A Probabilistic Approach for Power Transformer Dynamic Loading Capability Assessment

B. Shahbazi¹, M. Savaghebi ², M. Shariati³

Abstract – Power transformers are among the most critical and expensive equipment of the power system. So, transformer proper loading has been an important issue in power system operation. In order to have a reliable estimate of transformer loading capability, it is necessary to consider the uncertainty of load and ambient temperature. To cover this mater, a probabilistic method for dynamic loading capability assessment is proposed in this paper. In this method, probability distribution functions of load and ambient temperature is determined and loadability assessment is carried out using Monte Carlo simulation. The proposed approach is illustrated by a case study on the load and ambient temperature practical data of a transformer equipped with a transformer online monitoring system.

Keywords: Power transformer, Dynamic loading, Probabilistic method, Mont Carlo simulation

Nomenclature

s: Laplace operator
K: Transformer load (pu)
Δθₜₗ: Hot spot to top oil gradient at rated current (°C)
Δθₜₗ: Hot spot to top oil gradient at the load considered (°C)
Δθₚ: Top oil temperature rise in steady state at rated losses (no-load losses + load losses) (°C)
θₚ: Hot spot temperature (°C)
θₜ: Top oil temperature (°C)
θₐ: Ambient temperature (°C)
x: Oil exponent
y: Winding exponent
R: Ratio of load losses at rated current to no-load losses
k₃₁, k₃₂, k₃₃: Thermal model constants
τ₅₆: winding time constant (min)
τ₅₆: Average oil time constant (min)
Fₐₐ: Ageing acceleration factor (ageing rate)
LL: Insulation loss of life.
NL: Insulation normal life (7500 days)
U: Randomly generated number considering the uniform distribution U(0,1)
F⁻¹: The inverse function of cumulative probability distribution function
Q: The domain of each of the parameter of the distribution.
HST: Hot (hottest) spot temperature
PDF: Probability density function
TMS: Transformer monitoring system
TREC: Tehran Regional Electric Company
NRI: Niroo Research Institute

I. Introduction

The largest portion of capital investment in transmission and distribution substations is made in power transformers. Furthermore, power transformer outages have considerable negative impacts on power system operation. The most important impacts are reliability reduction and economic losses due to time and cost consuming repair/replacement process of power transformers.

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 (hottest) spot temperature (HST) as the main limiting factor of loading capability [2].

So, in order to have a reliable assessment of transformer loadability, it is necessary to have as exact as possible estimation of HST. To do this, IEEE and IEC have proposed guides [1], [2] for loading of power transformers which include well-known and simple thermal models which have been used in the practical applications throughout the world.
Also, various other thermal models have been presented in recent years. Some of the models are based on analogous electrical model of the transformer thermal performance [3-9]. Utilizing these models, the accuracy of HST estimation is improved. But, calculation of HST is far more complex using these models compared to loading guides model, especially in terms of number of model parameters and computational effort.

In [10] and [11] a thermal model has been developed based on boundary value problem of heat conduction in transformer winding using finite integral transform techniques. The model requires, in addition to electrical parameters of the transformer, information on the actual design data. This model gives the winding temperature distribution of the winding and so, is capable of determination of the hot spot location. But, this model consists of numerous complicated differential equations with many parameters. Also, the experimental validation of the model is not presented.

The models presented in [12-16] are based on artificial intelligence techniques. In order to develop such a model, at first, it is necessary to have a large number of measured HST points to train the intelligent model. Then, the model can estimate the HST for other operating conditions. The intelligent models offer an excellent accuracy if the training set is selected properly. The main challenge of using these models is the exact measurement of HST which usually is done by fiber optic sensors. In practice, performing this measurement is technically difficult and economically unattractive [17]. On the other hand, the accuracy of these models is dependent on the smart selection of the training data [12]. Also, the models are valid only in the load and ambient temperature ranges that covered in the training stage.

