

Thermal Lifetime Evaluation of Electrical Machines Using Neural Network

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Abstract - This paper proposes a surrogate approach which utilises an supervised neural network to significantly shorten the time required for thermal qualification of electrical machines' insulation. The proposed approach is based on a feedforward neural network trained with Bayesian Regularization Back-Propagation (BRP) algorithm. The network predicts the winding's insulation resistance trend with respect to its thermal aging time. The predicted insulation resistance is evaluated against experimental measurements and an excellent match is found. Its trend is used for estimating the sample's time to failure under thermal stress at various temperatures. The temperature index of the insulating material, predicted by the neural network, matches with an error of just 0.4% margin against the experimental findings.

Index Terms — Aging time, Neural network, accelerated lifetime test, thermal life of insulation, and Insulation Resistance.

I. INTRODUCTION

THE thermal lifetime evaluation of an insulation system is a procedure aiming at extrapolating its thermal endurance characteristic i.e. the expected lifetime with respect to the applied stress (temperature of the insulating material). Such evaluation is conventionally based on accelerated lifetime tests, which consist in stressing the insulation at higher temperatures than those experienced during normal operating conditions, with the aim of tuning a lifetime prediction model [1-4].

Different stresses such as ambient, electrical, thermal and mechanical stress can shorten the life of insulation systems in electrical machine. Thermal stress among all is a primary source of gradual insulation deterioration resulting in eventual winding failure. Hence, the need to evaluate a winding insulation system for its capability in maintaining the dielectric properties under thermal aging [5, 6]. Based on the Arrhenius law, Insulation lifetime models are suitable for evaluating the lifetime consumption of electrical machines operating with continuous-duty cycle, where the winding temperature is remains consistent throughout the working operation. Arrhenius law states that the insulation lifetime reduces by half for every 8-10°C increase in temperature [7-10]. In terms of insulation, the weakest link is generally denoted by the winding turn-to-turn enamel layer [11]. The faults in the electrical machines, related to the insulation, are mostly originated with by a inter-turn insulation failure that results in over-temperaturesn[12]. This triggers the most severe failures and eventually lead to the machine outage. To avoid this condition, an accurate thermal lifetime evaluation of the

insulation system required [13]. The paper proposes a novel method for the thermal lifetime evaluation of electrical insulation systems, in order to reduce the experimental test time of the thermal aging which are traditionally based on the regression method [14-16]. This task has been performed using supervised feedforward neural network trained with Bayesian Regularization Back-Propagation (BRP) algorithm [17]. The results predicted using BRP are then tested and compared with the experimental results in order to validate the efficiency of the new methodology. The paper is arranged as follows: section II presents an overview of test setup and procedure for lifetime evaluation. In section III, the theoretical background of the adopted neural network is presented. In section IV, considerations on the diagnostic parameters and the breakdown criterion are discussed. The predicted results, obtained from BRP are presented in section V, followed by the thermal lifetime modelling in section VI. Lastly, section VII concludes the paper.

II. MEASUREMENT TEST SETUP

A. Test Sample

A twisted pair enameled wire with thermal class of 220 °C and a bare copper diameter of 0.4mm is used a test sample as shown in Fig 1a. The wire is insulated using a double enamel layer of 25µm, namely a modified-polyester as base coat which is overcoated with polyamide-imide. The length of the sample wire is 200mm with 20 twists on it, whose insulation characterization is required ASTM standards D2307 has been followed for choosen sample's arrangement [14]. Such wire topology is commonly employed for the windings of low voltage (< 1000 V) rotating machines [18, 19].

