Forecasting transformer reliability

van Schijndel, A.; Wetzer, J.; Wouters, P.A.A.F.

Published in:
IEEE Conference on Electrical Insulation and Dielectric Phenomena 2006

Published: 01/01/2006

Document Version
Publisher’s PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

• A submitted manuscript is the author's version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.

Link to publication

Citation for published version (APA):
Forecasting Transformer Reliability

Arjan van Schijndel\textsuperscript{1}, Jos M. Wetzer\textsuperscript{1,2} and P.A.A.F. Wouters\textsuperscript{1}

\textsuperscript{1}Group Electrical Power Systems, Eindhoven University of Technology, the Netherlands
\textsuperscript{2}KEMA, Arnhem, the Netherlands

Abstract: In this paper the concept of an integral transformer lifetime model is presented. The model provides the best possible prediction of future behaviour given the data available. It treats remaining life in terms of future failure probability, thereby giving better support to the decision taking process than a mere remaining life estimate. The core of the model is a generic description of ageing processes, coupled to a probabilistic approach. The approach presented utilizes various techniques to reduce the uncertainty that is inherent to modelling processes with incomplete knowledge of the operational history. One technique couples the process model to externally measurable quantities; another technique involves a sensitivity analysis, which shows what additional input data gives the most efficient way to improve accuracy. We will illustrate the approach by applying it to a well-known degradation process: thermal degradation of the transformer winding insulation.

Introduction

In electrical power transmission and distribution networks power transformers represent a crucial group of assets both in terms of reliability and of investments. The major concerns which drive asset managers to decisions are related either to the age of equipment or to the power demands that have increased over the years. In order to safeguard the required quality at acceptable cost, it is of great importance to base decisions on a reliable forecast of future behaviour. The work presented forms part of a research project aiming at transformer reliability forecasting models.

Most transformer lifetime models developed so far are limited to the degradation of the transformer winding insulation. The aim of the present study is to develop an integral transformer lifetime model which involves all relevant degradation mechanisms for all relevant subsystems, applicable to individual power transformers and transformer populations, and allowing for a variety of external input (measured data, historical information) to improve the forecast accuracy.

In this paper we focus on forecasting power transformer reliability or, more accurately, on forecasting power transformer failure probability. We will present the conceptual design of a predictive model which involves three essential ingredients: failure statistics, physical understanding of the degradation process, and actual knowledge of the present condition. The core of the model is a generic description of ageing processes that allows one to predict lifetime in terms of future condition and failure probability.

For the purpose of illustration and validation the model will be applied to (but is not limited to) one degradation process: the degradation of the transformer winding insulation.

Present status and model requirements

Most transformer lifetime models employed focus on paper degradation as the dominant mechanism determining the transformer remnant life. Other common failure modes such as bushing and tap changer failures are not included in predictive models.

Commonly used paper degradation models are based on Arrhenius’ law and are presented in one of different versions of the loading guide \cite{1}–\cite{3} which predicts the relative degradation as compared to a default loading pattern. This approach has several drawbacks. First of all, the loading guide does not predict the remnant life but the amount of consumed life compared to a not well specified reference. Secondly, the prediction can not be verified or calibrated by measuring externally accessible indicators. Finally the loading guide does not take into account the probabilistic nature of the degradation process and thereby gives no information on uncertainty intervals.

The present research aims at an integral power transformer lifetime model. The integral aspect refers to the requirement that the model is able to treat all relevant degradation mechanism of all relevant subcomponents. The model will be able to handle different types of diagnostic and failure data and gives the best possible prediction of failure probability given the data available. The model is being developed for application to both individual transformers and transformer populations.

In order to facilitate the development of such a model we have first designed a generic "condition change model" which describes an arbitrary "change of condition" process, and which may be applied to various types of degradation processes. In order to overcome the drawbacks in present models we have introduced:

- the concept of quality parameters (externally measurable indicators by which relative degradation information can be transformed to absolute values)
- a probabilistic approach (yielding the failure probability as a function of time rather than the remnant life), and
a feedback loop including a sensitivity analysis which enables accuracy improvement by adding specific additional data.

Figure 1: Asset model.

Figure 2: Generic condition change model.

Conceptual design

Asset model

The driving force for this work is the asset manager’s need for a tool to support decisions. This tool is the power transformer asset model. This asset model involves a technical part, the component model, and a decision model that uses the component model to analyse decision scenarios. A schematic view of the asset model is shown in Fig. 1.

The aim of the present work is to develop the component model: an integral transformer lifetime model which is able to treat all relevant degradation mechanism of all relevant subcomponents, and which can handle different types of input. In order to facilitate the development of such a model we first present a generic "condition change model". Consecutively a component model is constructed by combining the relevant condition change models and their interactions.

Condition change model

In the model condition change is regarded as the transition from one state to a next state. The present state is given by the present condition, the present running mode and the present triggers that may provoke state changes. The change of state describes the degeneration or regeneration which leads to a next state. The change process may be influenced by external stimuli (enhanced stress, lightning, short circuit) or by internal stimuli that are already part of the present state (design or manufacturing errors, natural and previous ageing). Some change processes are gradual (thermal ageing), some are sudden (lightning, short circuit). Also gradual processes may provoke a sudden change when a threshold is exceeded. The condition change model is schematically shown in Fig. 2.

