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ORIGINAL RESEARCH

A novel artificial neural network approach for residual life estimation of paper insulation in oil-immersed power transformers

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Abstract

Avoiding financial losses requires preventing catastrophic oil-filled power transformer breakdowns. Continuous online transformer monitoring is needed. The authors use paper insulation to evaluate transformer health for continuous online transformer monitoring. The study suggests a new artificial intelligence method for estimating paper insulation residual life in oil-immersed power transformers. The four artificial intelligence models use backpropagation-based neural networks to predict paper insulation lifespan. Four primary transformer insulating paper failure indices—degree of polymerisation, 2-furfuraldehyde, carbon monoxide, and carbon dioxide—form the basis of these models. Each model, including the backpropagation-based neural networks, estimates paper insulation life using one failure index, along with moisture and temperature data. Optimisation techniques enhance hidden layer neurons and epoch count for improved performance. Results are validated against literature-based life models, establishing a precise input–output correlation. This method accurately predicts the remaining useable life of power transformer paper insulation, enabling utilities to take proactive measures for safe and efficient transformer operation.

KEYWORDS

condition monitoring, fault diagnosis, neural nets, power transformer insulation, power transformers, remaining life assessment

1 | INTRODUCTION

In the modern life of industrial dependence, electrical power is very essential. To avoid serious power outages, the utilities need to look after the major components of the power system continuously. The liquid filled electrical power transformers (LFEPT) are an uncertain constituent of the power system. It is a significant asset to which everyone relies. Its failure will cause unwanted interruption in the power supply leading to serious financial consequences [1, 2]. So, it is pertinent to spot the severe faults of an LFEPT at earlier stages for its rectification to enjoy an uninterrupted supply and get rid of costly outages.

Generally, the insulation of transformers has two components, that is, the mineral oil (MO) and the cellulosic solid Kraft paper (CSKP). The insulating MO directly reflects its dielectric strength using the concentration of dissolved gases evolved into it. The LFEPT windings use CSKP as its solid insulation, serving as a major backbone of the power transformer. The CSKP undergoes harsh circumstances and thereby decomposed to lose its mechanical and dielectric strength [3]. The early breakdown of the CSKP insulation affects the useful service life of the power transformers. Though the accelerated thermal ageing of the solid insulation is the major cause of its early degradation but the moisture also plays an important role in its fault severity [4, 5] The rapid degradation of CSKP insulation produces its ageing by-products in the transformer MO. 2-Furfuraldehyde (2-FAL) and carbon oxides (CO_2 and CO) are the major constituents of the by-products. These by-products can directly provide the extent of CSKP degradation with high degree of preciseness as these by-products are a direct function of degree of polymerisation (DP) [6–12]. The DP is found to be the most prominent structural parameter of CSKP and thereby used as its direct ageing indicator. However, the DP is obtained through destructive methods interrupting the transformer's operation. The value of DP direct infers about the physical state of CSKP. The value of DP for a new CSKP is around 1200 with 100% tensile strength, however, this value gets lower with the progressive ageing of the CSKP as the matter of time. The value of DP when reached about 250–200 are supposed to be end of its useful life. Thus, it is important to analyse the CSKP insulation through its deterioration status and diagnostic testing and fixed its useful residual life.

