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Published in:
Proceedings of IEEE Universities Power Engineering Conference

DOI (link to publication from Publisher):
10.1109/UPEC.2008.4651476

Publication date:
2008

Document Version
Early version, also known as pre-print

Link to publication from Aalborg University

Citation for published version (APA):

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A Fuzzy-Based Approach for Transformer Dynamic Loading Capability Assessment

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Abstract— In this paper, a new method is proposed for transformer dynamic loading capability assessment using fuzzy modeling. Firstly, the hot spot temperature is estimated by fuzzy thermal model and then is compared with the temperatures obtained by measurement and IEEE thermal model. Afterwards, the method of dynamic loadability assessment is described and implemented by the fuzzy model. Comparison between the results obtained by the fuzzy thermal model and the IEEE model demonstrates the usefulness of the fuzzy model application.

NOMENCLATURE

- \( \tau_{oil} \): Top-oil temperature time constant (hour)
- \( \tau_{hs} \): Winding time constant (hour)
- \( \theta_{amb} \): Ambient temperature (°C)
- \( \theta_{oil} \): Top-oil temperature (°C)
- \( \theta_{hs} \): Hot spot temperature (°C)
- \( \theta_{hs,\text{rated}} \): Rated hot spot temperature (°C)
- \( \Delta \theta_{oil} \): Top-oil temperature rise above ambient (°C)
- \( \Delta \theta_{oil,\text{u}} \): Ultimate top-oil temperature rise above ambient (°C)
- \( \Delta \theta_{hs,\text{rated}} \): Rated hot spot temperature rise above ambient (°C)
- \( \Delta \theta_{hs} \): Hot spot temperature rise above top-oil (°C)
- \( \Delta \theta_{hs,\text{u}} \): Ultimate hot spot temperature rise above top-oil (°C)
- \( \Delta \theta_{hs,\text{rated}} \): Rated hot spot temperature rise above top-oil (°C)
- \( m \): Empirical constant (dimensionless)
- \( n \): Empirical constant (dimensionless)
- \( R \): Ratio of rated load loss to no load loss (dimensionless)
- \( K \): Transformer load (per unit)
- \( N \): Number of patterns (input vectors)
- \( U \): Membership function matrix
- \( W \): Cluster center matrix
- \( \mu_{ij} \): Value of the membership function of the \( i^{th} \) pattern belonging to the \( j^{th} \) cluster
- \( M \): Constant to control fuzziness or amount of clusters overlapping
- \( W_j^{(q)} \): Cluster center of the \( j^{th} \) cluster for the \( q^{th} \) iteration
- \( d_{ij} \): Euclidean distance between the pattern \( x_i \) and cluster center vector \( W_j^{(q)} \)
- \( N_r \): Number of fuzzy clusters
- \( m_a \): Number of antecedent parameters (fuzzy sets)
- \( m_c \): Number of consequent parameters
- \( m_r \): Number of fuzzy rules constituting the model
- \( m_p \): Number of fuzzy model parameters
- \( \theta_{hs,\text{mer}} \): Measured hot spot temperature (°C)
- \( \theta_{hs,\text{e}} \): Estimated hot spot temperature (°C)
- \( F_{AA} \): Aging acceleration factor (per unit)
- \( LL \): Insulation loss of life (day)
- \( NL \): Insulation normal life (day)
- \( T \): Transformer loading period (day)
- \( q \): Number of iteration in the FCM method
- \( p \): Dimension of the pattern vectors
- \( X \): Set of pattern vectors
- \( x_j \): Pattern vector
- \( x_{1,...,p} \): Elements forming the pattern vector
- \( x_h^* \): Center of the \( h^{th} \) rule
- \( A_{h,1,...,p} \): Fuzzy sets
I. INTRODUCTION

Insulation electrical breakdown is the main reason of faults in transformers. It is well-known that insulation deterioration is a function of temperature, moisture and oxygen content. Today, with modern oil preservation systems, the moisture and oxygen content can be minimized, leaving the temperature as the controlling parameter [1]. Since temperature distribution in most of the transformers is not uniform, a common practice is to consider the hot spot temperature (HST) as the main limiting factor of loading capability [2,3].

