An Improved Transformer Top Oil Temperature Model for Use in An On-Line Monitoring and Diagnostic System

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Abstract—In this paper we examine dynamic models of transformer top oil temperature for use in an on-line monitoring and diagnostic system. Data taken from large transformers in the field indicate that the IEEE model of top oil temperature rise over ambient temperature does not adequately account for daily variations in ambient temperature. We propose a modification that accurately predicts top oil temperature and can be implemented in an on-line system. This model is verified using data from a large transformer in service.

1 Introduction

The transformer monitoring group at MIT is presently involved with the monitoring and diagnosis of several large transformers at a number of sponsoring utilities. Our goal is to detect and diagnose fundamental changes in the operating characteristics of the transformer to warn of and avoid catastrophic failures. Our monitoring approach will also be useful for dynamic loading.

To check for rapidly developing failures, certain measurable quantities, such as (mixed) top oil temperature and dissolved gas content, are compared to predictions obtained from mathematical models. The model parameters are determined to best fit past measurements. Using the models, one can identify instances when the measurements differ from previous measurements taken under similar operating conditions. Measurements deviating significantly from predictions may indicate a problem with the transformer. To monitor long term behavior and allow the models to "tune" to each individual transformer, the model parameters are adaptive. Their values are periodically estimated to make the model best fit the observations. By tracking the parameter values, slowly developing problems and effects due to the natural aging of the transformer can be monitored. The details of this approach and its implementation in the MIT pilot transformer test facility are documented in two graduate theses [1, 2], one undergraduate thesis [3], and [4, 5].

96 WM 220-4 PWRD A paper recommended and approved by the IEEE Transformers Committee of the IEEE Power Engineering Society for presentation at the 1996 IEEE/PES Winter Meeting, January 21-25, 1996, Baltimore, MD. Manuscript submitted August 1, 1995; made available for printing January 5, 1996.

For this approach to be successful, the models must satisfy the following criteria:

1. The models must be accurate.
2. Their form should be transformer-independent.
3. For diagnostic purposes, the models must be physically-based.
4. The measured states must be *observable* in the model.
5. The parameters must be *estimable* from on-line measurements using easily placed sensors.

As an on-line thermal model, one may expect the IEEE/ANSI top oil temperature rise over ambient temperature model to be a reasonable starting point, and it is implemented in the MIT monitoring system. However, data recently collected from large transformers in the field indicate that the IEEE/ANSI top oil temperature rise over ambient temperature model is not as accurate as desired for an on-line monitoring system and fails to capture some basic thermal phenomenon. It is the goal of this paper to explain the shortcomings of the IEEE/ANSI thermal model and propose modifications for use in on-line monitoring and diagnostic systems.

2 Background

In this section we review the IEEE/ANSI C57.115 model [6] and compare data collected from the field to predictions obtained from use of the model.

2.1 The Model for Top Oil Temperature Rise Over Ambient Temperature

The model for top oil temperature rise over ambient temperature captures the basic idea that an increase in the loading (current) of the transformer will result in an increase in the losses within the device and thus an increase in the overall temperature. This temperature change depends upon the overall thermal time constant of the transformer, which in turn depends upon the heat capacity of the transformer (i.e. the mass of the core, coils, and oil), and the rate of heat transfer out of the transformer. As a function of time, the temperature change is modeled as a first-order exponential response from the initial temperature state to the the final temperature state:

$$\theta_o = (\theta_u - \theta_i)\left(1 - e^{-t/T_o}\right) + \theta_i. \tag{1}$$

In (1) the initial and final (ultimate) temperature rises are denoted by θ_i and θ_u respectively, T_o is the thermal time constant, t is time referenced to the time of the loading change, and θ_o is the top oil temperature rise over ambient temperature variable. Equation (1) is the solution of the first-order differential equation

$$T_o \frac{d\theta_o}{dt} = -\theta_o + \theta_u, \qquad \theta_o(0) = \theta_i. \tag{2}$$