In digest, these thermal models presented in [3-16] are not completely proper for practical applications such as power system operation and planning for at least two reasons. At first, these models are not widely accepted, because their performance in various operating conditions has not been assured. Secondly, their implementation is not straightforward because their relative complexity and various necessary parameters.

On the other hand, the estimation of HST is just the first step toward transformer loading capability assessment. Then, according to the estimated HST, the operator must decide on transformer loading.

It is not practical for large scale power systems to be operated based on instantaneous HST of the transformers. So, especially for long term planning, it is necessary to evaluate the thermal performance of the power transformers based on the estimated load profiles. In all the previously mentioned studies, it is assumed that the ambient temperature and loading profiles are known exactly. In the other words, the hot spot estimation is carried out in a deterministic approach. But, in practice it is not necessarily correct. Because, load and ambient temperature are probabilistic in nature and always there is some uncertainty in the estimated values [18]. Usually, the uncertainty is considered by conservative loading of power transformers in order to avoid the damages originated from overloading. This can lead to substantial revenue loss especially in the deregulated environment.

In this paper, the uncertainty is taken into account by considering PDF for load and ambient temperature. Based on these PDFs, the loading limit is assessed probabilistically and the confidence interval of the assessment is evaluated. The proposed method is illustrated based on practical load and ambient temperature data. The data are measured by an TMS installed by the authors on a transformer in one of the substation of TREC.

This paper is organized as follows. In Section II, a brief introduction on the TMS is presented. The proposed approach for loading capability assessment is described in Section III, IV. Section V presents a case study using the proposed method. Finally, the paper is concluded in Section VI.

II. Online Transformer monitoring system

Nowadays, there is an increasing interest in applying TMS which can provide exact status information to extend transformer lifetime as well as save cost through reduced maintenance.

For these reasons, NRI pioneered the design of such systems in Iran and following successful results obtained from functional and Electromagnetic Compatibility tests, TMS was installed and tested in the 230 kV Kan substation of TREC. The configuration of TMS installed in Kan is presented in Fig. 1.

In TMS data from different parts of the transformer are acquired by appropriate sensors and transferred to the process control layer. Furthermore, in order to display online and historical data, an additional feature is provided by a PC which consists of HMI software.

![Fig. 1. The configuration of TMS installed in Kan substation](image_url)

The main capabilities of TMS are as follows:

- **Main capabilities of TMS**
  - Display online and historical data
  - Provide additional features through PC with HMI software

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- Ambient temperature measurement (measurement range: -30-60°C, tolerance according to EN 60751 cl. B [19])
- Tank top and bottom oil and tap-changer temperature measurement (measurement range: -20-140°C, Tolerance according to EN 60751, cl. B [19])
- Dissolved gas monitoring (with accuracy of 5%+/−15ppm)
- Moisture in-oil measurement (measurement range: 0-1, with accuracy of +/-0.02 in 0-0.9 and +/- 0.03 in 0.9-1)
- Winding hot spot temperature calculation (using IEC60076-7 thermal model)
- Voltage, load and power measurement (for both HV and LV windings and calculation of reactive power and power factor using these measurements)
- Calculation of transformer loss of life
- Transformer cooling system control

More details about NRI-TMS are presented in [20]-[23].

### III. Loading capability assessment

#### III.1. Transformer thermal model

In TMS, HST is calculated using IEC thermal model [2]. The block diagram of HST calculation is depicted in Fig. 2. Parameters used in this figure are as follows:

Among these parameters, ambient and top oil temperatures and transformer load are measured by sensors and other parameters are extracted from transformer documents.

![Block diagram of HST calculation](image)

As it is shown in Fig. 2, either measured or calculated values of $\theta_0$ may be used. In order to enhance the accuracy of $\theta_0$ calculation, measured value $\theta_0$ is used in TMS. However, $\theta_0$ is also calculated to enable some features of TMS such as cooling system malfunction detection [23] or used for HST estimation in the case of oil temperature measurement problems.

