monitoring of thermal and electrical behavior of ONAN distribution transformers. For the development of this soft sensor, different transformers has been modelled in a wide range of power (160 to 800kVA).

Keywords: *Smart meter, Power Quality, Distribution transformer monitoring, Thermal model, Electrical model*

INTRODUCTION

A soft sensor emulating a coupled thermal and electrical models of MV/LV distribution transformer is designed. This non-intrusive soft sensor is implemented in a smart meter connected on the LV side of the distribution transformer either for indoor or outdoor substations (Fig.1). The originality of this approach is based on data measurements on the LV side to perform an accurate estimation of the primary quantities corresponding to measurement on the MV side of the grid, and the internal active and reactive losses inside the transformer. An identification process is used to estimate accurately the thermal models parameters. These two models (thermal & electrical) are coupled and also linked to the PQ analysis performed by the meter, THD and harmonic spectrum decomposition of the currents and voltages measured on the LV side.

Fig.1: Non-intrusive meter for LV grid monitoring installed in MV/LV substations in cabinet (indoor) or aerial (outdoor)

In addition to the standard functions of the electricity meter, these options are embedded inside the firmware of the meter. Thermal model ensures real-time thermal transformer monitoring (top oil temperature, hot-spot temperature, ageing rate) and electrical model provides estimation of the voltages on MV side, and internal active and reactive losses without requiring any other sensors. These DTM (Distribution Monitoring Transformer) meters (Fig.2) are part from a network based supervision.

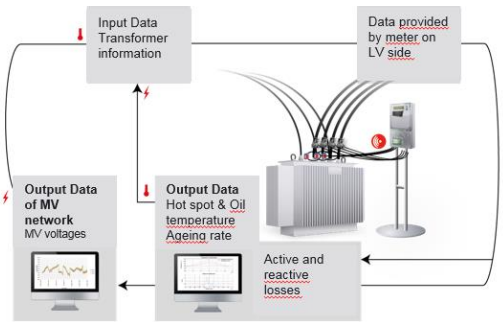
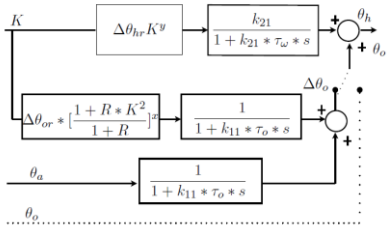


Fig.2: Global synoptic of the DTM meter

TRANSFORMER THERMAL MODELLING

The main factors that determine the transformer life are the windings hot-spot temperature and the oil temperature which are directly influenced by transformer load, ambient temperature and active losses in the transformer [8], [9]. This paper presents the advantages of using an accurate electricity meter on the LV side of the transformer to implement this thermal model, without requiring any other sensors. It is chosen to present the thermal model based on equations given by the IEC60076-7 standard. This method uses heat transfer differential equations applicable for arbitrarily time-varying load factor K and time varying ambient temperature θa. The corresponding block diagram is shown in Fig.3.



Parameters	IEC values	settling
τ_ω	4	constant
k_{21}	1	constant
y	1.6	constant
$\Delta\theta_{hr}$	19	constant
k_{11}	1	constant
x	0.8	estimated
R	5	estimated
τ_o (min)	180	estimated
$\Delta\theta_{or}$	55	estimated

Fig.3: Thermal differential model and parameters table (IEC60076-7 standard)

The inputs are: K the load factor, θa the ambient temperature. The parameters are: Δθht the hot spot to top oil gradient at rated current, y the winding exponent, Δθor the top oil temperature rise in steady state at nominal rated losses, R the ratio between the internal losses at rated load over the losses without load, x the oil exponent, k11 k21 k22 thermal model constants, τw and τo are the winding time constant and the average oil time constant ; the output is θo the oil temperature at the top of the tank and θh the windings hot spot temperature.

Thermal model parameters identification:

As estimating the windings hot spot temperature is a real difficulty, the choice has been made to identify the oil temperature of the tank. One of the best solution to identify the transformer parameters is to use the Levenberg-Marquardt (LM) algorithm. Our model is composed by two inputs (load factor K and the ambient temperature) and the output (the top-oil temperature). The technique is iterative and locates the minimum of a sum of squares of non-linear real-valued functions .Table 1 shows the values of the critical parameters of the thermal model which were chosen to be identified using the program of LM algorithm.