In the IEEE model, the final (ultimate) temperature rise depends upon the loading and is approximated by

$$\theta_u = \theta_{fl}\left(\frac{K^2 R + 1}{R+1}\right)^n \tag{3}$$

where θ_{fl} is the full load top oil temperature rise over ambient temperature obtained from an off-line test, and R is the ratio of load loss at rated load to no-load loss. The variable K is the ratio of the specified load to rated load:

$$K = \frac{I}{I_{rated}}. \tag{4}$$

The exponent n depends upon the cooling state. The loading guide recommends the use of $n = 0.8$ for natural convection and $n = 0.9 - 1.0$ for forced cooling. As a quick check, one can easily verify that when $I = I_{rated}$, $\theta_u = \theta_{fl}$. Equations (1) and (3) form the IEEE top oil temperature rise over ambient temperature thermal model.

2.2 The IEEE Model in Practice

For purposes of prediction and parameter estimation using discrete data points, a discrete-time form of (2) and (3) is required. Using a forward Euler approximation for the time derivative, $d\theta_o[k]/dt \approx (\theta_o[k] - \theta_o[k-1])/\Delta t$, where Δt is the sampling period, a corresponding difference equation is derived:

$$\begin{aligned}\theta_o[k] &= \frac{T_o}{T_o + \Delta t}\theta_o[k-1] \\ &+ \frac{\Delta t\ \theta_{fl}}{T_o + \Delta t}\left(\frac{\left(\frac{I[k]}{I_{rated}}\right)^2 R + 1}{R+1}\right)^n. \end{aligned} \tag{5}$$

When the load current is near its rating, or, more precisely, when $R > 1$ and $K^2 R > 1$, the following continuous and discrete approximations can be employed:

$$\theta_u = \theta_{fl}\left(\frac{I}{I_{rated}}\right)^{2n} \tag{6}$$

$$\theta_u[k] = \theta_{fl}\left(\frac{I[k]}{I_{rated}}\right)^{2n}. \tag{7}$$

This results in Model A discussed below.

Model A: An approximation of the IEEE top oil temperature rise over ambient temperature model:

$$\begin{aligned}\theta_o[k] &= \frac{T_o}{T_o + \Delta t}\theta_o[k-1] + \frac{\Delta t\ \theta_{fl}}{T_o + \Delta t}\left(\frac{I[k]}{I_{rated}}\right)^{2n} \\ &= K_1\theta_o[k-1] + K_2 I[k]^{2n}. \end{aligned} \tag{8}$$

This is the model used in the MIT monitoring system, and has been shown to be accurate in the MIT pilot transformer test facility. It has the significant advantage that the parameters K_1 and K_2, and subsequently T_o and θ_{fl}, can be estimated from observed data using standard *linear* least squares techniques since both parameters appear linearly in the model. The model given by (5) is slightly more general but lends itself to linear least squares estimation only when $n = 1$. In the loading guide this corresponds to a recommended value for a transformer in the forced cooling state. We note that there is some question concerning the accuracy of this recommendation (see [7]), however, we employ this value as it facilitates the calculation of parameter values and appears to be a reasonable number for the transformer under study. Using the value $n = 1$, the difference equation corresponding to (5) is given by Model B below.

Model B: The IEEE top oil temperature rise over ambient temperature model with $n = 1$:

$$\begin{aligned}\theta_o[k] &= \frac{T_o}{T_o + \Delta t}\theta_o[k-1] \\ &+ \frac{\Delta t\ \theta_{fl} R}{(T_o + \Delta t)(R+1)}\left(\frac{I[k]}{I_{rated}}\right)^2 \\ &+ \frac{\Delta t \theta_{fl}}{(T_o + \Delta t)(R+1)} \\ &= K_1\theta_o[k-1] + K_2 I[k]^2 + K_3. \end{aligned} \tag{9}$$

Using standard least-squares techniques [8], values for the coefficients K_1, K_2, and K_3 can be estimated from measured data. From these, the physical parameters T_o, θ_{fl}, and R can be estimated.