In recent 10 years, artificial intelligence methods such as neural networks, genetic algorithm (GA), and fuzzy logic are applied for precise HST estimation. Comparing these methods, transformer dynamic loading capability is determined using the concept of the fuzzy thermal modeling. TSK model is identified in two steps [8,9]:

A. FCM clustering

Using the FCM method, data samples are organized in clusters, each of which is associated with a center. In this manner, the TSK model is based on a set of fuzzy IF–THEN rules, extracted by using the FCM clustering technique.

Supposing a set of unlabelled patterns (input vectors) $X = (x_1, x_2, ..., x_N)$, $x_i \in \mathbb{R}^p$, clustering procedure is performed to minimize the following objective function [11]:

$$F(U, W) = \sum_{j=1}^{N_r} \sum_{i=1}^{N} (\mu_{ij})^M d_{ij}^2$$

FCM, A two-step iterative process, works as follows:

Given the membership values $\mu_{ij}^{(q)} (\mu_{ij}$ at the $q^{th}$ iteration), the cluster center matrix $W$ is calculated by:

$$w_{jq}^{(q)} = \frac{\sum_{i=1}^{N} (\mu_{ij}^{(q-1)})^M x_i}{\sum_{i=1}^{N} (\mu_{ij}^{(q-1)})^M}$$

Given the new cluster centers $W^{(q)}$, the membership values $\mu_{ij}^{(q)}$ are updated by:

$$\mu_{ij}^{(q)} = \frac{1}{\sum_{l=1}^{N_r} \left( \frac{d_{ij}^{(q)}}{d_{lj}^{(q)}} \right)^2}$$

where, if $d_{ij} = 0$ then $\mu_{ij} = 1$ and $\mu_{ij} = 0$ for $l \neq j$. The process stops when $\|U^{(q)} - U^{(q-1)}\| < \epsilon$, or a predefined number of iterations is reached.

B. Thermal model structure and parameters

For multi-input single-output systems, the typical TSK model consists of a set of IF–THEN rules having the form:

$$\theta_{hs} = \theta_{oil} + \Delta \theta_{hs}$$

$u$ and rated represent ultimate and rated values, respectively.

III. FUZZY THERMAL MODEL

In this section, the Takagi-Sugeno-Kang (TSK) fuzzy modeling method is presented and applied to transformer thermal modeling. TSK model is identified in two steps [8,9]:

- A fuzzy clustering technique is applied to input-output space data, with a number of clusters, being determined by GA, equal to $N_r$.
- Assuming the cluster centers to be furnished by the previous step, the number of fuzzy rules equal to $N_r$ and the spreads of the memberships functions equal to $s$, the model’s parameters are identified by a recursive least-squares procedure.

To perform partitioning of the input–output space, various approaches can be used. Amongst them pattern recognition methods of fuzzy clustering, such as fuzzy c-means (FCM) [10-13], are suitable tools for the partitioning process.

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following form \[14\]:

\[ R_h: \text{IF } x_1 \text{ is } A^h_1 \text{ and } \ldots \text{ and } x_p \text{ is } A^h_p \text{ THEN } y \text{ is } f_h(x) \quad (h = 1, \ldots, m_r) \]

where

\[ f_h(x) = a_{0h} + a_{1h}x_1 + a_{2h}x_2 + \ldots + a_{ph}x_p \quad (9) \]

in which \( f_h(x) \) is a linear function which its parameters are calculated by the least-squares procedure.

For any input, \( x_i \), the inferred value of the TSK model, is calculated as:

\[
y = \frac{\sum_{h=1}^{m_r} A_h(x_i) \cdot f_h(x_i)}{\sum_{h=1}^{m_r} A_h(x_i)} \quad (10)
\]

where the weight of each rule \( \tau_h \), for the current input \( x_i \) is determined by the Gaussian law, which ensures the greatest possible generalization

\[
\tau_h = \exp(-\alpha \|x - x_h^*\|^2) \quad h = 1, \ldots, m_r \quad (11)
\]

where \( \alpha = \frac{4}{\sigma^2} \).

