Soft Computing Techniques to Model the Top-oil Temperature of Power Transformers

H. Nguyen, G. W. Baxter and L. Reznik

Abstract—This paper presents an investigation and a comparative study of four different approaches namely ANSI/IEEE standard methods, Adaptive Neuro-Fuzzy Inference System (ANFIS), Multilayer Feedforward Neural Network (MFNN) and Elman Recurrent Neural Network (ERNN) to modeling and prediction of the top-oil temperature for the 8 MVA Oil Air (OA)-cooled and 27 MVA Forced Air (FA)-cooled class of power transformers. A comparison of the proposed techniques is presented for predicting top-oil temperature based on the historical data measured over a 35 day period for the first transformer and 4.5 days for the second transformer with either a half or a quarter hour sampling time. Comparison results indicate that hybrid neuro-fuzzy network is the best candidate for the analysis and predicting of power transformer top-oil temperature. The ANFIS demonstrated the paramount performance in temperature prediction in terms of Root Mean Square Error (RMSE) and peaks of error.

Index Terms—Adaptive Neuro-Fuzzy Inference System (ANFIS), neural networks, power transformers, top-oil temperature, soft computing.

I. INTRODUCTION

A power transformer is one of the most expensive pieces of equipment in an electrical power delivery system. Monitoring a transformer’s thermal conditions is important in order to predict possible break downs that are crucial in minimizing power outages through appropriate maintenance thereby reducing the total cost of operation. The transformer top-oil temperature value is one of the most critical parameters when defining the power transformer characteristics [1]. Traditional approaches to modeling a transformer’s top-oil temperature rely a great deal on mathematical formulae, which require a high level accuracy of each parameter involved. The use of these mathematical formulae is valid and acceptable when the transformer system is simple and properly monitored. However, in the case of a typical transformer system like one under consideration, which is not a straightforward linear system, mathematical formulae like ANSI/IEEE [2] standard methods become less effective. The paper investigates an application of soft computing techniques in order to improve a prediction of top-oil temperature of power transformers and compares them against conventional modeling techniques. It is organized as follows. In Section II we provide some background information and transformer’s parameters used in modeling and simulation. In Section III a brief overview of the conventional techniques is given. In Section IV we provide details of the neural network models. In Section V, we show the operation and structure of an ANFIS model. The results of comparison analysis between various modeling techniques for top-oil temperature prediction of two transformers are given in Section VI. Conclusions are drawn in Section VII.

II. THE TOP-OIL TEMPERATURE PREDICTION

The transformer parameters that are routinely monitored at the industrial installations include top-oil temperature ($\theta_{\text{top}}$), bottom-oil temperature ($\theta_{\text{bot}}$), ambient temperature ($\theta_{\text{amb}}$) and load current ($I_{\text{load}}$) of the distribution transformers. In the data sets obtained from power industrial installations in Kendall and Devil Brook (USA) and used in this study these parameters were measured every 30 minutes for the 8 MVA OA-cooled transformer and every 15 minutes for the 27 MVA FA-cooled transformer. Load current figures were rounded to their closest integer value in Amperes. The top-oil, bottom-oil and ambient temperature measurements were rounded to one tenth of a degree, Celsius. Figures 1(a) to (d) represent the measured data of the 8 MVA OA-cooled transformer received from Kendall installation that include both top-oil temperature and a number of influencing factors used in simulation and prediction.