In the earlier contribution of various investigators towards fixing the health of the CSKP insulation, many experimental arrangements have been suggested in recent times. In ref. [9], Emsley et al. have shown the role of furfurals in the reduction of DP of the CSKP taking moisture as a means of degrading factor. In ref. [11], the authors claimed a kinetic process based on an activation energy model to analyse the state of cellulosic decay under the influence of accelerated temperature and moisture. They referred to DP as a failure index to figure out the remaining useful insulation life. Mandlik and Ramu [13] developed a multi-stress model to trace the remnant life of CSKP based on an enhanced Arrhenius relation. This empirical model is also compared to his ageing experimental model by simulating the actual condition of the transformer's insulation system in real-time, which yields the status of the paper by carefully observing the value of DP along with the evolution of 2-FAL and carbon oxide gases in MO. A few studies have been reported in the literature indicating uncertainties in the used data for predicting the insulation's physical state. In ref. [14], the issues related to data unavailability to fix the health index (HI) for the conventional power transformer has been addressed. Also, the influence of the unavailable data on HI is assessed, and some recommendations are suggested for interpreting the HI with certainty. The study in ref. [15] introduces a novel technique for assessing the apparent age of power transformers by means of a probabilistic HI. Unlike the conventional weighted-score-sum approach, the proposed method exploited a Bayesian belief network to fuse various transformer condition monitoring data for calculating the probabilistic HI. Zeinoddini et al. in ref. [16] present a procedure for combining transformer insulation specifications and dissolved gas analysis (DGA) data to create a single numerical HI value. This index serves as a comparative measure of the overall status of the transformer. Various intelligent techniques such as neural networks (NN), the fuzzy inference system (FIS), the adaptive neuro-fuzzy inference system (ANFIS), the support vector machine (SVM) and machine learning (ML) models are reported in refs. [17–24] which are showing some useful contributions towards the condition assessment of the transformer's CSKP insulation.

In the field of transformer insulation health assessment, several notable research gaps have emerged from the discussion and the literature review. One significant gap is the need for a more comprehensive approach that effectively integrates multiple data sources and modelling techniques to provide a holistic assessment of transformer insulation health. While many studies have explored various data sources and modelling methods, the development of a unified framework that leverages the strengths of these diverse approaches remains an area for further investigation.

Furthermore, the concept of probabilistic health indices is briefly introduced, but the literature review lacks a thorough exploration of this approach. Future research could delve into the development and practical application of probabilistic health indices, shedding light on their potential to assess transformer insulation health in a more nuanced and accurate manner. The review mentions various intelligent techniques, including NNs, FIS, and SVMs, but it offers limited insight into the specific strengths and limitations of these modelling techniques within the context of transformer insulation assessment. Additionally, there is an underexplored research gap related to the long-term performance of these assessment methods in real-world scenarios. Accounting for factors such as ageing, maintenance, and changing operational conditions, this research would provide insights into the robustness and reliability of the methods over extended periods, ensuring that they remain effective and accurate in practical applications.

The major contribution of the present work focuses on the efficacious optimisation, validation, and development of intelligent NN models that evaluate the remaining useable life (RUL) of CSKP insulation in oil-immersed power transformers. The proposed framework to identify the RUL is shown in Figure 1. Based on the different indices of failure, that is, DP, 2-FAL, CO and carbon dioxide (CO_2), four NN models have been designed and optimally configured for improved and precise prediction accuracy. The optimisation procedure likely involved tuning hyperparameters alongside adjusting the architecture of NN and sanitising the input attributes to have the best possible outcomes. To validate the effectiveness of the proposed models, experimental data points