B. Test Procedure

Accelerated aging test are performed for test procedures which are generally used for thermal qualification of electrical machines in which the samples are thermally aged with stresses above the insulation thermal class. According to the technical standard ASTM D2307, 10 twisted pair samples need to be used for each aging temperature. The aging process was carried out, in a controlled oven (Fig. 1b), at the aging temperature 290°C with an aging cycle of 8 hours (or 8h). In other words, after every 8h of thermal exposure, the samples were cooled down to ambient temperature and their dielectric properties were assessed. Parameters such as insulation capacitance (IC), dissipation factor, (Tanδ), and insulation resistance (IR) were measured using a MEGGER Delta 4000

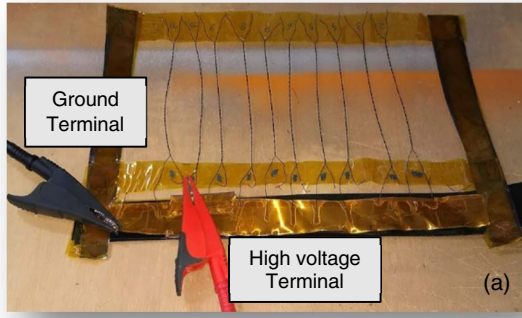


Fig. 1. Measurement Setup (a) Specimen's Holder in an unaged condition (b) MEMMERT UF260 Oven (c) Diagnostic Device MEGGER 4000

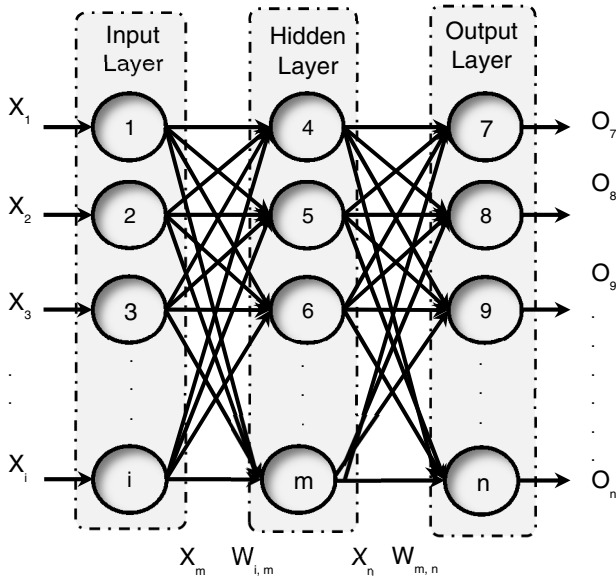


Fig. 2. Architecture of BP Neural Network

as shown in Fig. 1c. Throughout the aging procedure, the samples are also subject to the AC hipot test, used for, eventually, detecting the insulation breakdown. Such test consists in assessing the wire's dielectric withstand capability when a voltage from 0 to 500V is applied across the insulation layer, in step of 50V. In case a sample fails the AC hipot test, the time-to-failure is recorded. The aging procedure was carried out until the insulation breakdown is detected on all the considered samples [20].

III. NEURAL NETWORK

A feedforward neural network is used, that was trained with Bayesian Regularization Back-Propagation algorithm, to predict the diagnostic properties of the samples. The algorithm selection was based on a trade-off study among 4 neural networks, the details of which can be found in [2].

A. Theoretical Background

A BP neural network is a one-way multi-layer forward network as shown in Fig. 2. The network comprises of one input and output node, with one more hidden nodes implied, with no coupling between the nodes in the same layer. Transmission of input signals takes places from input layer in turn through the hidden layer nodes, and reaches the final output nodes at the last. Hence, the output of next layer is only influenced by the nodes of previous layer [22, 23]. Having advantage of a reliability and simple structure, this neural network is an outstanding tool for modelling of complex systems. When a certain pattern is fed in the input layer, the weighted sum W of the input X to the j^{th} node is represented by Equation (1) in the hidden layer calculating combined input to neuron. The weighted value from a bias node is represented by θ with an output value of 1.

$$S_m = \sum_{i=1}^n W_{i,m} X_{jm} + \theta \quad (1)$$

Action potential of neuron is decided by an appropriate activation function (i.e. sigmoid function as shown in (2)). The output value from activation function estimates the neuron's output and is an input value for the neurons in the successive layer connected to it.

$$O_m = X_n = \frac{1}{1 + e^{-S_m}} \quad (2)$$

Considering the predicted activation value of the output node, n , is O_n and the targeted value is t_n , then the difference between them can be calculated as given by (3).