The output of a condition change model is the new state the condition is transformed into. This state is expressed in the values of the condition parameters. Since the present model is developed as a tool for decision support it also involves the option of a classification of condition parameters, based on significant thresholds. As an example we regard a condition decay process with two threshold limits, the technical specification limit and the functional requirement. Initially the component exceeds both limits and is regarded healthy. In the course of time the condition will drop below the specification threshold: it no longer meets the specification but is still able to function properly. We call this a defective state. Eventually the condition drops below the threshold required for functioning properly. We call this the faulty state: as soon as this requirement is called upon the component will fail and enter the failed state. Hence we distinguish 4 states: healthy, defective, faulty and failed. The classification is illustrated in Fig. 3.

Component model

The aim of the component model is to provide the best possible prediction of future failure probability, given the data available. The generic condition change model is applied to calculate the condition of the relevant subcomponents based on their degradation processes. Consecutively a probabilistic approach is used to calculate the failure probability and its uncertainty margin. Further the model involves two techniques to reduce the uncertainty that is inherent to modelling processes with incomplete knowledge of the
history. The first one is coupling the model to externally measurable quantities, the so-called quality parameters. The second technique involves a feedback loop with a sensitivity analysis. This analysis shows what additional input data gives the most efficient way to improve accuracy. The component model is shown in Fig. 4.

**Application to winding insulation**

As an example of our lifetime modelling approach we discuss the well-known thermal degradation process of the winding insulation. The approach commonly applied makes use of a loading guide, relating transformer load to loss of life. This approach does not provide an indication of the accuracy of the result, nor can it be directly related to measurable quantities to validate the output or improve the accuracy. In the approach presented here we reintroduce the physical degradation process and develop a probabilistic approach coupled to the degree of polymerisation (DP) as the externally measured quantity.

**Loading guide**

The original IEC loading guide [1] and the IEEE loading guide [2] have recently been combined in an updated IEC document [3]. The key quantity governing loss of life is the hot-spot temperature, $\theta_h$, in degree Celsius. The relative ageing rate, $V$, for Kraft paper is given by

$$ V = \frac{\theta_h - 98}{6}. $$

(1)

For thermally upgraded paper the relative ageing rate yields

$$ V = \exp\left(\frac{15000}{110 + 273} - \frac{15000}{\theta_h + 273}\right). $$

(2)

The loss of life $L$ as a function of time is then given by

$$ L = \int_{t_1}^{t_2} V \, dt. $$

(3)

Figure 5 shows the loss-of-life of Kraft paper and thermally upgraded paper for different temperatures. In the majority of transformers the hot-spot temperature is not measured, but is calculated from the top-oil temperature with a model relating top-oil and hot spot temperature. The top-oil temperature can be measured or it may be calculated from dynamical or semi static load-profiles [1–3]. The different loading guides show a good agreement between the different approaches provided an accurate load-profile is used.

**Insulation paper**: Most transformers manufactured in Europe before 1990 use Kraft paper as winding insulation, which was later replaced by thermally upgraded paper. In the USA the winding insulation predominantly uses thermally upgraded paper.

**Reference lifetimes**: The loading guide predicts ageing relative to a reference lifetime, the nominal life of the insulation. Table I presents values for the nominal life of Kraft paper derived from different sources. Similarly Table II shows the results obtained for thermally upgraded paper. The values derived from the loading guide [3], [4] seem to be in agreement with the work of Emsley [5], whereas Lundgaard [6] predicts a much lower nominal life.

**Restrictions**: The loading guides allow a comparison between different loading scenarios with respect to ageing but do not predict the lifetime with sufficient accuracy, nor can they easily be linked to diagnostic information for comparison or improvement. Further it should be taken into account that the presence of water and oxygen may seriously affect the results [7].

**Degradation process**

The loading guides implicitly refer to the quality of the insulation paper, which is directly linked with the tensile strength or the degree of polymerisation (DP) [5-10]. In a laboratory situation the degree of polymerisation may be determined from paper samples; in practice it may be determined indirectly from oil analysis [11–14]. In this work
Table 3: Parameters used in simulations.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP_{threshold}</td>
<td>250 ±50</td>
</tr>
<tr>
<td>DP_{initial}</td>
<td>1100 ±10 %</td>
</tr>
<tr>
<td>DP_{5 yrs}</td>
<td>497 ±10 %</td>
</tr>
<tr>
<td>A</td>
<td>1.07\times10^8 s^{-1} ±25 %</td>
</tr>
<tr>
<td>ΔA_{5 yrs}</td>
<td>10%</td>
</tr>
<tr>
<td>E_a</td>
<td>111 kJ/mol ±0 %</td>
</tr>
<tr>
<td>T=θ</td>
<td>98 ±5 °C</td>
</tr>
</tbody>
</table>

The DP-value is chosen as the "quality parameter" linking relative ageing to absolute values because it is most directly linked with the ageing process and is externally measurable.

