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A Monte Carlo approach for calculating the thermal lifetime of transformer insulation

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ABSTRACT

This paper presents an accurate method for estimating the thermal lifetime of solid insulation in a power transformer. The method estimates the ambient temperature using the monthly average ambient temperature and the monthly solar clearness index. The average daily load curve and the standard deviation for each hour in the daily load curve are used to model the transformer load. The uncertainties associated with the transformer load and the ambient temperature are used to simulate the transformer artificial history using Monte Carlo technique. This artificial history is used to estimate the average lifetime of the transformer solid insulation. The method is tested on a real field transformer data taken from a local utility. The outcome of the test showed that the proposed method provides reliable results.

1. Introduction

Predicting the end of life of a transformer is an essential parameter in transformer asset management activities because accurate decisions with respect to the end of life save considerable money in the long run and protect the power system against expensive transformer outages. The degradation of solid insulation (paper) can be considered the primary reason for a transformer to reach the end of its life [1–8].

Most of the methods that are used to determine the lifetime of a transformer are based on measuring the solid insulation failure under controlled experiment [1,3–5,8]. The outcome of this controlled experiment is to only decide if the transformer has reached its end of life or not, the remaining lifetime of the transformer cannot be estimated. Furthermore, the effect of the stochastic nature of the load and the ambient temperature on the insulation failure was not addressed adequately before. This paper is an attempt to determine the transformer remaining lifetime based on studying the transformer solid insulation breakdown and the effect of variability of load and ambient temperature on the insulation deterioration using Monte Carlo simulation.

For oil-immersed power transformers, the main factor affecting the life of well-dried solid insulation is thermal stress, and the primary reason that the end of life is accelerated or decelerated under different loading conditions is an increase or decrease in the hot spot temperature (HST) of the insulation [6,10–12]. Details about calculating the HST can be found in [11]. The relationship between the HST and transformer life consumption is governed by the Arrhenius reaction rate theory [9–11,13,14], which states that:

$$per\ unit\ life = Ae^{\frac{B}{\mathrm{HST}+273}} \tag{1}$$

where A and B are empirical constants, with values of (9.8×10^{-18}) and (15,000), respectively [9–11,13,14]; HST is the transformer hot spot temperature in degrees Celsius.

The value of per unit life is unity for HST of 110 °C. The reciprocal of (1) is the aging acceleration factor (F_{AA}), which can be used to calculate the equivalent aging factor of a transformer as follows [9,11,14]:

$$F_{eq} = \frac{\sum_{n=1}^{N} F_{AA_n} \Delta t_n}{\sum_{n=1}^{N} \Delta t_n} \tag{2}$$

where F_{eq} is the equivalent aging factor for the total time period; n is the index of the time interval (t); N is the total number of time intervals (usually 24 h for one day or 8760 h for one year); F_{AA_n} is the aging acceleration factor for the temperature that exists during the time interval Δt_n; Δt_n is the time interval (h).

The hours of life lost in the total time period is determined by multiplying the equivalent aging factor by the total time period in hours. This gives equivalent hours of life at the reference temperature (110 °C), which are consumed in the time period.

The real problem in applying this insulation end-of-life model lies in determining the correct treatment of the transformer load and the ambient temperature, including the associated uncertainties. In [15], measured or estimated daily load profiles and a one-day average ambient temperature are used to determine the equiv-

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alent aging factor and the expected end of life of the insulation. Eleven curves were used to represent the daily temperature and load as well as their standard deviations. The main drawback of this method is that it requires a large amount of data. Furthermore, the loading of the transformer during its entire lifetime was assumed to follow eleven similar load curves with no changes in peak time or in the shape of the curve, which does not represent the actual case. In addition, the same pattern of temperature variation was assumed over the entire lifetime of the transformer.

In [9], the estimation of loss of life for a generator step-up transformer was calculated using simulated load values and daily ambient temperatures. Ref. [9] assumed that the variation in the daily ambient temperature is sinusoidal. However, a sine curve cannot represent a typical temperature range over the course of a day. Assuming a sinusoidal temperature variation that starts at 12 AM implies the minimum temperature occurs at 6 AM and the maximum temperature in the same day should occur at 6 PM (the difference is 12 h), which is not always the real case. The maximum daily temperature can occur at any hour in the afternoon, while the minimum temperature can occur at any time in the morning. Furthermore, the hourly load values used in [9] were selected randomly without conformance to any load curve pattern. According to [9], the simulation would need about 2450 simulation years in order to determine the lifetime of the transformer. This number of simulations is very large compared to the 76 years required with the method presented in this paper.