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Table 1: Thermal model parameters, five are constant and four are estimated by LM algorithm

The MISO (Multi Input Single Output) system is defined by: z = f(u, θ) where u and z are respectively the system inputs (load factor K and the ambient temperature θa) and output (transformer oil temperature θo).

The predicted output is given by $\hat{z} = f(u, \hat{\theta})$ where $\hat{\theta} = [\hat{x}\ \hat{R}\ \Delta\hat{\theta}_{or}\ \hat{\tau}_o]$ is the parameters vector to be estimated.

The output prediction error is: $\varepsilon = z(n,\theta) - \hat{z}(n,\hat{\theta})$. The minimization of the quadratic criterion J can give us the optimal value of $\hat{\theta}$ where z represents the measured output.

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

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

Identification process results:

The results for the 800kVA transformer are described in the following figures. In Fig. 4 the inputs of the thermal model can be found.

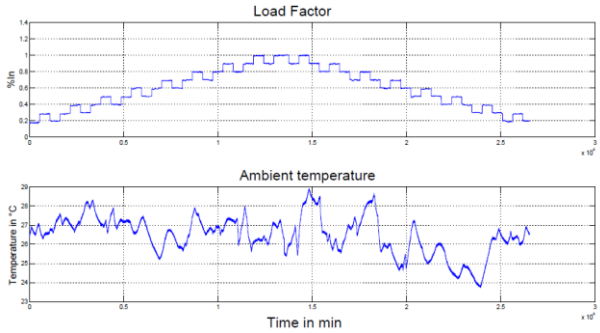

Fig.4: Experimental set up for a 800kVA transformer (Load factor and ambient temperature)

The results for the norm parameters are shown in Fig.5 and the identified parameters in Fig.6. These figures show that in the case of the IEC norm parameters, there is significant error between the both temperatures (error between ±12◦C). This error can be explained by the fact that the thermal parameters of the transformer used in this model, as recommended by the IEC standard, are not reliable enough. In order to reduce this error, some critical parameters must be estimated for each transformer model using an identification algorithm.

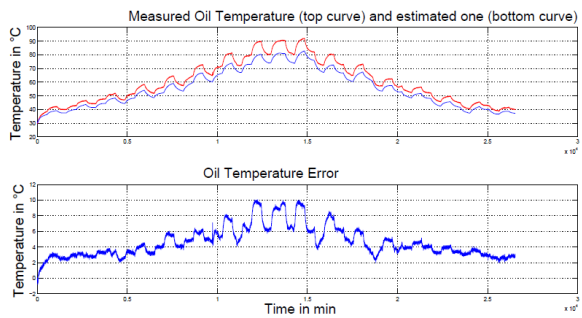

Fig.5: Error between estimated an measured top oil temperature (thermal parameters from the norm)

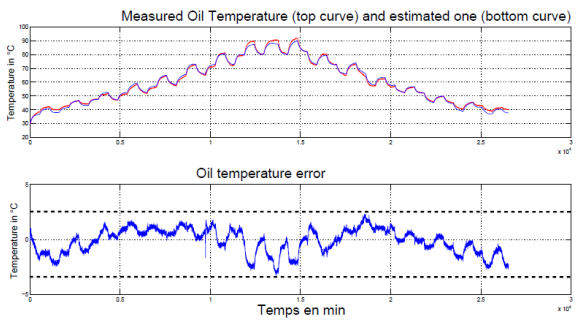

Fig.6: Error between estimated an measured top oil temperature (thermal parameters from LM identification)

The Table 2 shows the results of the fitting between the norm and identified parameters for three class of transformer power (160kVA, 400kVA and 800kVA).

	Norm Fitting	Identification Fitting
160kVA	84.69%	93.96%
400kVA	72.02%	94.82%
800kVA	67.9%	92.83%

Table 2: Fitting between Norm and estimated parameters

With the L.M identification process, the error between the measured and the estimated top oil can be reduced in a remarkable way. In these experiments, the error was reduced from ±12◦C to ±3◦C.