Characteristics of the power transformer on which the TMS is installed are shown in Table I. Also, cooling system basic control settings are presented in Table II. These settings may be changed by TMS according to transformer operating conditions [20], [21].

IEC60076-7 has proposed some typical values for thermal model parameters. Of course, the exact thermal model parameters differ from one transformer to another. In order to enhance the accuracy HST estimation, the parameters of the thermal model of the considered transformer are extracted from design data.

Another noteworthy point is that the real parameters are a little different from design data due to manufacturing tolerances and transformer minor changes due to operation, probable repairs and etc.

#### TABLE I

<table>
<thead>
<tr>
<th>POWER TRANSFORMER PARAMETERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type Core type</td>
</tr>
<tr>
<td>Number of Phases</td>
</tr>
<tr>
<td>Rated Power (ONAN/ONAF/OFAF)</td>
</tr>
<tr>
<td>Vprimary/Vsecondary</td>
</tr>
<tr>
<td>Rated Frequency</td>
</tr>
<tr>
<td>Iron Loss</td>
</tr>
<tr>
<td>Copper Loss (full load)</td>
</tr>
<tr>
<td>Weight of Copper</td>
</tr>
<tr>
<td>Weight of oil</td>
</tr>
<tr>
<td>Total weight</td>
</tr>
<tr>
<td>Cooling modes</td>
</tr>
<tr>
<td>Nominal hot spot temperature</td>
</tr>
</tbody>
</table>

#### TABLE II

<table>
<thead>
<tr>
<th>BASIC COOLING SYSTEM SET POINTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooling Mode Transition</td>
</tr>
<tr>
<td>ONAF1 ON</td>
</tr>
<tr>
<td>ONAF1 OFF</td>
</tr>
<tr>
<td>ONAF2 ON</td>
</tr>
<tr>
<td>ONAF2 OFF</td>
</tr>
<tr>
<td>OFAF ON</td>
</tr>
<tr>
<td>OFAF OFF</td>
</tr>
</tbody>
</table>

As mentioned before, $\theta_0$ is measured in TMS with a good accuracy. The measured values may be used to estimate the parameters used for $\theta_0$ calculation. In the TMS, these parameters are tuned to match the calculated $\theta_0$ values with the measured ones. The tuning is performed monthly to consider environmental conditions and possible changes due to other factors. The tuning process is based on making small deviations from parameters extracted considering IEC60076-7 and design data in a way that calculation error is minimized [23]. In Table III thermal parameters of the considered transformer is shown.

#### TABLE III

<table>
<thead>
<tr>
<th>THERMAL PARAMETERS OF THE CONSIDERED TRANSFORMER</th>
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III.2. Load limiting criteria

The winding hot spot temperature is considered to be the most critical parameter in the determination of transformer loadability. It determines the loss of insulation life (insulation ageing) and indicates the potential risk of releasing gas bubbles for a severe overload condition [24]. According to IEEE C57.91-1995 standard[1], transformer insulation normal life is 7500 days. So, the nominal daily loss of life is equal to 0.0133%. The following equations are suggested in this standard and IEC 60076-7 standard[2] for calculating the insulation loss of life:

\[
F_{AA} = \exp\left[\frac{15000}{383} - \frac{15000}{\theta_a + 273}\right] 
\]

\[
F_{AA} = 2^{(\theta_a - 98)/6} 
\]

\[
LL = \int_0^T F_{AA} dt 
\]

\[
%LL = \frac{LL \times 100}{NL} 
\]

On the other hand, when heat is generated during an overload condition, the dissolved water vapor in the cellulose insulation expands, causing bubble formation. Gas bubbles within transformers are of concern because the dielectric strength of the gases is significantly lower than the dielectric strength of the oil or the cellulose insulation. So, bubbles formation may lead to insulation breakdown [1], [24].

The most important factor in bubble formation is the water vapor content of the transformer. The temperature at which bubbles begin to form at the hot spot location varies considerably, depending on the moisture content. For transformers which have moisture of about 2% of insulating paper weight, bubbles have been observed to start to form at about 140 °C [25].