The selection of input variables for this project was carried out based on the factors chosen in conventional models [3]. The ambient temperature and load current are known as the main factors that affect the top-oil temperature of transformer [3]. In all the models considered, the inputs include the ambient temperature and load current signals while the prediction output will be the top oil temperature signal unless stated otherwise. In order to evaluate the prediction ability of each model, the available transformer parameters were divided into two sections, the first half of 1702 data points is used as the historical training set, and the remaining half of 1702 data points (from day 35.5 to day 71) as the test set. As neural networks are commonly trained on normalized data rather than raw data, both input variables ($\theta_{\text{amb}}$ and $I_{\text{load}}$) and output variable ($\theta_{\text{top}}$) were normalized such that all data are scaled in the normalized range from 0 to 1.
There are a few conventional models that are traditionally used in practice for predicting transformer temperatures [2]-[5]. These models can be used with manufacturer-supplied coefficients (e.g. rated load, thermal capacity, oil exponent, etc.) provided that the necessary transformer parameters are monitored. If the required parameters are not monitored routinely then the models cannot be applied. Parameters that are routinely measured include the ambient temperature, top-oil temperature, bottom-oil temperature and load current. One model that has been employed is the top-oil-rise model [2]. The top-oil-rise model is governed by the first order differential equation,
\[
T_o \frac{d\theta_o}{dt} = -\theta_o + \theta_u
\]  
which has the solution [2],
\[
\theta_o = (\theta_o - \theta_t)(1 - e^{-\frac{t}{T_o}}) + \theta_t
\]  
where,
\[
\theta_o = \text{top-oil-rise over ambient temperature (°C)};
\]
\[
\theta_t = \text{top-oil-rise over ambient temperature at rated load (°C)};
\]
\[
\theta_u = \text{ultimate top-oil-rise for load L (°C)};
\]
\[
\theta_t = \text{initial top-oil-rise for t = 0 (°C)};
\]
\[
\theta_{amb} = \text{ambient air temperature (°C)};
\]
\[
T_o = \text{time constant at rated KVA (h)};
\]
\[
P_{fl} = \text{rated load (MVA)};
\]
\[
P_{fl} = \text{initial top-oil-rise for t = 0 (°C)};
\]
\[
K = \frac{1}{I_r}\]
\[
C = \text{the thermal capacity of the transformer, Watt-hours/°C (Wh/°C)};
\]
\[
n = \text{an empirically derived exponent used to calculate the variation of top-oil temperature with changes in load.}
\]
\[
R = \text{ratio of load loss to no-load loss at rated load}.
\]
\[
K = \frac{\text{ratio of load }L \text{ to rated load}}{};
\]
\[
R = \frac{\text{ratio of load loss to no-load loss at rated load}}{}
\]
If (2) is solved, the top-oil temperature (\(\theta_{top}\)), is given by:
\[
\theta_{top} = \theta_o + \theta_{amb}
\]  
To accurately predict \(\theta_{top}\), we need to find the parameters \(T_o\), \(R\) and \(\theta_{fl}\). There are several ways to accomplish this parameter estimation. The most widely employed method is by using linear regression along with measured data. To use linear regression we must first construct a discrete-time form of (2). Applying the forward Euler discretization rule,
\[
\frac{d\theta_o}{dt} = \frac{\theta_o - \theta_o[k]}{\Delta t}
\]
where \(\Delta t\) is the sampling period. Solving we get,
\[
\theta_o[k] = \frac{T_o}{T_o + \Delta t}\theta_o[k-1] +
\]
\[
+ \frac{\Delta t \theta_{fl}}{(T_o + \Delta t)(R + 1)} \left( \frac{I[k]}{I_{rated}} \right)^n
\]
where \(I[k]\) is the per-unit transformer current (based on the rated value of transformer) at time step index \(k\).

From (5) and (9), when the load current is near its rating, or \(R>1\) and \(K^2 R>1\), top-oil temperature rise over ambient temperature may then be given by,
\[
\theta_o[k] = \frac{T_o}{T_o + \Delta t}\theta_o[k-1] +
\]
\[
+ \frac{\Delta t \theta_{fl}}{(T_o + \Delta t)(R + 1)} \left( \frac{I[k]}{I_{rated}} \right)^{2n}
\]

For comparison purposes, this model will be called Model 1. This is the model used in the Massachusetts Institute of Technology (MIT) monitoring system, and has been shown to be reliable in the MIT pilot transformer test facility [3].

For a transformer in the forced cooling state [2], (9) is given by [3]:
\[
\theta_o[k] = \frac{T_o}{T_o + \Delta t}\theta_o[k-1] +
\]
\[
+ \frac{\Delta t \theta_{fl}}{(T_o + \Delta t)(R + 1)} \left( \frac{I[k]}{I_{rated}} \right)^{2n}
\]