2.3 Field Experience

This technique has been applied to several large transformers in the field with less than satisfactory success. To identify where the problems occur, we examine typical data from one transformer in particular. This transformer is a single phase, FOA rated, 336 MVA, 60 Hz. core form autotransformer. It is part of a bank of 3 identical transformers. Data shown here is typical of all three. It is operating in a substation of a large electric utility. One week's worth of data from May 1993 are shown in Figs. 1 - 3. In Fig. 1 the *measured* (mixed) top oil temperature is shown, and in Figs. 2 and 3, the measured ambient temperature and primary current are shown respectively. The transformer is operating in the FOA state ($n = 1$) and the rated primary current is 1000A. The data was sampled at five minute intervals with integer value resolution.

An initial heat run on this transformer measured the full-load top oil temperature rise over ambient temperature to be 36.2°C, with 8 fans and 4 pumps running in the cooling system. Since this transformer is being operated far below its rated load (Fig. 3), only half of the cooling system is running at any given time. It has been noted that for this transformer the measured top oil temperature varies by approximately 10°C depending on which half of the cooling system is in operation. We note that the data used in this paper comes from a week during which the cooling state remained constant.

Using Model A, the parameters K_1 and K_2 are estimated from the data using a least squares technique. These parameters are then used to *predict* the (mixed) top oil temperature using

$$\theta_{top}[k] = K_1\,(\theta_{top}[k-1]-\theta_{amb}[k-1]) + K_2 I[k]^{2n} + \theta_{amb}[k], \tag{10}$$

which is identical to (8) except that θ_{top} is extracted from the definition of θ_o, $\theta_o = \theta_{top} - \theta_{amb}$. The measured and predicted top oil temperatures are shown in Fig. 4; the solid line is the measured temperature and the dotted line is the predicted temperature.

Qualitatively, it is clear from Fig. 4 that the prediction does not adequately represent the actual top oil temperature. This can be quantified in several ways. First we can check the error covariance related to the least squares approximation. In this case it is 4.91×10^{-6} which is, and should be, a small number. We also compute the corresponding physical model parameters. These are

$$T_o = 1042 \text{ min}, \quad \theta_{fl} = 268°\text{C}$$

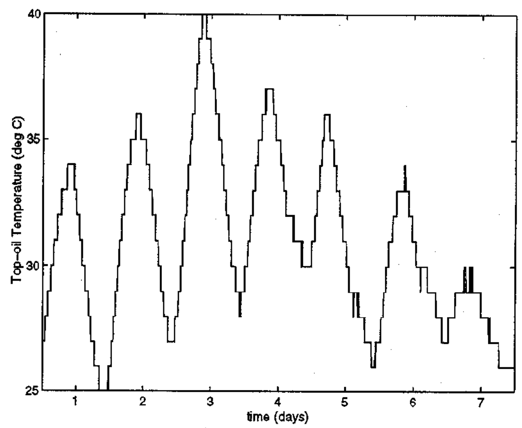

Fig. 1. Measured top oil temperature

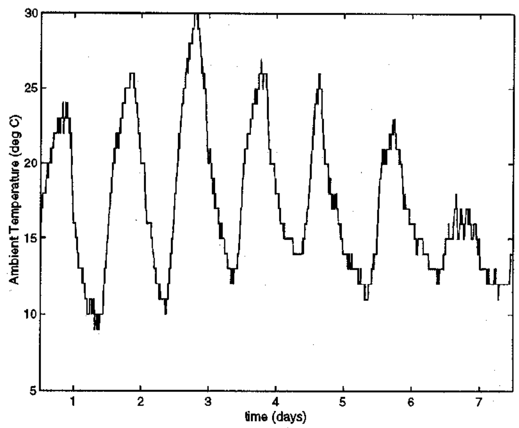

Fig. 2. Measured ambient temperature

and are both too high to make physical sense. From a diagnostic point of view these numbers give us no physical information.

One obvious explanation is that the transformer is very lightly loaded and the approximation used to justify (7) may not be valid. We estimate parameters using Model B given by (9) and plot the predicted and actual top oil temperatures in Fig. 5. Qualitatively, the prediction is somewhat improved and the corresponding parameters,

$$T_o = 329 \text{ min}, \quad \theta_{fl} = 59°\text{C}, \quad R = 4.17,$$

are more realistic; however, the error is still significant. (It is not possible to compare these numbers to those obtained from the initial heat run test since that test was performed with all the fans and pumps in operation, while these parameters are calculated from data obtained when only half of the fans and pumps were in operation.)