PQ and harmonic analysis for thermal modelling:

In recent years the increased density of renewable energy sources on LV and MV grids and nonlinear equipment like Variable Frequency Drives (VFD's) have grown rapidly in their usage, producing harmonics in current and voltage. These harmonics on the grids have no useful purpose, but add winding and core losses in MV/LV distribution transformer shortening its service life. The consequence is that ONAN distribution transformer should be de-rated. In parallel with the implementation of the thermal model, the PQ calculations of smart meters permit to extract from each waveform (LV current per phase and voltage between phase and neutral) the amplitude and phase of fundamental frequency and its harmonics; from these data the meter can calculate the K-Factor, defined by the ANSI/IEEE C57.110 standard (Fig.7). A K-Factor of 1.0 corresponds to a LV linear load (with no harmonics). The higher the K-Factor, the greater harmonics content and consequently the overheating caused by them. K-Factor can be calculated and compared to the transformer's nameplate K-Factor. As long as the load K-Factor is equal to or less than the transformer's rated K-Factor, the transformer does not need to be de-rated.

$$\left(\frac{\sum_{h=1}^{h_{max}} I_h^2 h^2}{\sum_{h=1}^{h_{max}} I_h^2} \right)$$

Fig.7: Factor calculated from harmonic current

TRANSFO ELECTRICAL MODELLING

The Kapp model is used to compute the MV side quantities (phase-to-phase MV voltages UMT, MV input currents IMT, active losses P, reactive losses Q).

Electrical parameters:

As expected, the leakage inductance and the transformer turns-ratio are independent from the oil temperature (Fig.8). The resistive part of the leakage impedance corresponding to total windings resistance is a linear function of the oil temperature (Fig.9), the reference point is known at 75◦C. The resistance can be expressed as:

$$R_s(T_o) = R_s(75°C) * [1 + \alpha * (T_o(°C) - 75°C)]$$

Where,

Rs(To) : secondary equivalent resistance at oil temperature (To)

To : Top oil temperature;

Rs(75◦C) : resistance at 75◦C

α: temperature coefficient depending of the winding metal

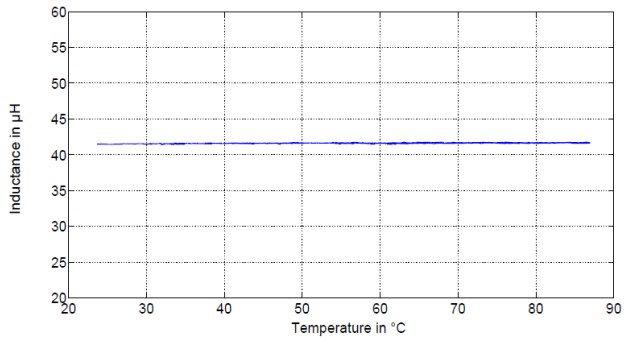

Fig.8: Leakage inductance function of top oil temperature

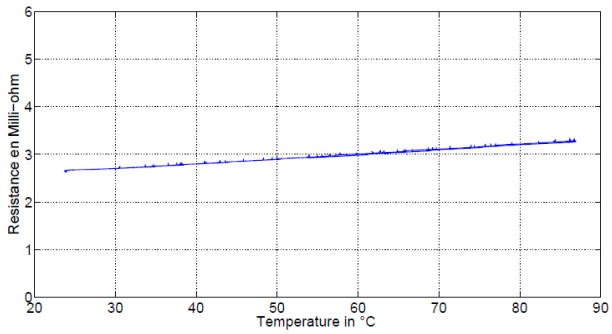

Fig.9: Windings resistors function of top oil temperature

In order to compute the MV-side quantities, a (6x6) matrix equation is used. In the case of a Dyn11 coupling windings, the equation is described in Fig.10.