$$\Delta_n = t_n - O_n \quad (3)$$

(7) is used to alter the weight, $W_{m,n}$, between the node m and output node, n , where $\Delta W_{m,n}$ is the variation in the weight between nodes m and n and l_r indicated learning rate.

$$\Delta W_{m,n} = l_r X_n \Omega_n \quad (4)$$

Ω_n is the error signal for node in the output layer and can be represented by (8).

$$\Omega_n = \Delta_n O_n (1 - O_n) \quad (5)$$

B. Network Training

To train the BRP network, the Bayesian regularization algorithm is used. In this case, the training is carried out on a

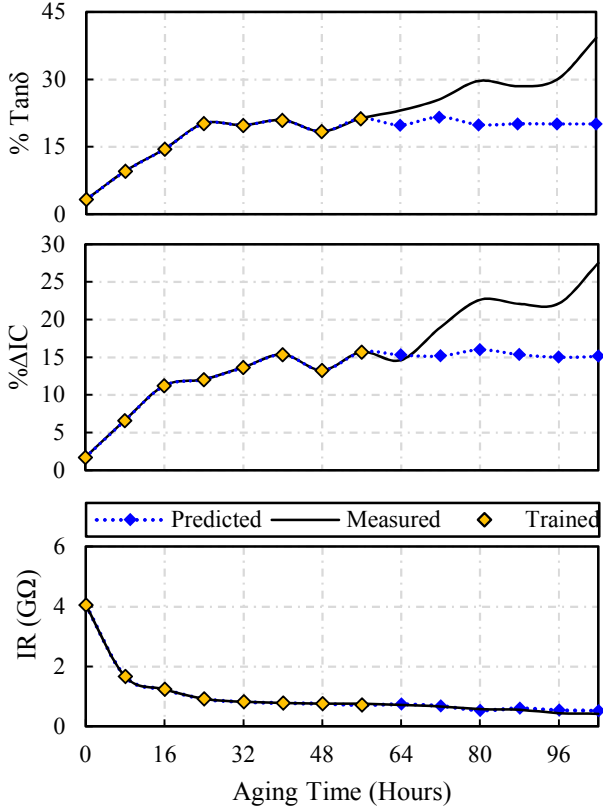


Fig. 3. Selection of Diagnostic Parameter for Prediction Purpose

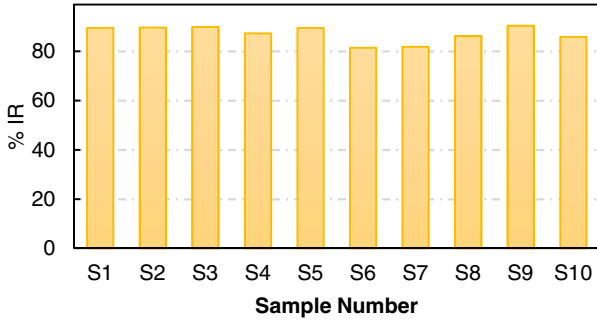


Fig. 4. %IR of each sample at 290°C thermal exposure

given set of samples having the form $(R_i + R_{i+1})$, where R_i indicates the insulation resistance value at aging time t_i whereas, R_{i+1} is the future or predicted value of the insulation resistance at t_{i+1} .

C. Prediction Approach

For every sample, the future value of diagnostic parameter R_{i+1} ($i=1,2,3,4,\dots,n$) can be predicted at a particular aging time t_{i+1} by performing the training on a set of data having the input parameter aging time as (t_i, t_{i+1}) and output parameter as insulation resistance (R_i, R_{i+1}) . The training is repeated from the beginning for each sample. To improve the prediction results, the first value is omitted from the dataset each time a future value is predicted. In this way, the network can be fed with an equal number of data points throughout and the

algorithm was trained on the latest target value which helped in the prediction of more accurate future values. With the dataset containing $IR_i \dots IR_n$, the network was trained until 7th aging cycle (i.e. 8th value or 56h learning time) to predict the future value IR_{i+1} (i.e. 9th value). However, in order to get the R_{i+2} (10th value), the latest predicted value R_{i+1} (9th value) was included in the dataset $(IR_i \dots IR_{i+1})$. The first value of the dataset was omitted simultaneously when each future value was predicted.