In this paper this is called Model 2. This is a simplified model, which has the limitation that it does not accurately account for the effects of ambient temperature dynamics on top-oil temperature. It can be shown that the model proposed...
by [3] accounts for dynamic variations in ambient temperatures. The model proposed by [3] can be viewed as a slight modification of (1),
\[ T_o \frac{d\theta_{top}}{dt} = -\theta_{top} + \theta_{amb} + \theta_u \]  
where \( \theta_u \) is still defined by (3) and \( \theta_{amb} \) is the ambient temperature. Following the same assumptions as above, (12) has the solution:
\[ \theta_{top}[k] = \frac{T_o}{T_o + \Delta T} \theta_{top}(k-1) + \frac{\Delta T}{T_o + \Delta T} \theta_{amb}(k) + \frac{\Delta T \theta_f}{(T_o + \Delta T)(R+1)} \left( I[k] I_{rated} \right)^{2n} + \frac{\Delta T \theta_f}{(T_o + \Delta T)(R+1)} \]  
This model has been designated as Model 3.

IV. NEURAL NETWORK MODELS

A Multilayer Feedforward Neural Network is the most extensively used neural network, particularly with applications in the area of systems and control [6]. Elman Recurrent Neural Network (ERNN) is a partial recurrent network model that was first proposed in 1990 [7]. ERNNs have been applied widely in the fields of identification, prediction and control. Recently, ERNNs have been found to provide excellent results in daily peak temperature forecasting [8], detecting and classifying attacks in computer networks [9] and top-oil temperature prediction for transformers [10]. For these reasons, MFNNs and ERNNs were employed in this study. In all of our neural network models, we used networks with one hidden layer of nodes as shown in Figures 2 and 3.

V. NEURO-FUZZY MODEL

The modeling methodology used in this study is ANFIS (Adaptive Neuro-Fuzzy Inference System) developed by Roger Jang [11]. The ANFIS is based on the architecture of the Takagi-Sugeno-type fuzzy inference system [11]. ANFIS is one of the most popular and well-documented neuro-fuzzy systems, which has a good software support [12]. Jang presented the ANFIS architecture and application examples in modeling a nonlinear function, a dynamic system identification and a chaotic time series prediction. Given its potential in building neuro-fuzzy models with good prediction capabilities [13] and [14], the ANFIS architecture was chosen for modeling of this work.

As for the transformer’s top-oil temperature prediction, the presented ANFIS model is shown in Fig. 4. Layer 1 is the input layer which consists of two input variables \( \theta_{amb} \) and \( I_{load} \). Initially, six bell-shaped membership functions (MFs) were used in layer 2 (\( A_1, A_2, A_3, B_1, B_2 \) and \( B_3 \)). Every bell-shaped MF has three nonlinear parameters \( \{ a_j, b_j, c_j \} \). In layer 3 each of the nine nodes is fixed node that multiplies the incoming signals and sends out the product. In layer 4 each of the nine nodes is also a fixed node that performs a normalization of the firing strength from layer 3. In layer 5 the Takagi-Sugeno’s fuzzy if-then rules [15] were used. Each of the nine nodes in this layer has three linear parameters \( \{ p_j, q_j, r_j \} \). Layer 6 is the output of the network. The output of the jth node is given by:
\[ \bar{w}_j \times f_j = \bar{w}_j \times (\theta_{amb} \times p_j) + (I_{load} \times q_j) + r_j \]  

Hybrid learning algorithm [15] combining the gradient method and the least squares technique is adopted to identify the linear and nonlinear parameters in the ANFIS model.

VI. RESULTS AND COMPARISON

This Section presents in detail the results of an application of ANSI/IEEE, ANFIS, MFNN and ERNN models. This Section also compares the results of all four models and identifies the most successful model based on the accuracy of the prediction given by each model. In order to evaluate the predicting accuracy of different models, the transformer’s top oil temperature prediction uses the Root Mean Square Error
(RMSE) to measure the difference between the predicted and measured temperature values.

For example with top-oil temperature,

\[ \theta_{top\_p} = \text{predicted top-oil temperature} \]

and

\[ \theta_{top\_m} = \text{measured top-oil temperature} \]

The RMSE is given by the following equation,

\[ \text{RMSE} = \sqrt{\frac{1}{P} \sum_{i=1}^{P} (\theta_{top\_m} - \theta_{top\_p})^2} \]  \hspace{1cm} (15)

where P is the total number of temperature samples.