IV. Probabilistic method for loading capability assessment

In this section, a probabilistic approach is proposed for transformer loadability assessment. This approach is mainly based on Monte Carlo simulation method. So, a brief introduction of this method is presented, at first. Then, the details of loadability evaluation are discussed.

IV.I. Monte Carlo Simulation

Monte Carlo simulation is a type of simulation that relies on repeated random sampling and statistical analysis to compute the results [26]. The following steps are typically performed for the Monte Carlo simulation of a physical process:

- **Deterministic (Static) Model Generation [27],[28]:** Every Monte Carlo simulation starts off with developing a deterministic model which closely resembles the real scenario. In this deterministic model, most likely value (or the base case) of the input parameters (K and \( a \) in this paper) are used. Then, mathematical relationships (transformer thermal model in this paper) are applied to use the values of the input variables, and transform them into the desired output (HST in this paper).

- **Input Distribution Identification:**

  Then, the risk components are added to the deterministic model. In the other words, the underlying distributions which govern the input variables are identified [27]. This step is also called distribution fitting and needs historical data for the input variables. Each probability distribution can be uniquely identified by its parameters, so, distribution fitting is essentially the same as finding the parameters of a distribution that would generate the given data in question.

  Some methods have been presented for distribution fitting such as ML, Method of Moments and Nonlinear Optimization [27]. Amongst them, ML method is most popular and efficient method [29]. So, this method is used in this paper.

  To describe the ML method, let \( q \) be the parameter vector for \( f \), which is the probability density function and the sample drawn from the distribution be \( x_1, x_2, \ldots, x_n \). Then, the likelihood of getting the sample from the distribution is given by [27]:

  \[
  L(q) = f(x_1, x_2, \ldots, x_n \mid q) 
  \] (5)

  This can be thought of as the joint probability density function of the data, given the parameters of the distribution. Given the independence of each of the datapoints, this can be expanded as follows [27]:

  \[
  L(q) = \prod_{i=1}^n f(x_i \mid q) 
  \] (6)
In the ML method, the objective is to find the value of $q$ so that the value of $L(q)$ can be maximized. Since this is a product of probabilities, it is more convenient to consider the log of this function for maximization. So, the ML method can be thought of as a nonlinear unconstrained optimization problem as given below [26]:

$$\max LL(q) = \sum_{i=1}^{n} \ln f(x_i | q) \quad q \in Q \quad (7)$$

- **Random Samples Generation:**
  In this step, a set of random samples are generated from the distributions. One set of random numbers, will be used in the deterministic model, to provide one set of output values. Then, this process is repeated by generating more sets of random numbers, one for each input distribution, and different sets of possible output values are collected. [26,27]. This part is the core of Monte Carlo simulation.

  There are a couple of methods for generating random samples from distributions such as Composition, Convolution, Acceptance-Rejection and Inverse Transformation [26-29]. Inverse Transformation method provides the most direct route for generating random samples from a distribution [27] and is used in this paper.

  In this method, the inverse of the PDF is used to convert a random number between 0 and 1 to a random value for the input distribution. The process can be mathematically described as follows.

  Assuming $X$ as the random variable, the following two steps will generate a random value of $X$ from the PDF [27]:
  1- Generate $U \sim U(0,1)$
  2- Return $X = F^{-1}(U)$

- **Analysis and Decision Making:**
  Then, statistical analysis is performed on the output values. This step provides the statistical confidence for the decisions which are made after running the simulation [28].

  Aggregating the output values into groups by size and displaying the values as a frequency histogram provides the approximate shape of the probability density function of an output variable [27].

  Alternatively, the output values can be fitted to a probability distribution, and the theoretical statistics of the distribution can be calculated. These statistics can then be used for developing the confidence bands [27]. The precision of the expected value of the variable and the distribution shape approximations improve as the number of simulation trials increases [29].