With the new method presented here, the model from [11] is used in order to estimate the lifetime of transformer insulation; however, the uncertainty with respect to the transformer load is modeled more accurately. The ambient temperature is more accurately estimated using the solar clearness index, and the uncertainty with respect to the ambient temperature is considered in the treatment of the end of life model input. The thermal lifetime of the transformer insulation is estimated using a Monte Carlo simulation technique. A transformer lifetime is simulated through the generation of two artificial histories that represent the uncertainty: one for the ambient temperature and the other for the load. These artificial histories are used to calculate the lifetime of the transformer insulation.

2. Proposed end-of-life estimation technique

The proposed approach for estimating the lifetime of transformer insulation is based on the simulation of transformer loss of life using a Monte Carlo technique. The Monte Carlo simulation is used in order to account for the uncertainty inherent in both the daily temperature and the transformer loading. The approach consists of three steps: building an artificial history of the ambient temperature using Monte Carlo technique, building an artificial history of the transformer loading using Monte Carlo technique, and simulating the transformer loss of life based on the model presented in [10,11].

2.1. Building the artificial history of the ambient temperature

The HST value depends on the ambient temperature, the rise in the top oil temperature over the ambient temperature, and the rise in the winding HST over the top oil temperature [11]. The latter two terms can be calculated using the top oil temperature rise over the ambient at the rated load, the winding HST rise over the top oil at the rated load, and the load value. The first term is found using the historical ambient temperature data to calculate the equivalent past loss in transformer life. The ambient temperature should, however, also be estimated in order to project the future equivalent loss of life of the transformer. The correct estimation of the ambient temperature can be used to obtain a correct estimation of the transformer HST, from which a correct estimation of the equivalent future transformer loss of life and the remaining lifetime can be determined.

For the purposes of this research, the estimation of the ambient temperature is based on the monthly average ambient temperature and the monthly solar clearness index (K_{Tm}). It was found that monthly average temperatures have lower standard deviations than average temperatures for the same day over several years [16,17].

The average daily ambient temperature for a specific hour (h) for a month (m) can be calculated using the mean value of the average ambient temperature and the diurnal temperature swing (peak to peak) for this month as follows [17]:

$$T_{m,h} = \overline{T}_m + A_m \begin{bmatrix} 0.4632\cos(t - 3.805)+ \\ 0.0984\cos(2t - 0.36)+ \\ 0.0168\cos(3t - 0.822)+ \\ 0.0138\cos(4t - 3.513) \end{bmatrix} \tag{3}$$

where $T_{m,h}$ is the average daily ambient temperature for a specific hour (h) for a month (m); $\overline{T}_m$ is the mean value of the average ambient temperature for a month (m) in °C; A_m is the diurnal temperature swing (peak to peak) for a month (m) in °C; t is a dimensionless expression for the hour of the day.

From (3), an average daily ambient temperature curve for each month of a year can be calculated. This curve represents the average temperature along this month.

A_m and t can be calculated as follows [17]:

$$A_m = 25.8\overline{K}_{Tm} - 5.21. \tag{4}$$

$$t = \frac{2\pi(h-1)}{24} \tag{5}$$

where $\overline{K}_{Tm}$ is the average solar index for month (m); h is an index for the hour of the day, starting from zero at 12:00 midnight.

K_{Tm} is the ratio of the monthly average daily radiation on a horizontal surface (H_m) to the monthly average daily extraterrestrial radiation ($H_{o,m}$). Solar radiation data are commonly available in the form of hourly total radiation on a horizontal surface (I) for each hour for extended periods of one or more years [18]. The term (I) is used to calculate (H_m).

The average solar index for month (m), $\overline{K}_{Tm}$), is calculated by

$$\overline{K}_{Tm} = \frac{\overline{H}_m}{H_{o,m}} \tag{6}$$

where ($\overline{H}_m$) is the mean value of the monthly average daily global solar radiation on a horizontal surface for the data years.

The monthly average daily extraterrestrial radiation for month (m), ($H_{o,m}$), in J/m^2 is calculated as follows [16,18]:

$$H_{o,m} = \frac{24\times 3600}{\pi} \times \left(1 + 0.033\cos\frac{360\times midday_m}{365}\right) \times G_{sc} \times \left(\cos(\varphi)\cos(\delta)\sin(\omega_s) + \frac{\pi}{180}\omega_s\sin(\phi)\sin(\delta)\right) \tag{7}$$

where G_{sc} is the solar constant (=1367 W/m^2); φ is the latitude of the site (weather station); δ is the solar declination; ω_s is the main sunshine hour angle for the month; $midday_m$ is the middle day of month (m).