IV. SELECTION CONSIDERATIONS

A. Selection of Diagnostic Parameter for Prediction

Using the device called “MEGGER Delta 4000”, diagnostic parameters such as , IC, Tanδ and IR were measured for a random sample (i.e. S1) aged at 290°C. Fig. 3 illustrates the predictive results of differential IC (ΔIC), Tanδ and IR using BRP neural network. The ΔIC is estimated using (6), where IC_{500} is the IC measured at 500V and IC_{100} is the IC measured at 100V [3, 4]. As can be seen in Fig. 3 the prediction results, using neural network, gives the closest match for IR against the measured data as opposed to other diagnostic parameters. Therefore, the “IR” is selected as diagnostic parameter for prediction purpose i.e. to predict and build the lifetime model of insulating material.

$$\% \Delta IC = 100 \times \frac{IC_{500} - IC_{100}}{IC_{500}} \quad (6)$$

B. Breakdown Criterion

The breakdown criterion was made, at 290°C thermal exposure, using time-to-failure of each sample. Fig. 4 shows %IR of all the samples that was calculated with respect to its unaged IR value by using (7), where, IR_{zero} is the unaged value of IR and $IR_{endlife}$ is the IR value recorded one cycle before insulation breakdown had occurred, at 500V applied voltage. The %IR corresponding to the sample’s mean time-to-failure is equal to 87.22% (using (8)) and therefore chosen as insulation’s breakdown criterion which will be used, to predict the time-to-failure, for thermal exposures other than 290°C.

$$\% IR = 100 \times \frac{IR_{zero} - IR_{endlife}}{IR_{zero}} \quad (7)$$

$$IR_{breakdown} = \frac{1}{N} \sum_{k=1}^n \% IR \quad (8)$$

V. RESULTS & DISCUSSIONS

For prediction analysis, the test procedure was started and completed at maximum thermal exposure (i.e. 290°C) until a breakdown in every test sample was perceived, in order to set a breakdown criterion for other thermal exposures. The test procedure continued for 250°C and 270°C aging temperatures until the 7th aging cycle, where, the test procedure was intentionally ceased to predict the life of each sample using neural network approach. Once the prediction phase was