In the next section we discuss possible sources of error in the model and parameter estimation algorithms, and propose a slight modification to improve the model.

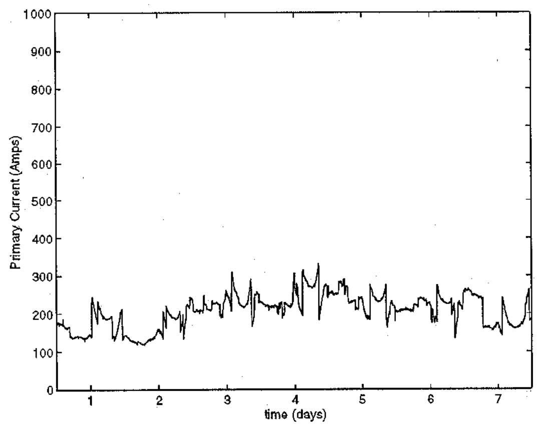

Fig. 3. Measured primary current

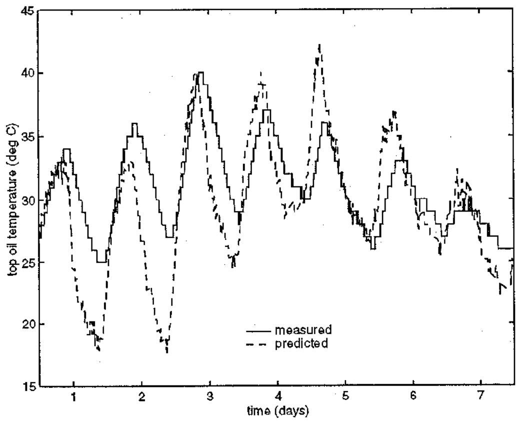

Fig. 4. Measured and predicted top oil temperature (Model A)

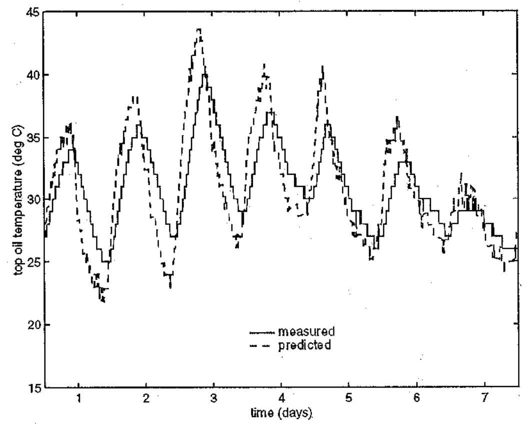

Fig. 5. Measured and predicted top oil temperature (Model B)

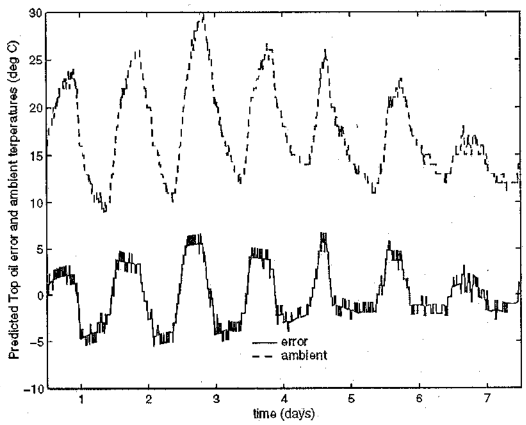

Fig. 6. Error in the predicted top oil temperature (Model B) and measured ambient temperature

3 An Improved Model

There are three major components in the modeling and estimation process described in the previous section:

1. The least-squares parameter estimation
2. from collected data,
3. given a specified model.

This suggests three possible sources of error. The least squares estimation technique is usually reliable and is unlikely to be the source of significant error. Presently the data is measured to integer precision. Since the daily variation in temperature is on the order of 5-20°C, the measured resolution of 1°C introduces $5-20\%$ error in the useful time-varying temperature signal. This may be significant, but a proper analysis of the quantization noise introduced by this 1°C resolution and the five minute sampling period is a nontrivial problem. We do not pursue this further except to note that the five minute sampling period was chosen to enable the consistent estimation of parameters, and is based on the examination of data from several large transformers. Instead, we demonstrate and discuss problems due to the modeling.