C. Trade-off between complexity and accuracy

Among various methods to obtain a trade-off between complexity and accuracy of the fuzzy model, an improved Akaike Information Criterion (AIC) \[15\] is used in this paper. Number of model parameters may be considered as the model complexity criterion. So, using equation 12, model error and complexity are minimized simultaneously.

\[
AIC = N \log(\text{MSE}) + 2m_p \quad (12)
\]

\[
m_p = m_a + m_c + cm_r \quad (13)
\]

where \( m_r \) is equal to the number of clusters \((N_r)\), and \( c \) is a constant that allows the user to incorporate heuristics regarding the relative importance for reducing the number of fuzzy rules. \( m_r \) is determined using GA.

D. Genetic algorithm application

GA minimizes the AIC as the fitness function. GA has a chromosome of two elements \((m_r, s)\) and is implemented to find the optimal values. The fitness function is as follows:

\[
f(m_r, s) = \log(\text{MSE}) + \frac{2(m_a + m_c + cm_r)}{N} \quad (14)
\]

MSE is calculated using:

\[
\text{MSE} = \frac{\sum_{k=1}^{N} \left(\theta^c_{hs}(k) - \theta^{m_{sr}}_{hs}(k)\right)^2}{N} \quad (15)
\]

Finally, the procedure of TSK fuzzy model identification is summarized in Fig. 1.

IV. CASE STUDY

In this section, fuzzy and IEEE thermal models of a sample distribution transformer are identified. Then, based on these models, dynamic loading capability of this transformer is assessed. The transformer main characteristics are shown in Table I.

The measured values of the hot spot temperature which is required for fuzzy thermal model training and validation are gained through cooperation with the authors of [9]. These measurements are carried out using fiber optic sensors.

| TABLE I. SAMPLE TRANSFORMER PARAMETERS |
|------------------|------------------|
| Rated Power      | 25kVA            |
| \( V_{primary} / V_{secondary} \) | 10kV/400V    |
| Iron Loss        | 195W             |
| Copper Loss (full load) | 776W        |
| Weight of core and core assembly | 136kg      |
| Weight of oil    | 62kg             |
| Total weight     | 310kg            |
| Dimensions of tank | 64×16×80cm |
| Cooling mode     | ONAN             |
| Nominal hot spot temperature | 78˚C         |

A. Thermal modeling

IEEE and fuzzy thermal models parameters are shown in
Tables II and III, respectively. Transformer load and the HST profiles (Training Set) shown in Fig. 2 are used for fuzzy thermal model training. To show the fuzzy model ability to maintain its accuracy for different load profiles, values shown in Figs. 3 are used as the Validation Set.

Hot spot temperatures for the Training and Validation load profiles, estimated by the fuzzy and IEEE models, are compared with the measured temperatures in Figs. 4 and 5. Also, Peak Error (PE) and MSE of each model (estimated temperature subtraction from measured temperature) are presented in Table IV. It is observed that the fuzzy model is significantly more accurate than the IEEE model. Furthermore, temperatures estimated by the IEEE model are generally greater than the measured values. In the other words, IEEE model has conservative results.

**TABLE II. IEEE MODEL PARAMETERS**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \theta_{hs, \text{rated}}$</td>
<td>5°C</td>
</tr>
<tr>
<td>$\Delta \theta_{oil, \text{rated}}$</td>
<td>54°C</td>
</tr>
<tr>
<td>$\tau_{hs}$</td>
<td>0.1 h</td>
</tr>
<tr>
<td>$\tau_{oil}$</td>
<td>3 h</td>
</tr>
<tr>
<td>$R$</td>
<td>4</td>
</tr>
<tr>
<td>$m$</td>
<td>0.8</td>
</tr>
<tr>
<td>$n$</td>
<td>0.8</td>
</tr>
<tr>
<td>$\theta_{\text{amb}}$</td>
<td>18°C</td>
</tr>
</tbody>
</table>