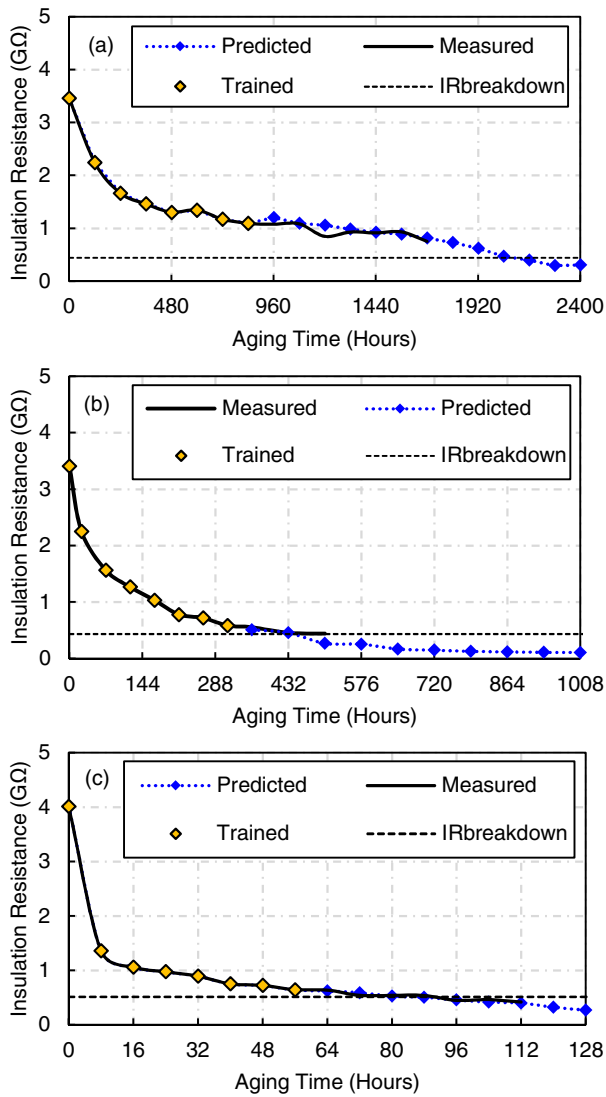


Fig. 5. IR Prediction Results (a) at 250°C thermal exposure, S10 (b) at 270°C thermal exposure, S1 (c) at 290°C thermal exposure, S5

completed, the test procedure was resumed and completed for validation purpose. The IR of every sample was predicted using the methodology discussed in the preceding section. The BP network was trained until the 7th aging cycle (i.e. total 8 data points including unaged value) and the samples whose failure was detected before the 7th aging cycle were discarded and hence, not included in the prediction analysis. To estimate the time-to-failure of each sample at various thermal exposures, the BP network was designed to predict the IR values for longer time span (i.e. 2400h, 1008h for thermal exposures of 250°C and 270°C respectively). A limited number of thermal aging cycles were experimentally carried out on two sets of 10 samples each, at thermal exposures of 250°C and 270°C. The recorded IR values were used for training the neural network, with the aim of predicting the samples' insulation breakdown, without actually carrying-out the tests until all samples were "dead". It is worth recalling that a sample is considered as "dead" when a %IR variation of

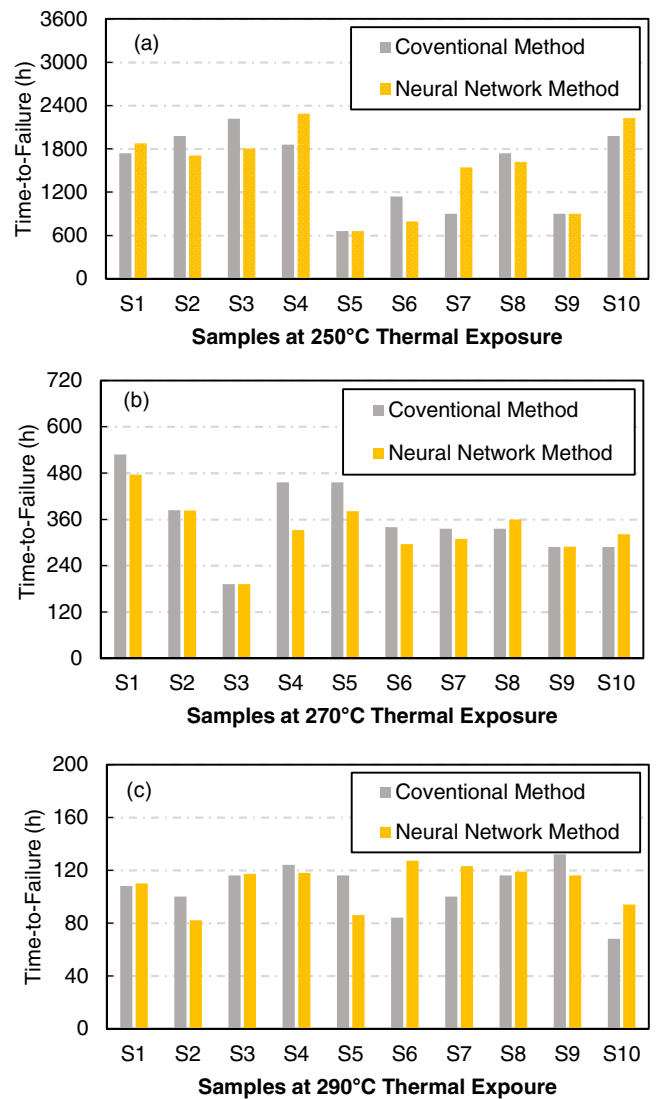


Fig. 6. Time-to-Failure (a) at 250°C thermal exposure (b) at 270°C thermal exposure (c) at 290°C thermal exposure

87.22%, with respect to its unaged value, is reached. Fig. 5a to Fig. 5c shows the results of the predicted IR trend for one sample aged at 250°C, 270°C and 290°C respectively. As clearly visible in Fig. 5, the neural network results are essentially able to match the experimental measurements, providing an excellent IR estimation. At this point, it is possible to employ the network's prediction to estimate the time-to-failure of all 30 samples at three thermal exposures, which are reported in Fig. 6a to Fig. 6c.