The IEEE/ANSI thermal model is a simple model designed to capture the basic thermal dynamics associated with transformer *loading*. Implicit in this model is the assumption that all changes in the top oil temperature rise are caused by changes in the current. This is seen in the model described by (1) and (3). If the current remains constant, the ultimate temperature rise θ_u is equal to the initial temperature rise θ_i; the difference variable θ_o remains constant indicating the top oil temperature rise over ambient temperature is constant.

This first-order model captures the change in temperature due to loading; indeed, the transformer temperature is different (warmer) than ambient temperature largely due to the losses in the windings. However, this is not the only reason that the temperatures can vary. The ambient temperature varies naturally on a daily (24 hr.) and seasonal basis. The thermal time constant of a large transformer can be on the order of hours; thus, the transformer temperature will naturally lag behind the daily cycle of ambient temperature changes. Even if the loading were constant, the top oil temperature rise over ambient temperature would not be. This effect is not captured by the IEEE/ANSI model but is significant for a transformer placed in an environment subject to daily variations in ambient temperature that are of the same order of magnitude as the top oil temperature rises due to load loss. For monitoring and diagnostic purposes it is essential to capture this phenomenon.

In Fig. 6 we show that indeed the ambient temperature and the error in the prediction of the top oil temperature (predicted minus measured) are correlated. The solid line is the error, the dotted line is the ambient temperature. Elementary thermodynamics would suggest that a better first-order characterization of both loading and ambient temperature variations can be accomplished through a slight modification of (2),

$$T_o \frac{d\theta_{top}}{dt} = -\theta_{top} + \theta_{amb} + \theta_u, \tag{11}$$

where θ_u is still defined by (3) but should be interpreted as the ultimate top oil temperature rise over ambient temperature for a given loading and constant ambient temperature. Following the same assumptions used in the previous section we obtain the corresponding first-order discrete model, Model C.

Model C: A modified model that incorporates ambient temperature variations for the forced cooling state, $n = 1$.

$$\begin{aligned}\theta_{top} &= \frac{T_o}{T_o+\Delta t}\theta_{top}[k-1] + \frac{\Delta t}{T_o+\Delta t}\theta_{amb}[k] \\ &+ \frac{\Delta t\ \theta_{fl} R}{(T_o+\Delta t)(R+1)}\left(\frac{I[k]}{I_{rated}}\right)^2 \\ &+ \frac{\Delta t\ \theta_{fl}}{(T_o+\Delta t)(R+1)} \\ &= K_1\theta_{top}[k-1] + (1-K_1)\theta_{amb}[k] \\ &+ K_2 I[k]^2 + K_3 \end{aligned} \tag{12}$$

Using this model and the raw data shown in Figs. 1-3 we obtain the parameters K_1-K_3 and predict the top oil temperature. The corresponding physical parameters are calculated to be

$$T_o = 150 \text{ min}, \quad \theta_{fl} = 48°\text{C}, \quad R = 3.02$$

The measured and predicted top oil temperatures are shown in Fig. 7. Compare this figure with Fig. 5.

Fig. 7 indicates that the top oil temperature model given by (11) does capture some phenomenon that the IEEE/ANSI model does not. This can be quantified further. If a model is accurate then the error between the prediction and the measurements should essentially be noise. The mean and variance of the error in the predictions using Models A, B, and C are given in Table 1.