The solar declination and main sunshine hour angle in degrees for the calculation month are as follows [18]:

$$\delta = 23.45\sin\left(\frac{360}{365}(284 + midday_m)\right) \tag{8}$$

$$\omega_s = \cos^{-1}(-\tan(\varphi)\tan(\delta)) \tag{9}$$

The monthly average daily global solar radiation on a horizontal surface for any year (i), ($H_{m,i}$), can be calculated as follows:

$$H_{m,i} = \frac{\sum_{d=1}^{e}\sum_{h=1}^{24} I_{d,h} \times 3600}{e} \tag{10}$$

where $H_{m,i}$ is the monthly average daily global solar radiation on a horizontal surface for month (m) in year (i) in J/m^2; $I_{d,h}$ is the hourly radiation on a horizontal service for day (d) at hour (h) for month (m) in W/m^2; d is an index for the day of the month; h is an index for the hour of the day; e is an index for the end day of the month, e.g., $e = 31$ for Jan.

After ($H_{m,i}$) is calculated for each month of the year, the mean value of the monthly average daily global solar radiation on a horizontal surface ($\overline{H}_m$) for multiple data years can be calculated as follows:

$$\overline{H}_m = \frac{\sum_{i=1}^{n} H_{m,i}}{n} \tag{11}$$

where (n) is the total number of data years.

The average ambient temperature for hour (h) in month (m) can be calculated using (3). However, (3) calculates the mean average daily ambient temperature for a month. The average daily global solar radiation on a horizontal surface (H_m) for any month (m) is not constant for every year. The value of (H_m) has a mean value ($\overline{H}_m$) and a standard deviation (SD_{Hm}).

To account for the uncertainty in the average daily global solar radiation on a horizontal surface for any month and for the uncertainty in the average daily temperature for any month, a Monte Carlo simulation is performed in order to generate an artificial history of the ambient temperature. To generate the artificial history of the ambient temperature, the value of (H_m) is assumed in this research to be a normally distributed random variable with a mean value equal to ($\overline{H}_m$) and a standard deviation equal to (SD_{Hm}). A set of random numbers between zero and one (0, 1) is generated for each month, with the size of each set being equal to the number of days in each month (e.g., 31 random numbers for January, 28 random numbers for February, and so on). Using the random numbers generated for each month, a normally distributed random variable is generated with an average equal to ($\overline{H}_m$) and a standard deviation equal to (SD_{Hm}). The result is 12 normally distributed random variables that represent the whole year. The mean and standard deviation values of these random variables are the mean and standard deviation values of the monthly average daily global solar radiation on a horizontal surface for each respective month.

Using these random variables for each month provides as many values of (H_m) as the number of days for each month. As a result, as many values of (K_{Tm}) as the number of days in each month can be calculated, and accordingly, as many values of the diurnal temperature swing (peak to peak) for each month as the number of days in the month can also be determined. Using (3), the number of daily temperatures equal to the number of the days in the respective month is generated. In this way, the changes in the diurnal temperature swing (peak to peak) during the month are accounted for. To account for the changes in the average monthly temperature, 12 normally distributed random variables (T_1–T_{12}) are generated Each random variable represents the respective mean value and standard deviation for the average monthly temperatures for each month in the available data years. The length of each of these random variables equals the number of days in its respective month. Thus, using the elements of (K_{Tm}) generated from the random variables of (H_m) and the monthly temperature random variables, different daily temperatures for each month can be generated.

Typical data show that the daily temperature increases from February 15th to July 15th and decreases from August 15th to January 15th. Moreover, the average temperatures seem nearly constant in the periods from January 15th to February 15th and from July 15th to August 15th. In the developed temperature model, the elements of the 12 random variables (T_1–T_{12}) are therefore sorted in ascending order from element 16 of T_2 (February) to element 15 of T_7, (July) and in descending order from element 16 of T_8 (August) to element 31 of T_{12} (December) and from element 1 of T_1 (January) to element 15 of T_1. The other elements, from 16 of T_1 to 15 of T_2 and from 16 of T_7 to 15 of T_8, are kept without sorting. This sorting algorithm prevents unrealistic jumps in temperature from month to month.

The values of the random variables (T_1–T_{12}) are then merged with the generated values for the diurnal temperature swings, which permit temperatures for the entire 365 days of the year to be generated, taking into consideration the uncertainty present in the temperatures.

2.2. Building the artificial history of the transformer loading

Typical daily load data for the whole lifetime of a transformer are not easy to find. No utility collects load data for 24 h, 365 days for the whole lifetime of the transformer. Even if this data were available, they would be past data, and a method for projecting the future load of the transformer would still be required. The developed approach for calculating the thermal lifetime of transformer insulation can be used for transformers either with or without a complete loading history. It can also be used for transformers that have recently been put into service.