**IV.2. Loading capability assessment algorithm**

The procedure of the loadability capability assessment is shown in Fig. 3. The following algorithm is proposed for loadability assessment:

- Extract the PDFs of ambient temperature and transformer load at each hours (48 PDFs) using the measured values
- Generate $N$ random samples of ambient temperature and load for each hour from the identified PDFs (48*N data-points)
- Build $N$ 24-hour profiles for ambient temperature and transformer load
- Calculate DLF values for each pair of profiles (ambient temperature and load profile for each 24-hour sample) according to section.
- Identify the PDF of calculated DLF values and determine the confidence interval for DLF

![Fig. 3. Loading capability assessment algorithm](image)

**IV.3. DLF calculation**

In the proposed method, the transformer admissible load profile is calculated by multiplying DLF by the daily load profile. DLF is determined in such a way that under the resulted admissible load profile, the transformer daily insulation loss of life reaches its nominal value (0.0133%) as well as the hot spot temperature does not exceed the limit of 140°C. In fact, DLF is the maximum scaling factor which can be applied to current system load profile without exceeding the operating limits. Of course, the minimum of the DLF values calculated considering the nominal LL and maximum HST will be selected.
V. Case study

A three-month period of 1 July-30 September which is considered to be the hottest period of the year is considered. The measured load and ambient temperature of the transformer with the parameters of Table I are shown in Figs. 4 and 5 respectively. The data are recorded by TMS. The calculated HST values using the thermal model of Section III.1 are shown in Fig. 6.

Now, the algorithm described in Section IV is applied to these data. Of course, all of the numerous data generated for loadability assessment cannot be shown here. So, only the data of 2 hours (of 24 hours) are presented.

These hours are 2-3 AM, 2-3 PM. The Measured values of ambient temperature and transformer load for these hours are shown in Figs. 7-10.
The fitted distributions of Figs. 7-10 are shown in Figs. 11-14 respectively. For this purpose, it is assumed that the values have the normal distribution.

The sampled values from each distribution and the corresponding histograms are shown in Figs. 15-18. As it can be seen number of samples for each hour is N=500.
Now, the load and ambient temperature profiles are constructed for each sample and the corresponding DLF value is calculated. This calculation must be repeated 500 times. It is noteworthy that in this case the Nominal LL criterion is more limiting than maximum HST (140°C) criterion. So, the values calculated considering Nominal LL are reported.

The result is 500 DLF values which are depicted in Fig. 19. Also, the histogram of these values can be seen in Fig. 20.

Now, a normal distribution is fitted to the calculated DLF values. The resulted PDF is shown in Fig. 21. As it can be seen, Mean and standard deviation of this PDF are 1.555 and 0.132 respectively.

To make a physical sense of these values the confidence intervals [30] of DLF is determined. The calculated 95% and 99% confidence intervals are [1.297 1.812] and [1.218 1.892], respectively. X% confidence interval means that it is guaranteed with X% probability that the DLF values will be in the interval.

The confidence intervals can be used by power system operator to make wise decisions about the transformer loading. Of course, the high limit of the interval leads to more operation risk. In facts, the operator can select a DLF value from the intervals and scale the current transformer load according the amount of acceptable risk. It is obvious that although, the considered time interval in this paper is 3 months, the similar analysis may be carried out for any time interval. For example, to be more precise, the proposed approach may be applied to one-year intervals if the sufficient recorded data are available.
VI. Conclusion

A new probabilistic approach for transformer dynamic loading capability assessment has been proposed. This approach is mainly based on the Monte Carlo simulation which considers the uncertainty of transformer load and ambient temperature. To perform such statistical analysis it is necessary to have a large amount of recorded data. The data used in this paper are recorded by an online transformer monitoring system which is designed and installed by the authors.

A factor named DLF has been defined for loadability assessment. Monte Carlo method is applied for calculating confidence intervals for DLF. According to these intervals, the operator is able to make reasonable decisions about the transformers loading.

As a future study, risk assessment for transformer loading and the amount of acceptable risk is under investigation by authors.

References

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