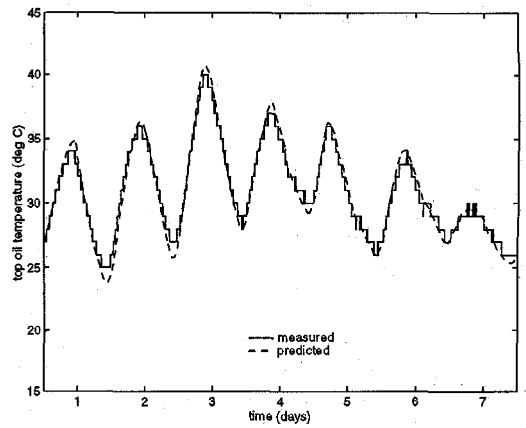

Fig. 7. Measured and predicted top oil temperature (Model C)

Table 1. Predicted top oil temperature error mean and variance

Model	mean	variance
Model A	-1.51	15.0
Model B	-0.41	8.7
Model C	-0.00	.4

4 Conclusions

We have argued that the IEEE/ANSI standard top oil temperature rise over ambient thermal model does not correctly account for ambient temperature variations. Model C, the discretized form of the continuous model described by (11), gives improved performance and satisfies the necessary criteria for an on-line monitoring system listed in the introduction. Through large deviations in the difference between measured top-oil temperature and predicted top-oil temperature using the model, we would expect to be able to detect gross cooling system failures, such as failure of one or more pumps, or failure of 20% or more of the fans associated with any pump. Gradual degradation, such as sludge build-up in the radiators would be indicated by an upward trend in the model parameter θ_{fl} over time.

Our results are consistent with prior results published in the literature concerning the inadequacies of the IEEE/ANSI model [9]. In [9], a new model is proposed that accounts for ambient temperature variations, oil viscosity, winding dynamics, and various types of thermal losses. The model is physically-based and could be useful for diagnostics if it could be implemented on-line. The model parameters in [9] are calculated from manufacturer's data and off-line tests. As the transformer characteristics change over time, it is unlikely that the many parameters could be estimated on-line from measurements obtained from easily placed sensors. In fact, it has been our experience that transformer thermal characteristics will change depending upon which combination of fans and pumps are operating during forced cooling.

The data examined in this paper came from a transformer operating in the FOA cooling state. Assuming $n = 1$ in this state enabled us to employ standard least squares techniques to estimate and verify parameters. In practice it would be better to estimate the value of the cooling exponent n along with the other parameters. This would require the use of a nonlinear least squares algorithm to estimate parameters. We will pursue this in our future work.

Further research is required to address the issue of quantization noise introduced in the measurements. Heuristically, we have chosen a sampling period of five minutes because it appears to consistently work well; however, the relation between data resolution, precision, sampling rate, and post-processing has not been studied.

5 Acknowledgement

The work presented here was supported by a consortium of utilities over a period of eight years. We have received great support and encouragement from Ann Hueston of Boston Edison and Rod Price of BPA.

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DISCUSSION

L. W. PIERCE (General Electric Company, Rome, Georgia) The authors have attempted to develop an improved model to correct a limitation in the referenced industry loading guide [6] to account for changes in ambient temperature. Practice in the industry has been to add the temperature rises predicted by the loading guide equations to the instantaneous ambient temperature. For short time overloads a constant ambient temperature is usually assumed. As noted by the authors, the first mathematical attempt to address ambient temperature variations is given in [9]. This approach, based on heat transfer and fluid flow theory, predicts loading capability for an anticipated 24 hour variable load and ambient temperature profile. The manufacturer's data supplied on the test report and outline drawing is used in the computer program. The authors have derived alternative equations and developed a system of monitoring temperatures and loads to determine the parameters to use in their equations.

Monitoring changes in cooling parameters to detect failures of pumps or changes in heat exchanger performance is an interesting concept. Another use of the authors' monitoring system might be to determine loading capability more accurately since it relies on temperature and load measurements under actual field conditions. The authors approach, however, appears to lack experimental validity indicating more work is required. The field test data given in Figures 1 and 2 indicates that the top oil temperature rise over ambient is on the order of 10 °C. The transformer is lightly loaded since full load top oil temperature rises are on the order of 35 to 65 °C depending on transformer type. If the errors shown in Fig. 6 are divided by this 10 °C than the per cent error is large. Do the authors have any additional test data since this paper was submitted? Does the large error indicate the authors' equations are in error?