An alternative solution for modeling transformer load is to simulate the load or to build what is called an artificial history of the transformer load. To model the artificial history of the transformer load, the average transformer daily load curve is used. The average load curve may differ from one transformer to another. The uncertainty with respect to the hourly load is used to generate multiple daily load curves (artificial history) for the transformer.

A normal distributed random variable is constructed so that its mean value is the loading at a specific hour on the average daily load curve, as shown in Fig. 1. A set of these normally distributed random variables is generated thereafter for every hour on the average daily load curve using the above approach. The standard deviations of these generated random variables are SD_l% of the rated transformer load. This technique allows the generation of different daily load curves with different shapes. In this approach, the uncertainty of the average daily load curve is utilized in order to represent different modes of transformer operation, such as normal loading, planned loading beyond nameplate, and short-time emergency loading [11].

The next step is to construct the daily load curves for every day of the year. For any daily load curve, the load for each hour is selected randomly from the corresponding normally distributed random variable constructed for that hour. This process is repeated thereafter for the remaining days and years. Fig. 1 shows three randomly selected daily load curves generated according to this approach. It is clear that the three curves are different in shape. As shown in Fig. 1, three hours have been selected (hours 4, 11, and 21) in order to show the generation of the hourly load for the daily load curves that represent the artificial history. From the mean load curve, the probability distributions of the hourly loads are used to generate each hourly load for the artificial history daily load curves. The loads during these hours may be larger than, less than or equal to the mean load at these hours. The artificial history of the loading is then generated as follows:

(1) Find the average daily load curve for the transformer.
(2) Generate 24 vectors of random numbers between zero and one (corresponding to the 24 h in a day). The length of the vector equals the number of days in a year.

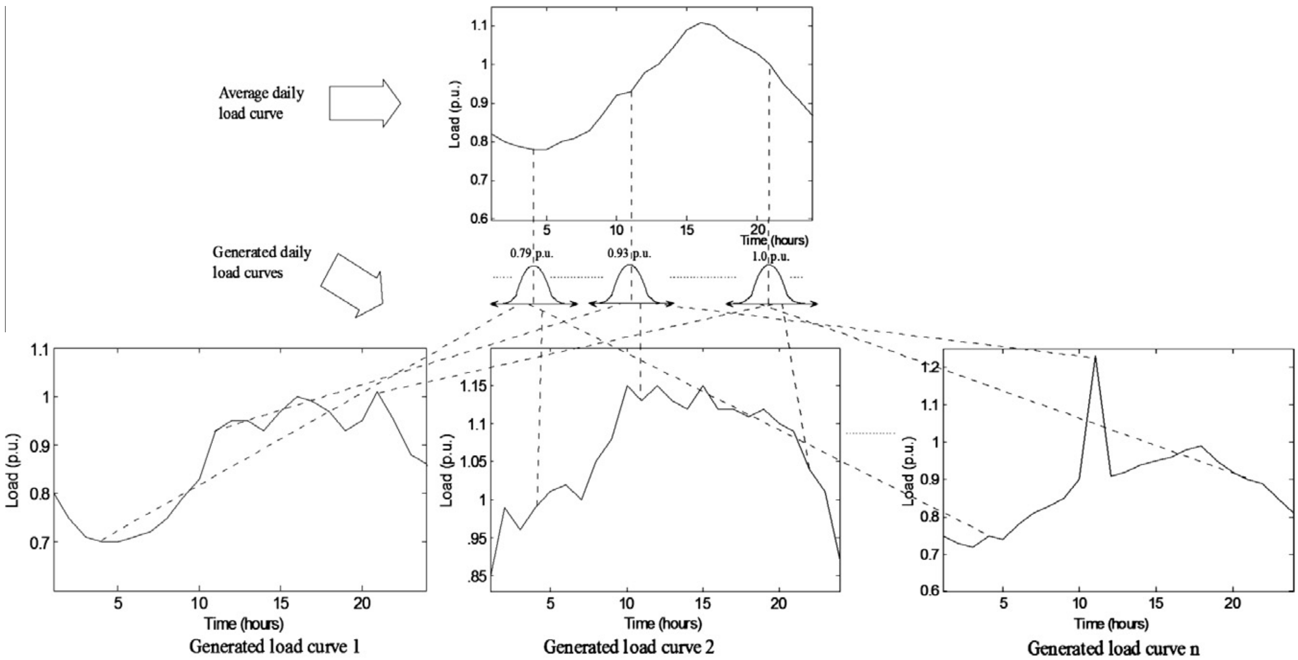

Fig. 1. Generation of daily load curves.

(3) Generate 24 normally distributed random variables with mean values equal to their hourly mean values and with standard deviations equal to SD_l% of the normal load.
(4) Use these 24 random variables to generate different daily load curves as previously explained.