VI. THERMAL LIFETIME MODEL

For a constant mode of operation, insulating material used in electrical machines is characterised by a constant winding temperature throughout their working operation [24]. In this case, for low voltage electrical machines, thermal stress is the most recognised aging factor that gradually deteriorates the insulation's lifetime. Therefore, a thermal lifetime model, based on the Arrhenius Law, is developed in this section. According

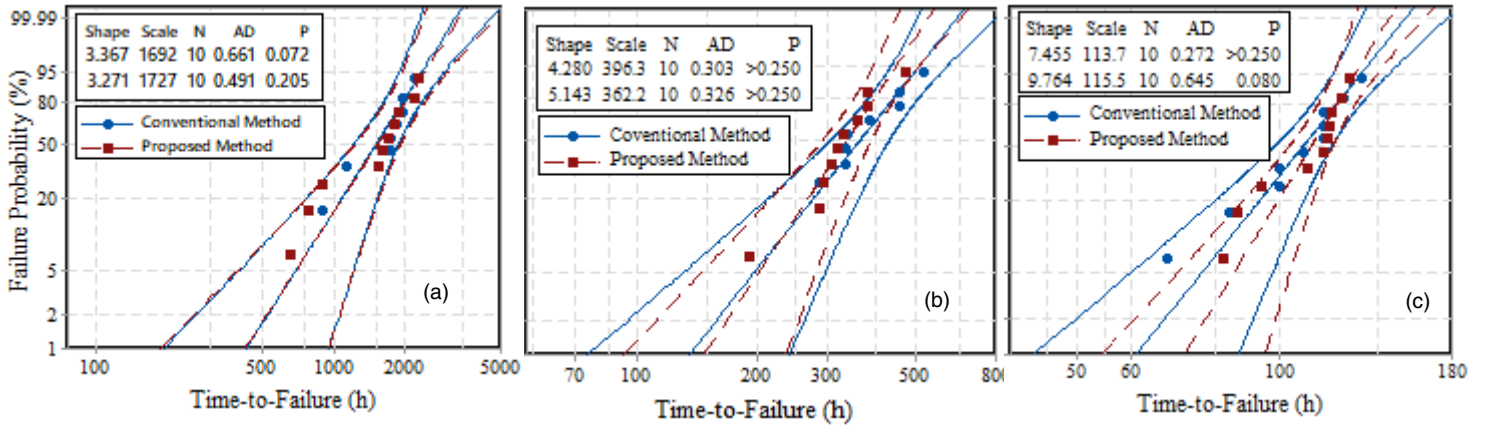


Fig. 7. Weibull Probability Plot (a) 250°C Thermal Exposure (b) 270°C Thermal Exposure (c) 290°C Thermal Exposure