**TABLE III. FUZZY MODEL PARAMETERS**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of rules</td>
<td>2</td>
</tr>
<tr>
<td>Number of membership functions</td>
<td>2</td>
</tr>
<tr>
<td>Membership function type</td>
<td>Gaussian</td>
</tr>
<tr>
<td>Membership functions spreads</td>
<td>0.1567</td>
</tr>
</tbody>
</table>

**Fig. 2.** Training Set: a. Transformer load profile b. HST profile

**Fig. 3.** Validation Set: a. Transformer load profile b. HST profile

**Fig. 4.** Training Set estimated HST profile

**Fig. 5.** Validation Set estimated HST profile

**TABLE IV. THERMAL MODELS ERROR (°C)**

<table>
<thead>
<tr>
<th>Model</th>
<th>Training Set</th>
<th>Validation Set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MSE PE</td>
<td>MSE PE</td>
</tr>
<tr>
<td>IEEE Model</td>
<td>16.55 -7.70</td>
<td>37.63 -8.45</td>
</tr>
<tr>
<td>Fuzzy Model</td>
<td>1.07 3.59</td>
<td>1.92 -3.95</td>
</tr>
</tbody>
</table>

**Table IV. THERMAL MODELS ERROR (°C)**
### B. Dynamic loading capability assessment

In this section, a new method for transformer dynamic loading capability assessment based on previously identified thermal models is presented. In this method, a dynamic loading factor (DLF) is defined. Then, the transformer admissible load profile is calculated by multiplying DLF by daily load profile. DLF is determined in such a way that the transformer insulation loss of life reaches its nominal value under the calculated admissible load profile.

According to IEEE C57.91-1995 standard [2], the relationship between HST and aging acceleration factor, $F_{AA}$, is as follows:

$$ F_{AA} = \exp \left[ \frac{15000}{\theta_{hs,rated} + 273} - \frac{15000}{\theta_{hs}} \right] \text{ (per unit) } \tag{16} $$

where “per unit” is based on the normal ageing rate, i.e., the rate at $\theta_{hs} = \theta_{hs,rated}$.

The insulation loss of life, $LL$, over a given loading period, $T$, is given by [3]:

$$ LL = \int_{0}^{T} F_{AA} \, dt \tag{17} $$

So, the insulation loss of life in percentage terms is:

$$ \% LL = \frac{LL \times 100}{NL} \tag{18} $$

Insulation normal life, $NL$, is 7500 days [2]. So, the nominal daily loss of life is equal to 0.0133%.

According to equations 16-18, DLF is calculated based on the fuzzy and IEEE models estimated HST profile. Calculated DLF values considering Training and Validation load profiles are shown in Table V. As observed, DLFs calculated using the IEEE model for training set, validation set 1, and validation set 2 are approximately 0.06, 0.1, and 0.05 less than ones calculated by the fuzzy model. It is due to the conservative nature of the IEEE model. So, application of this model underestimates the transformer loading capability.

<table>
<thead>
<tr>
<th>Training Set</th>
<th>Validation Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEEE Model</td>
<td>Fuzzy Model</td>
</tr>
<tr>
<td>1.313</td>
<td>1.373</td>
</tr>
<tr>
<td>IEEE Model</td>
<td>Fuzzy Model</td>
</tr>
<tr>
<td>1.569</td>
<td>1.671</td>
</tr>
</tbody>
</table>

### V. Conclusion

A new method for transformer dynamic loading capability assessment has been presented. Firstly, high accuracy of the fuzzy model was demonstrated through the comparison of the estimated values with the measured ones.

Then, the method of transformer dynamic loading capability assessment has been described and applied to a sample distribution transformer using the fuzzy and IEEE thermal models. It has been observed that the application of IEEE model underestimates the transformer loading capability due to its conservative nature. Transformer loadability underestimation leads to considerable loss of revenue of utilities particularly in deregulated environment.

### REFERENCES