2.3. Simulating the transformer lifetime

The artificial histories of the loading and the ambient temperature are used in the Monte Carlo simulation in order to find the annual equivalent aging factors. To complete the artificial histories, the steps explained in Subsections 2.1 and 2.2 are repeated in order to generate more annual data for the load and ambient temperature. The loading and ambient temperature artificial histories are used year over year in order to calculate the hourly HST, from which the hourly acceleration factor (F_{AA}) can then be determined. The annual equivalent aging factor is thus calculated using (2). The expected lifetime is then

$$EL_j = \frac{\mathrm{NIL}}{F_{eq_j}} \tag{12}$$

where EL_j is the expected lifetime using the equivalent aging factor for simulation year (j); NIL is the normal solid insulation lifetime based on 50% retained tensile strength and a continuous HST of 110 °C according to [11] (7.42 years); F_{eqj} is the equivalent aging factor for the simulation year (j).

It should be noted that the equivalent aging factor is calculated every year and that the expected lifetime is calculated using (12), assuming that the equivalent aging factors for the whole transformer lifetime are the same as the equivalent aging factor for the simulation year (j).

The average expected lifetime is calculated for every year of the simulation using the following equation:

$$\overline{EL}_c = \frac{\sum_{j=1}^{c} EL_j}{c} \tag{13}$$

where $\overline{EL}_c$ is the average expected lifetime until year (c) of the simulation; j is the index for the simulation year; c is the number of simulation years until year (c).

The simulation continues until the stopping criterion is reached. The stopping criterion used in the Monte Carlo simulation depends on the variation of the estimate function ($\overline{EL}_c$ here). The simulation stops when the variation of the estimate function goes below 0.08 year (around one moth) for five successive simulation years.

3. Case study

Data for 8 MVA, 22 kV/6.6 kV transformer is assumed for the case study. These data are taken from a local utility. This transformer is installed in 1983, and is manufactured in France. The thermal characteristics for this transformer are as follows:

(1) rise in top oil temperature over ambient at the rated load: $\Delta\Theta_{TO,R}$ = 47 °C;
(2) rise in hot spot conductor temperature over top oil temperature, at the rated load: $\Delta\Theta_{HS,R}$ = 36 °C;
(3) ratio of load loss at the rated load to no-load loss: R = 8.46;
(4) thermal time constant of the oil for the rated load: $\tau_{TO,R}$ = 4.6 h.

The average daily load served by the transformer which is shown in Fig. 2 is used to build the loading artificial history. A 10% standard deviation is assumed for the hourly load. Ten years of data about the hourly ambient temperature and hourly incident radiation on a horizontal surface (I) were collected from the weather station at the University of Waterloo (latitude: 43.4738 N; longitude: 80.5576 W; elevation: 334.4 m above sea level). The monthly mean values for the temperature and their standard deviations for the 10 recorded data years are shown in Table 1. The hourly total radiation on a horizontal surface (I) for each hour in W/m^2 is used in order to find the monthly average daily global solar radiation on a horizontal surface ($H_{m,i}$) for month (m) in year (i) using (10). The mean values of the monthly average global daily radiation ($\overline{H}_m$) for the available data years are calculated using (11). ($\overline{H}_m$) values with their standard deviations for the 10 recorded data years are shown in Table 1. When (8) and (9) are applied, the solar declination (δ) and the main sunshine hour angle for the month (ω_s) can be calculated for each month of the year. Because

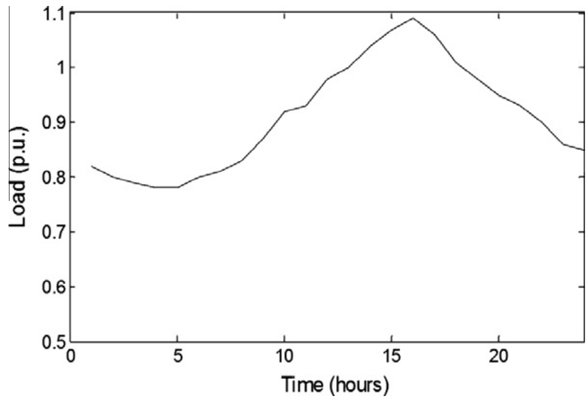

Fig. 2. Average daily load curve for the transformer used in case study.

Table 1
Monthly average temperature and monthly average daily global solar radiation data.