Although RMSE is a good characteristic to measure the prediction accuracy but sometimes it might not give a good indication of how well a model performs. The RMSE value can be small but the model does not work properly due to big but short deviations. In order to mitigate the peak deviation factor, the models comparison in this paper is done on the basis of both peaks of error (the units of both minimum and maximum errors are in degree Celsius) and RMSE results.

A. Top-oil Temperature Prediction Using ANSI/IEEE Models

The top-oil temperature prediction results by using models 2 and 3 are described here. The calculation of transformer's maximum errors are in degree Celsius) and RMSE results. The RMSE is given by the following equation,

\[ \text{RMSE} = \sqrt{\frac{1}{P} \sum_{i=1}^{P} (\theta_{top\_m} - \theta_{top\_p})^2} \]  \hspace{1cm} (15)

where P is the total number of temperature samples.

2) ERNN: To find the parameters for the ERNN we followed the same methodology as in the case of MFNN. The architecture of ERNN used in this paper is an Elman network consisting of 6 logsig in the hidden layer and 1 purelin in the output layer. This network is also trained by the L-M method.

C. Top-oil Temperature Prediction Using Neuro-Fuzzy Models

For the most common case, the variable ANFIS parameters are: the number and the type of membership function for each input, the output membership function type (either ‘linear’ or ‘constant’), the training epoch number, the training error goal, the initial step size, the step size decrease rate and the step size increase rate. In addition to the parameter selection one can also ensure that appropriate test data are used to detect overfitting of the training data set. The test data have the same format as the training data. Overfitting can be detected when the test error (difference between the measured and predicted outputs) starts increasing while the training error is still decreasing.

The ANFIS prediction of top-oil temperature of the 8 MVA transformer with 2 input variables (\( \theta_{amb} \) and \( I_{load} \)) has produced the following results: RMSE = 3.53, minimum peak error = -23.24°C, maximum peak error = 21.46°C, number of MFs = 2 Gaussian MFs (\( \text{low} \) and \( \text{high} \)), initial step size = 0.04, step size decrease rate = 0.9, step size increase rate = 1.1, epoch number = 100 epochs, learning type = hybrid, linear type output and no overfitting was detected. However, the peaks of error values are significantly high as shown in Fig. 5. In order to overcome this problem, one can increase the number of input variables.

The ANFIS model now has three inputs, \( \theta_{amb} \), \( \theta_{bot} \) (using the bottom-oil temperature to predict the top-oil temperature is unhelpful in practice as it is just as simple to measure the top-oil temperature as it is to measure the bottom-oil temperature. However the success of the bottom-oil temperature in predicting the top-oil temperature demonstrates the value of the technique when a strong link exists between the predictor and the parameter being predicted) and \( I_{load} \). The input and output data sets have been divided into two sections similar to the ANFIS with two input variables case. As a result of the findings for the two inputs case the same ANFIS characteristics were set here. The measured and predicted top-oil temperature of the 8 MVA transformer are shown in Fig. 6, whereas the error waveform is depicted in Fig. 7. The changes in the Gaussian MFs before and after training are shown in Figures 8(a) to (f).

From Figures 5 and 7, the 3 inputs ANFIS model
demonstrates that by using more input variables, the performance is improved dramatically. Inputs should be carefully selected by using experience from the expert, or by trial and error. For the 8 MVA transformer, the bottom oil temperature has a similar pattern to that of the top oil temperature and therefore, was a logical choice for the input selection process for the ANFIS.

D. Comparisons of the Three Soft Computing Models for Top-oil Temperature Prediction

To summarize the results obtained from the three different soft computing models, we tabulated RMSE and peaks of error values in Tables III and IV. We noticed that ANFIS outperforms the other two models in terms of RMSE and peaks of error. As an extension, the data of the 27 MVA transformer was used to further examine the capability of all models. We tabulated the results for this transformer in Tables V and VI.