One limitation of the authors' monitoring system is that the winding hot spot temperature is not monitored or predicted. Do the authors have plans to incorporate winding hot spot temperature measurement or prediction into their system?

Manuscript received February 20, 1996.

LAMBERT PIERRAT (Senior Member), General Technical Division, Electricité de France, 37 rue Diderot, 38040 Grenoble Cedex, France, M.J. RESENDE, J. SANTANA, Instituto Superior Técnico, Av. Rovisco Pais, 1096 Lisboa Codex Portugal. We would like to felicitate the authors of the paper for their work. The chosen load profile (fig. 3) for analysis is a good one to reenforce the author's method since, comparing figures 1 and 2, transformer top-oil temperature variations look mainly due to ambient temperature ones.

1-Are differences between models A, B and C as great, when analysing transformer top-oil temperature under a much severe load profile (load current closer to rated one)?

2 -It would be interesting to present correlation coefficients between θ_{amb} (fig.1) and θ_{top} (fig.2), I (fig.3) and the 3 models predicted θ_{top} , as well as θ_{amb} and the top-oil temperature predicted with model C.

3-Transformer physical parameters identified from the 3 models are quite different from each other. Did the authors estimated T_0, θ_{fl} and R with any other alternative method (IEC-354, p.e.) to check the validity of parameters identified from model C?

4-Similar to represented on fig.6, error in the predicted top-oil temperature with model C should also be represented. Table 1 (which lacks units!) by itself gives little information about errors; assuming that units are [°K] and considering that top-oil temperature ranges from 25 °C to 40 °C, even a mean error of -1.51 °C would be good and the reduction in variance values, correspond to the improvement on model dynamic behaviour. Would it result clearer represent the statistical distribution of errors from models A, B and specially C? Are they normally distributed?

We would like to thank the authors for the answers to our questions as well as their opinion about our comments.

Manuscript received February 22, 1996.

Bernard C. Lesieutre, Wayne H. Hagman, and James L. Kirtley, Jr. Room 10-050, MIT, Cambridge, MA 02139. We would like to thank the discussors for their interest in our paper, and their pertinent questions.

First we address the specific questions of Mr. Pierrat, Resende, and Santana.

1. The data in the paper comes from a transformer that is always lightly loaded. We can only speculate on how the models would react for this transformer at higher loadings. Based on the arguments presented in our paper, we would expect that the error would persist at higher loadings. Our results suggest that the error depends intimately on the overall thermal time constant of the transformer and not the loading. We do have data from several large transformers and the ambient temperature variations appear to affect the top oil temperature in all of them.

2. We agree that the presentation of correlation coefficients is informative and they are given in Table 1 below. For each of the top-oil temperatures used in this study, the correlation coefficients related to the ambient temperature and the load are computed. Those of Model C are very close to the measured data.

Table 1. Correlation Coefficients between measured and predicted θ_{top} and the inputs θ_{amb} and I.

θ_{top}	Correlation Coefficients	
	θ_{amb}	I
Measured	0.778	0.143
Model A	0.837	0.260
Model B	0.987	0.027
Model C	0.777	0.144

3. The three sets of parameters are quite different. We did not calculate their values using any other method. We would have liked to have compared these values to those computed from data from the initial heat run test, however the transformer is being operated in a manner different than that of the test, prohibiting direct comparison. Furthermore, all measurements were taken while the transformer was in service. No out-of-service tests were performed on the transformer to verify the accuracy of the parameter values.

   This does not prevent us from commenting on the values. The values for Model A are clearly nonsense. The full-load temperature rise over ambient temperature, θ_{fl}, is computed to be 268°C. This is far out of the expected range of 35 to 65 °C. The values for θ_{fl} computed for Models B and C do appear within the expected range. The values of the time constant, T_o, also appear reasonable (although for FOA the lower number is probably more reasonable). The value of the ratio of full-load to no-load loss, R, in both Models B and C seems small. This would indicate that the transformer with significant core losses.