Month	(°C) $\overline{T}_m$	SD_{tem}	$\overline{H}_m$ (MJ/m^2 day)	SD_{Hm}
January	−5.73	3.09	5.18	0.53
February	−5.49	2.32	8.65	0.62
March	−0.92	1.95	12.6	1.76
April	6.55	1.16	16.0	1.70
May	12.8	1.7	18.8	1.79
June	18.7	1.3	20.8	1.60
July	20.6	1.33	20.8	1.46
August	19.6	1.2	18.5	1.24
September	16.0	1.28	14.7	1.54
October	9.15	1.67	8.7	0.80
November	3.41	1.55	5.05	0.49
December	−3.15	2.58	4.12	0.48

(δ) and (ω_s) have been determined, the monthly average daily extraterrestrial radiation ($H_{o,m}$) can then be calculated using (7). The values of ($H_{o,m}$) are shown in Fig. 3.

The 12 monthly average global daily radiation values (H_1–H_{12}) are assumed to be normally distributed random variables with the mean values and standard deviations shown in Table 1. The normally distributed random variables can be built by generating 12 uniformly distributed vectors of random numbers (U_1–U_{12}) between zero and one that correspond to the 12 months of the year. The length of each vector equals the number of days in the respective month. The 12 normally distributed random variables can be generated using the Box–Muller method [19]. When each element of the 12 random variables (H_1–H_{12}) is divided by its respective monthly average daily extraterrestrial radiation value ($H_{o,1}$–$H_{o,12}$), a number of solar indices are produced for each month. The number of solar indices equals the number of days in the respective month. The values of the solar indices for each month are substituted for $\overline{K}_{Tm}$ in (4) in order to generate a number of diurnal temperature swings (peak to peak) for each month equal to the number of days in the month. To account for the changes in the average daily temperature for each month, the average monthly temperatures are assumed to be normally distributed random variables with the means and standard deviations shown in Table 1. The mean value of the average ambient temperatures ($\overline{T}_m$) for month (m) in (3) is replaced with (T_m) in order to account for the daily changes in the average temperature, where (T_m) represents (T_1–T_{12}). The simulated ambient temperature for one month (30 days) is shown in Fig. 4, while the simulated ambient temperatures for one complete year are shown in Fig. 5.

The artificial history of the transformer loading is modeled as discussed in Section 2.2. Twenty-four random variables are generated. The mean values and the standard deviations of each random variable are the mean values and the standard deviations of the 24 h of the daily load curve. The mean values are shown in Fig. 2, and the standard deviation is taken as 10% of the normal load [9]. The length of each random variable is the number of hours in one year (8760 h) multiplied by the number of simulation years (s). The simulated load for one month is shown in Fig. 6.

A Monte Carlo simulation is then performed for the transformer using the artificial histories of the loading and ambient temperature. The HST is calculated for every hour according to [11], using the thermal data given in this study and the artificial load and ambient temperature data generated. The aging acceleration factor (F_{AA}) is calculated for every hour, from which the equivalent aging factor (F_{eq}) for the total year is calculated. The simulation continues year over year. (F_{eq}) is calculated for each year of the simulation, and (EL_c) is calculated accordingly.

The simulation continues until the stopping criterion is reached. When the criterion was applied, the simulation stopped after 76 years. The mean expected age at the end of the simulation was found to be 45.7 years. The fluctuation in the expected average age of the transformer along the simulation time is shown in Fig. 7. Fig. 8 shows the histogram of the expected age according to the annual aging acceleration factor and beta distribution to represent the best fit. The boundary parameters for the beta distribution are a minimum value $a = 22.584$ and a maximum value $b = 76.636$. The shaping parameters are $\alpha = 151.95$ and $\beta = 203.36$. The distribution mean is 45.707 years, and the mode of the distribution is 45.785 years. The mode represents the most probable event, and it is very close in value to the mean. The most probable value of the transformer life as calculated by the proposed analysis

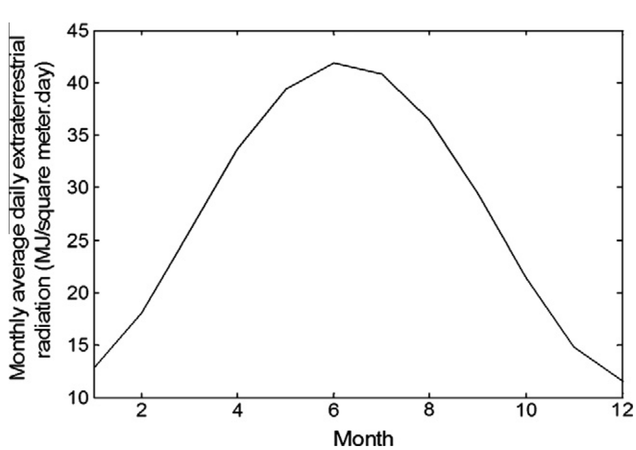

Fig. 3. Monthly average daily extraterrestrial radiation (MJ/m^2 day).