$$\begin{bmatrix} \bar{U}_{MT12} \\ \bar{U}_{MT23} \\ \bar{U}_{MT31} \\ \bar{I}_{MT1} \\ \bar{I}_{MT2} \\ \bar{I}_{MT3} \end{bmatrix} = K_T \cdot \begin{bmatrix} 1 & 0 & 0 & \bar{Z}_{sc} & 0 & 0 \\ 0 & 1 & 0 & 0 & \bar{Z}_{sc} & 0 \\ 0 & 0 & 1 & 0 & 0 & \bar{Z}_{sc} \\ \bar{Y}_m & 0 & -\bar{Y}_m & a_1 & 0 & -a_1 \\ -\bar{Y}_m & \bar{Y}_m & 0 & -a_1 & a_1 & 0 \\ 0 & -\bar{Y}_m & \bar{Y}_m & 0 & -a_1 & a_1 \end{bmatrix} \cdot \begin{bmatrix} \bar{V}_1 \\ \bar{V}_2 \\ \bar{V}_3 \\ \bar{I}_1 \\ \bar{I}_2 \\ \bar{I}_3 \end{bmatrix}$$

Fig.10: Kapp model and matrix conversion of LV to MV quantities

Other calculations can be done, based on previous electrical data as three phased active and reactive losses in the transformer (Fig.11).

$$P = R_s(T_o)\sum_{i=1}^{3} I_i^2 + \frac{U_{MT12}^2 + U_{MT23}^2 + U_{MT31}^2}{R_F}$$

$$Q = L_s\omega\sum_{i=1}^{3} I_i^2 + \frac{U_{MT12}^2 + U_{MT23}^2 + U_{MT31}^2}{Lm\omega}$$

Fig.11: Transformer internal losses

The expressions of P and Q will change slightly, depending on windings coupling. They are always a proportion of RF , Rs(To), Lsw And Lmw

COUPLED MODELS

The synoptic of the coupled thermal and electrical models is presented in Fig. 12.The thermal model output data are: Top oil temperature, hot spot temperature, ageing rate of the transformer.
The electrical model output data are:
the MV side phase-to-phase voltages, the MV currents and the transformer internal active and reactive losses.

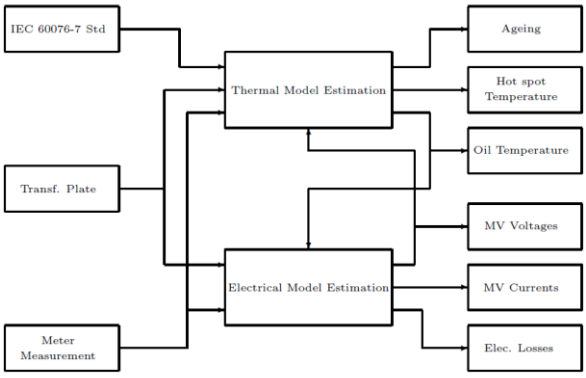

Fig.12: Coupled thermal and electrical model

Interaction from thermal model to electrical one
At a determined sampling period, the top oil temperature estimated value is updated. This value is injected in the calculation of the leakages inductance resistive part. This value interfere with the estimated voltages and currents on the MV side of the transformer and also in the internal active losses calculation.

Interaction from electrical model to thermal one
At a determined sampling period, the three estimated phase-to-phase MV voltages are updated. These values influence the internal transformer heating state (iron losses). In order to take into account the influence of MV voltages on the total active losses, a corrective formula of the load factor is introduced (Kcor) (Fig.13)

$$K_{cor} = K\sqrt{1 - \frac{1 - \left(\frac{U_{MV}}{U_{pn}}\right)^2}{K^2(R-1)}}$$

Fig.13: Load factor corrected via electrical model

The coupled thermal and electrical models will increase the accuracy of MV voltages and currents. Also, the active internal losses will take into account the oil heating influence. These coupled models were tested on a MV/LV distribution transformer during one week:
Fig. 14 shows the thermal model outputs.
Fig. 15 gives the estimated voltages and currents amplitudes on the MV side of the transformer.
Fig.16 present the transformer internal active and reactive losses