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
<th>Min Error</th>
<th>Max Error</th>
</tr>
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<tbody>
<tr>
<td>Model 2</td>
<td>21.48</td>
<td>12.18</td>
<td>38.31</td>
</tr>
<tr>
<td>Model 3</td>
<td>5.88</td>
<td>-10.58</td>
<td>13.59</td>
</tr>
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TABLE II

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
<th>Min Error</th>
<th>Max Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 2</td>
<td>6.07</td>
<td>1.49</td>
<td>11.62</td>
</tr>
<tr>
<td>Model 3</td>
<td>2.54</td>
<td>-3.05</td>
<td>7.92</td>
</tr>
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TABLE III

<table>
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<tr>
<th>Method</th>
<th>RMSE</th>
<th>Min Error</th>
<th>Max Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>MFNN</td>
<td>3.69</td>
<td>-23.13</td>
<td>21.98</td>
</tr>
<tr>
<td>ERNN</td>
<td>3.60</td>
<td>-23.46</td>
<td>21.97</td>
</tr>
<tr>
<td>ANFIS</td>
<td>3.53</td>
<td>-23.24</td>
<td>21.46</td>
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TABLE IV

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<tr>
<th>Method</th>
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<tr>
<td>MFNN</td>
<td>0.94</td>
<td>-6.08</td>
<td>5.09</td>
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<tr>
<td>ERNN</td>
<td>0.91</td>
<td>-5.20</td>
<td>5.13</td>
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<tr>
<td>ANFIS</td>
<td>0.89</td>
<td>-4.38</td>
<td>4.50</td>
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TABLE V

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
<th>Min Error</th>
<th>Max Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>MFNN</td>
<td>3.20</td>
<td>-7.86</td>
<td>2.26</td>
</tr>
<tr>
<td>ERNN</td>
<td>3.01</td>
<td>-6.72</td>
<td>1.10</td>
</tr>
<tr>
<td>ANFIS</td>
<td>2.96</td>
<td>-6.61</td>
<td>2.75</td>
</tr>
</tbody>
</table>

Fig. 5. The error waveform between the measured and predicted top oil temperature of the 8 MVA transformer by using the ANFIS model with 2 inputs.

Fig. 6. The measured and predicted top-oil temperature of the 8 MVA transformer by using the ANFIS model with 3 inputs.

Fig. 7. The error waveform between the measured and predicted top-oil temperature of the 8 MVA transformer by using the ANFIS model with 3 inputs.
In this paper, three different soft computing techniques have been applied for modeling and prediction of the transformer top-oil temperature. Comparison with the commonly used ANSI/IEEE standard techniques showed superior performance of the proposed techniques in terms of predictability (RMSEs and peaks of error were improved significantly) and adaptability (tested on unseen data) of reconstruction results. In addition, the developed techniques show a strong link between the top and bottom oil temperatures and overcome the problem of accuracy of transformer’s parameters necessary when using the ANSI/IEEE numerical techniques. The described techniques are fast and easy to implement in any iterative reconstruction algorithm. Of the three soft computing models, the ANFIS model provided the best performance consistently in terms of both the RMSE and the absolute values of error.

Neuro-fuzzy models like ANFIS is a well documented technique which has been widely applied to other problems. In order to use it with a significant effect sufficient training data has to be collected, and data has to be representative of the problem for successful prediction.

VIII. REFERENCES


VII. CONCLUSIONS

IX. BIOGRAPHIES

Huy Nguyen received his B.Eng. degree in electrical and electronic engineering from Victoria University, Melbourne, Australia, in 1998, where he is currently pursuing the Master degree in the area of power system. His research interests include power transformers temperature forecasting, intelligent power systems, neuro-fuzzy and artificial neural networks.

Gregory W. Baxter is a Professor of Physics at Victoria University. He received both his BSc(hons.) and PhD from the University of Melbourne. His main research interests are in the application of optical fibers as amplifiers and sensors. He has also contributed to the development of optical imaging techniques for the characterization of optical fiber based devices.

Leon Reznik is a Professor of Computer Science at the Rochester Institute of Technology, New York. He received his BS/MS degree in Computer Control Systems in 1978 and a PhD degree from St.Petersburg Polytechnic Institute in 1983. He has worked in both industry and academia in the areas of control, system, software and information engineering and computer science. Prof. Reznik is an author of the textbook “Fuzzy Controllers” (Butterworth-Heinemann, 1997) and an editor of “Fuzzy System Design: Social and Engineering Applications” (Physica Verlag, 1998), “Soft Computing in Measurement and Information Acquisition” (Springer, 2003), “Advancing Computing and Information Sciences” (Cary Graphic Arts Press, 2005).