The DP decay follows Ekenstam’s equation [5]:

\[
\frac{1}{DP_t} - \frac{1}{DP_{initial}} = rn(t),
\]

in which \( rn(t) \) is the time dependent reaction number. Emsley [5] describes \( rn(t) \) as a first order process:

\[
rn(t) = k t
\]

in which \( k \) is described with the Arrhenius’ relationship,

\[
k = A \exp \left( -\frac{E_a}{R \cdot T} \right),
\]

Here \( T \) is the temperature in Kelvin, \( R \) is the universal gas constant, \( E_a \) is the activation energy and \( A \) is a pre-exponential.

Error propagation

An error propagation analysis [15, Ch. 10] of (4) and (5) yields:

\[
\frac{\Delta DP(t)}{DP(t)} = \sqrt{\left(\frac{\Delta DP_{initial}}{DP_{initial}}\right)^2 + \left(\frac{\Delta k}{k \cdot DP_{initial}}\right)^2 \cdot t^2},
\]

Here \( \Delta DP_{initial} \) is the error of the initial DP-value and \( \Delta k \) the deviation of reaction rate. A graphical representation with the values given in Table 3 is presented in Fig. 6. It shows that an a priori calculation with realistic conditions may result in large uncertainties.

Failure probability

As presented in the previous paragraph the lifetime obtained from the loading guide shows large uncertainties. This calls for a probabilistic approach. Instead of determining a value for the residual life we will determine the failure probability as a function of time and consecutively aim at reducing the error by introducing externally measurable parameters.

The failure probability is defined as the probability for the DP-value to be lower than the threshold value. This involves two probability distributions. The first is the probability distribution of the DP-value at time \( t \). The probability of DP having a value between \( x \) and \( x+dx \) at time \( t \) is denoted as \( p_{DP}(x,t)dx \). The second distribution is that of the threshold DP-value below which the insulation fails. The probability of the threshold having a value between \( x \) and \( x+dx \) is denoted as \( p_{th}(x)dx \). The probability that the threshold is above a certain DP-value \( x \) is given by:

\[
P_{th}(x) = \frac{1}{x} p_{th}(x)dx.
\]

Finally the failure probability at time \( t \) is obtained:

\[
P_f(t) = \int_{0}^{\infty} p_{th}(x)p_{DP}(x,t)dx.
\]

As an illustration we have used normal probability density functions. This type of distribution is appropriate for physical processes with relatively modest deviations. The standard deviation is chosen equal to half of the accuracy bandwidth. The parameters used in the calculations are presented in Table 3. The \( A \) and \( E_a \) values correspond with the values for Kraft paper obtained by Emsley [5]. Figure 7 shows the resulting probability density functions at different times (1, 5 and 10 years) together with density function of the threshold DP-value. Also shown is a typical measured distribution function after 5 years and resulting DP distribution after 10 years. Finally, Fig. 8 and 9 shows the failure probability as a function of time, for the situation without measured input and with measured input.

Discussion

The application of the modelling concept to thermal degradation of paper insulation clearly demonstrates the advantages of the new approach. The probabilistic approach demonstrates how condition information is transformed to a prediction of future failure probability. The accuracy analysis shows that without additional experimental information the loading guide model is not able to provide sufficient accuracy. With incorporation of the measured DP value the
accuracy bandwidth is significantly reduced. Further improvement is possible when incorporating measurements at regular time intervals. The approach presented provides a more accurate tool for the asset manager to predict future failure probability, and to base decisions on a realistic prediction rather than on a worst case.

In the application presented choices were made that are still subject to debate. In particular this refers to the choice of reaction rate time dependence, and the choice of distribution function.

**Degradation reaction rate:** Some authors, [7, 12], claim that degradation reaction rate is not constant, as described in (5), but changes over time. In [7] double Arrhenius process is suggested:

$$m(t) = \frac{k_1}{k_2} (1 - \exp(-k_1 \cdot t)),$$

with Arrhenius constants $k_1$ and $k_2$.

**Distribution functions:** The use of normal distribution functions may be disputed. The disadvantage is the possibility that the probability of DP-values being inside the domain, $[1, \approx 1600]$, is not equal to one. This may be circumvented by using truncated normal distributions. Another option is to match the distribution with the physical process, which may lead to a log-normal distribution. A Weibull distribution as used in [16] seems inappropriate here since it more aimed at worst case estimations.

**Conclusions**

In this paper the concept of an integral transformer lifetime model is presented, and illustrated by modelling thermal degradation of paper insulation. The modelling concept is based on a physical description of the process, but adds a probabilistic approach, and incorporates externally measurable parameters and a feedback loop to limit the inaccuracy inherent to degradation process modelling. It is demonstrated that the probabilistic approach adopted enables

**Acknowledgement**

The research presented is made possible by the financial support and active participation of KEMA, Essent Netwerk and Eneco Netbeheer. We gratefully acknowledge the contributions of Harry Verhaart, Maarten Berende and Herman Arts.
References


Author address: Arjan van Schijndel, Eindhoven University of Technology, Den Dolech 2, Cr. 2.13, P.O. Box 513, 5600 MB Eindhoven the Netherlands, Email: a.v.schijndel@tue.nl