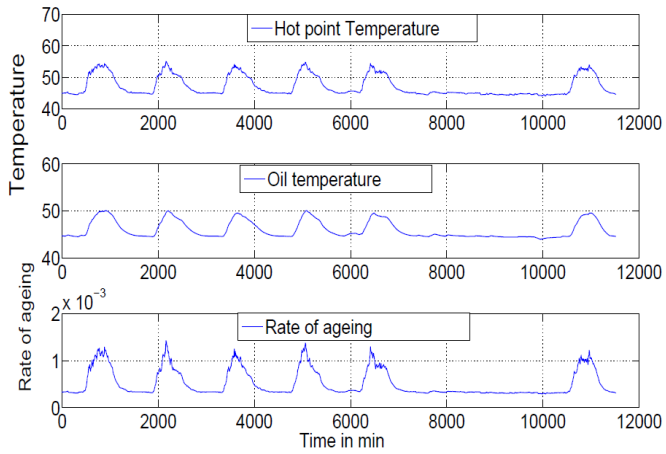

Fig.14: Outputs of the thermal model

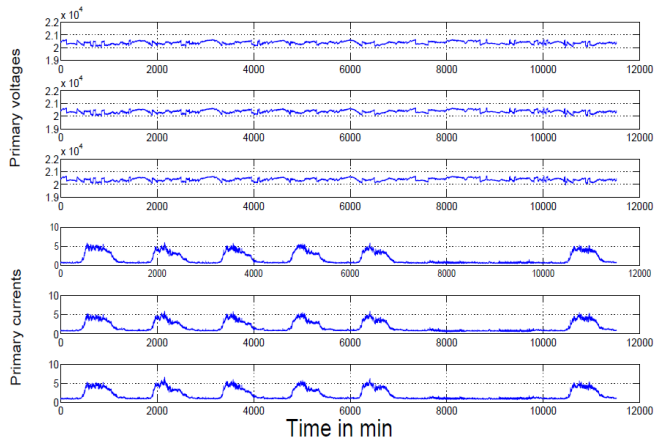

Fig.15: Outputs of the electrical model

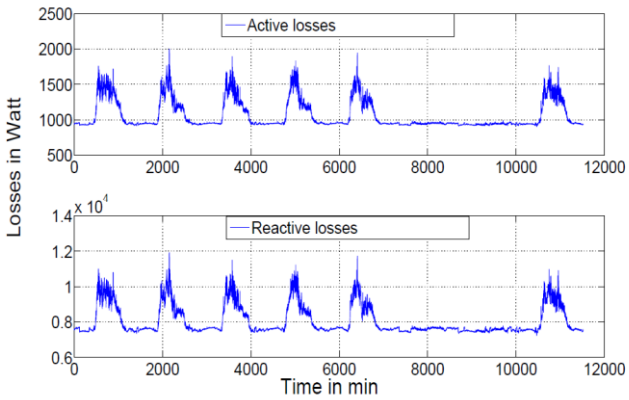

Fig.16: Transformer internal active and reactive losses

PERSPECTIVES

Some utilities are facing every year a high percentage of their distribution transformer burning, causing high cost and poor quality level from a customer point of view. The new capacities of smart meters in terms of calculation and communication permit now to embed inside the meter new intelligent soft sensors based on standardized thermal and electrical models of the MV/LV distribution transformer. These meters can push an alert to the utility before the transformer reach a destructive thermal threshold.

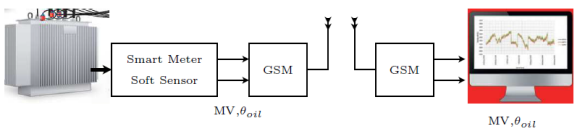

Fig.17: Soft sensor embedded in the smart meter

A different solution can be the transmission of sampled data by the communicating smart meter to a centralized soft sensor which will compute the models for a population of transformer.

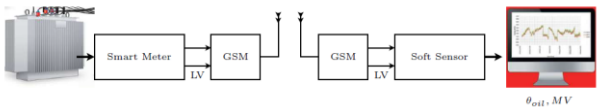

Fig.18: Centralised soft sensor

CONCLUSION

The concept presented in this paper is a new component for smart grids with increased intelligence based on standardized models of distribution transformers. It is economically more interesting to install the smart meter on the LV side. These new soft sensors distributed on the grid will enable the monitoring of the good thermal health of the transformers and the energy balance on LV and MV grids. The reconstructed MV data will be very useful for power flow management, MV energy balance and MV voltage monitoring from the HV/MV substation. Taking into account the LV voltages and currents harmonic contents will bring more accuracy to the thermal alarm threshold, also for active losses estimation. The waveforms on the MV side can be also reconstituted more accurately.

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