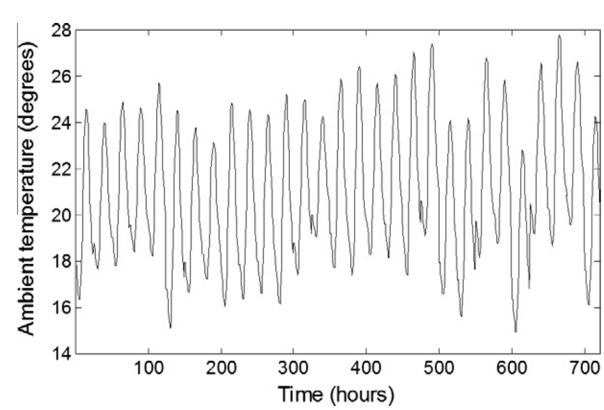

Fig. 4. Simulated ambient temperature for one month (30 days).

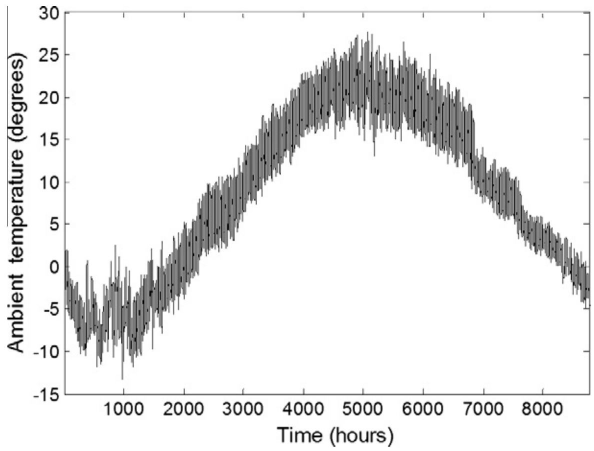

Fig. 5. Simulated ambient temperature for one year.

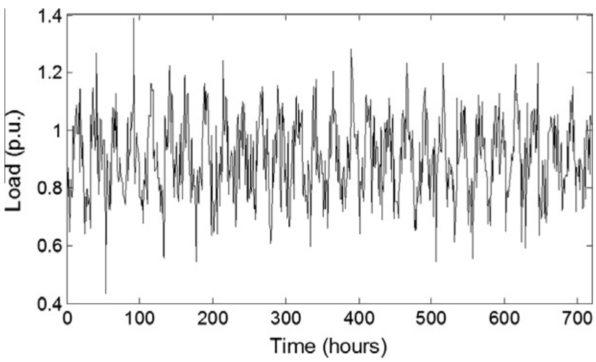

Fig. 6. Simulated load for one month (30 days).

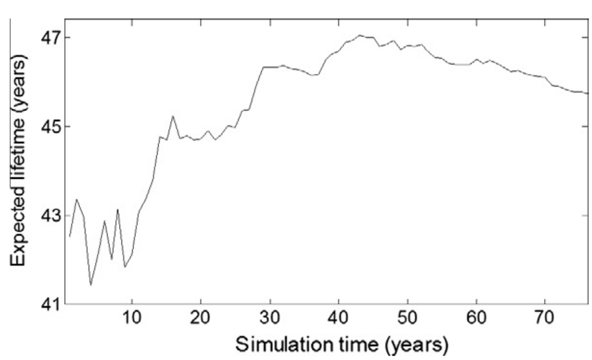

Fig. 7. Convergence of the expected lifetime.

is close to the most recorded retirement ages of power transformers [20–22]. According to the operation engineers in the transformer site, the diagnostic tests of the transformer show that it is working in order and it is expected to continue working without problems in the near future. When the authors proposed that the transformer, which is installed 29 years ago, will fail most probably after around 16.7 years, the response of the operation engineers was positive and the estimated remaining lifetime sounds good to them.

4. Comparison with previous work

In [9], an attempt was made to establish the time to failure for the insulation of a transformer. The method relies on the use of an

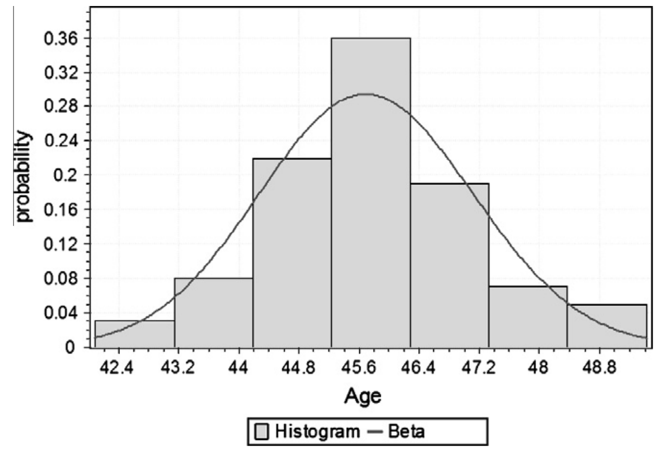

Fig. 8. Fitted beta distribution for the expected lifetime.

equivalent aging factor in order to find the lifetime of the insulation. An artificial model based on probability is used to model the load. More information about the method can found in [9]. The practical transformer data from Section 3 were used to test this technique.