4. We agree with the discussors that a figure of the error in the prediction of top-oil temperature using Model C is appropriate. This is shown below in Fig. 1. There is still an error and it appears to be correlated to ambient temperature. This might suggest that further refinement of the model could reduce the error further, however the error is within the precision of our measurements (1°C resolution). We can't realistically expect to do much better with the sensors that are presently in place.

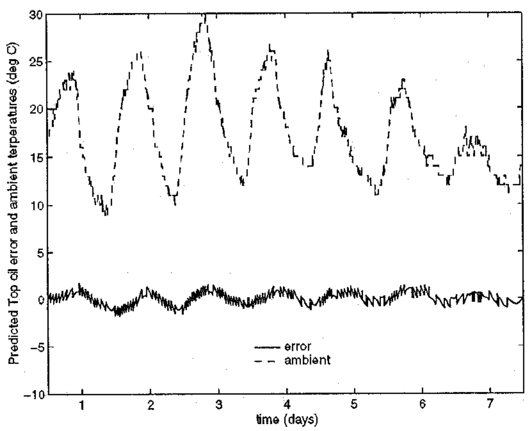

Fig. 1. Error in the predicted top oil temperature (Model C) and measured ambient temperature.

We computed the higher order moments for the prediction error in Model C: The skewness is 0.032 and the kurtosis is 0.383. A histogram is shown below in Fig. 2. The distribution is not perfectly normal but is close. We don't feel that this alone serves to justify the model because the distribution is dependent upon the choice of parameter estimation algorithm employed, and the disturbances in the system. We used a standard least-squares method. If the distribution was far from normal then we might examine other techniques.

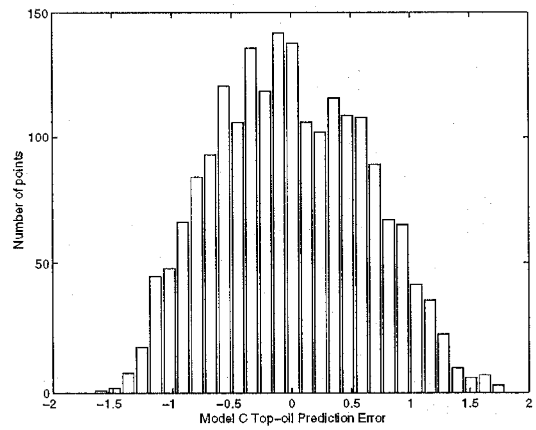

Fig. 2. Histogram of error in the predicted top oil temperature (Model C).

Now we would like to address the questions of Mr. Pierce.

We agree with Mr. Pierce's observation that the transformer is lightly loaded and that the relative error of the prediction (Model B.) is large. Our equations and calculations are not in error however. It was this large prediction error that necessitated this research. Our initial detailed study involved a test transformer for which the loading guide model worked sufficiently well. We were somewhat surprised to encounter such large errors in the transformers in the field. The results in the paper help describe the variations that we observed; our test transformer is inside a building and is mostly insulated from ambient temperature variations while most large transformers are outside and subject to ambient temperature variations. There are certainly other weather related effects that we see in some of our data including rainstorms.

Our monitoring system does include a model for winding hot-spot temperature prediction. We use the loading guide model for this prediction which is based on a temperature rise over top-oil temperature due to loading. Since we do not have a direct hot-spot temperature measurement, we can't comment on the accuracy of that model. Our monitoring system also includes a model for dissolved combustible gas in oil which serves as a important indicator for imminent failures.

We also agree with Mr. Pierce that an important application of an on-line monitoring system is that of estimating load capability. For such an application a detailed model, such as that of reference [9] in our paper, would be useful. In that model we don't believe that all the parameters can be estimated, or all the states can be observed from the easily-placed sensors we are using now. Given that this is an important application, we should ask what sensors would be required and where should they be placed to be able to use such a model in an adaptive on-line monitoring system. This is research that we intend to pursue.

In general it is desirable to use the best information available; in our system we would use the manufacturer's data as an initial estimate of parameters and then adaptively update parameters based on observations made during operation. We feel that the ability to adapt is essential; it allows us to track long-term trends and differentiate between slowly and quickly developing phenomenon.

Manuscript received April 2, 1996.