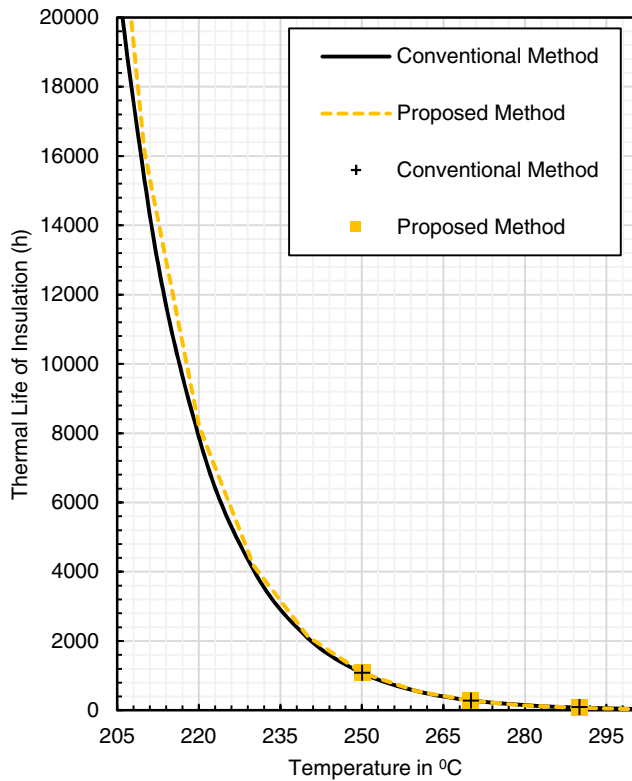


Fig. 8. Comparison of Insulation Life vs Temperature Characteristic on Linear Graph

to the Arrhenius law [8], the thermal life of a solid insulating material is given by (9)

$$L = Ae^{B/T} \quad (9)$$

where, A and B are material constants, whilst, L is the thermal life of insulating material in hours at operating temperature T in Kelvin. Using the time-to-failures of Fig. 6, the Weibull Probability Distribution, with a 95% confidence interval, is plotted at all three thermal exposures (Fig. 7). In order to predict the temperature index of the insulating material, using

TABLE I

| COMPARISON OF 20% CUMULATIVE PROBABILITY FAILURES | | | |
|---|--------|-------|-------|
| AGING TEMPERATURE | 250°C | 270°C | 290°C |
| Conventional Method | 1084.1 | 279.1 | 92.9 |
| Proposed Method | 1092.0 | 270.6 | 99.0 |
| Relative Error (%) | -0.73 | 3.05 | -6.57 |

| TABLE II MATERIAL CONSTANTS AND TEMPERATURE INDEXES | | | | |
|--|----------|----------|----------|--------|
| PARAMETERS | A | B | T.I (°C) | R |
| Conventional Method | 1.691e10 | -0.06626 | 205.97 | 0.9988 |
| Proposed Method | 2.218e10 | -0.06731 | 206.79 | 0.9986 |

both conventional and proposed method, the insulation lifetime corresponding to the 20% cumulative probability failures are extracted for all three thermal exposures which are illustrated in Table I. It should be noted that the lifetime models can be made with different failure percentile, depending on the reliability requirement of the specific applications [25]. From Table I, it can be seen that the lifetime of the insulation, predicted by the BP network, is consistent with the one obtained from the experimental test procedure. From the attained results, the highest error is -6.57% in the case of 290°C thermal exposure, whereas, the minimum error of -0.73% is achieved at 250°C thermal exposure which shows the effectiveness of the proposed method, in terms of shortening the test procedure of lifetime evaluation of insulating material. Once the samples' lifetime corresponding to the chosen reliability requirement is obtained from Weibull Distribution, the thermal life of insulating material is extrapolated, by using MATLAB curve fit exponential tool, to a lifetime of 20,000 hours (i.e. standard lifetime required for electrical machines), whose constants A and B are listed in Table II, for both conventional and proposed methods of lifetime evaluation. As can be observed from Table II, the proposed approach is actually able to predict the temperature index of the material which has made an excellent agreement, giving the percentage error of just 0.40% when compared to a conventional method of lifetime evaluation. Hence, by adopting the proposed approach, a significant amount of testing time can be saved since the thermal exposures do not need to be performed until the insulation breakdown is detected.

VII. CONCLUSIONS

Fast and accurate tool is developed in this paper, using the neural network approach, to predict the lifetime of insulating material used in electrical machines. The proposed approach employs a supervised neural network that significantly shortens the time required, in accelerated aging tests, for the thermal qualification of electrical machines' insulation. It predicts the trend of insulation resistance with respect to its aging time. The breakdown criterion was defined to evaluate the time-to-failure of each sample which was then used to build the thermal lifetime model of the insulation corresponding to 20% cumulative probability failures. The temperature index was determined through both conventional and proposed approaches and an excellent agreement was found, with an error of just 0.4%.

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