Fig. 9 shows the life consumption simulation curves that result after the transformer insulation lifetime is simulated 50 times, as stated in [9]. The Weibull distribution is used to fit the 50 average actual usage times (probable lifetimes) of the insulation. The average actual usage time in days to reach the insulation end of life (7500 days as stated in [9]), is 37780 days, or 103.5 years, which is not a practical insulation lifetime. All recorded transformer lifetimes, which depend mainly on the lifetime of the insulation, are very much shorter [20–22].

In [15], load and temperature are represented by a set of curves that give, for each instant, load and temperature values associated with a probability value. The particular load value at any time (t) can be calculated as follows [15]:

$$L(t) = m(t) + z \times sd(t) \tag{14}$$

where $L(t)$ is the load at time (t); $m(t)$ is the mean of the load; z is a standard normal random variable.

The ambient temperature value at any time can be calculated using similar approach to (14). To find the value of the standard normal random variable (z), the probability of the event should be known. For example, for a probability of 90%, the value of (z) is 1.28. If (z) is used as a parameter, a set of 11 daily load curves and 11 daily ambient temperatures can be obtained. These curves correspond to probabilities from 2.5% to 97.5%. If all combinations

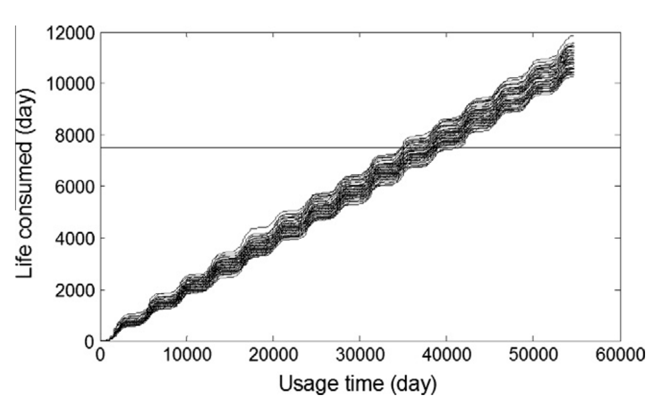

Fig. 9. The resultant life consumption simulation curves for the technique presented in [9].

of the daily load and ambient temperature are applied, 121 possible combinations can be found for every day. Because the daily load is assumed to be constant, 121 possible combinations can thus be found for each year. For each combination, the HST and the corresponding loss of life are calculated. The average loss of life is calculated as follows [15]:

$$LOL_{ave} = \sum_{i,j} F_{eq_{i,j}} \times Q_i \times Q_j \tag{15}$$

where LOL_{ave} is the average loss of life; $F_{eq_{i,j}}$ is the equivalent loss of life for load curve (i) and temperature curve (j); Q_i, Q_j are the corresponding probability values.

When this technique is implemented and the transformer parameters from the case study in Section 3 are used, the average annual loss of life is found to be 0.307. Applying the benchmark value for insulation life according to [10,11], which is 65,000 h, the transformer would be expected to last 24.17 years. This result is not reliable, since the transformer under study is already working for 29 years and still in service.

5. Conclusion

This paper presents a method of estimating the lifetime of transformer insulation based on the specific loading and location of the transformer. The drawbacks of the previous methods for estimating insulation lifetime are highlighted. The new approach incorporates the generation of two artificial histories for a transformer: one for the ambient temperature and the other one is for the load. The solar clearness index and average monthly temperatures are used to generate the artificial history of the ambient temperature. The uncertainties inherent in both the solar clearness index and the average monthly temperatures are considered when the ambient temperature is determined. The variations in the load are taken into account when the artificial history of the load is modeled. Both artificial histories are used as inputs to a Monte Carlo simulation technique in order to find the thermal lifetime of the insulation of a given transformer. A real field transformer data are used to verify the accuracy of the proposed method. The proposed method is compared with previous methods used to determine the thermal lifetime of transformer insulation using the same field transformer data. The lifetime estimated by the proposed method for the field transformer shows more accuracy than the previous lifetime estimation methods. The lifetime estimated by the proposed method is also significantly closer to the recorded statistical end of life data for power transformers compared to the results produced by the previous methods.

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