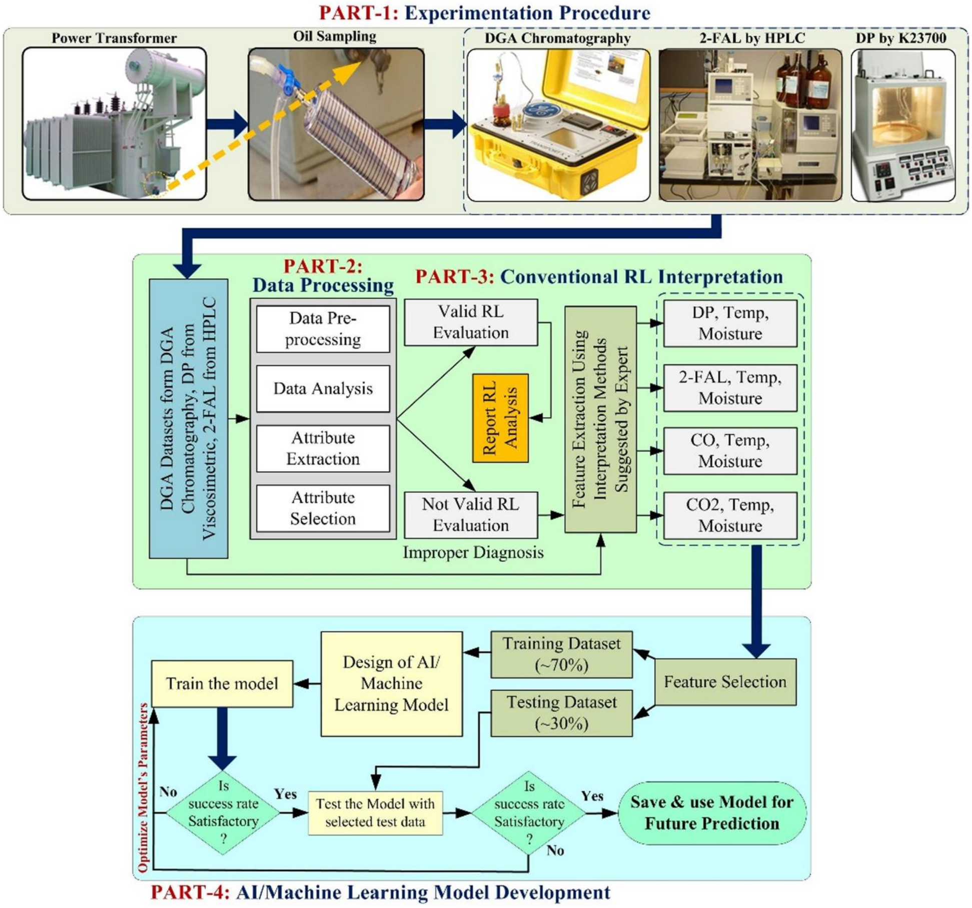

FIGURE 1 Development of ANN-based intelligent framework to evaluate the residual/useful life (RL) of CSKP insulation in oil-immersed power transformers.

are used in this study. The obtained results were compared to existing prototypes or other established methods for estimating transformer insulation life. The comparison likely showed that the proposed NN models provided comparable or even better predictions than the existing techniques. An additional noteworthy implication of this study is the potential utilisation of the NN models as a robust alternative to conventional DGA tools in the context of power transformer asset management. DGA stands as the predominant method for detecting potential faults within transformers, primarily by examining the composition of dissolved gases in the insulating transformer fluid. By offering a dependable and consistent alternative to DGA, the proposed NN models have the capacity to address challenges in transformer asset management, thereby contributing to the prolonged operational life of power transformers. This innovative approach can play a pivotal role in enhancing the reliability and longevity of power transformers, benefiting both industrial and utility sectors. The reliability and consistency of these NN models mark them as a promising alternative for the surveillance and management of transformer assets, demonstrating their significant potential for the industry.

2 | TRANSFORMER RESIDUAL LIFE ESTIMATION

Recent studies on the integrated insulation system of LFEPT reveal that the moisture content of insulation acts as a catalytic agent of its degradation. However, it is also verified experimentally that moisture in addition to temperature turns out to be a serious concern to integrated utility companies all around the world. It weakens the transformer insulation system badly which ultimately affects its overall health with severe faults, resulting in an early breakdown prior to its actual service life. To address towards residual life assessment (RLA) of power transformers, authors contributed various life models to analyse the feasible life. These models are aided with a single stress factor, especially the thermal stresses. Mandlik M. et al. [13] formulated a joint stress model by enhancing the classical Arrhenius correlation with the moisture content of the insulation system along with temperature to calculate the failure time of the insulation. The joint stress mathematical model will take like:

$$t = \lambda m^{-a} e^{\frac{B}{T}} \tag{1}$$

a, B, and λ are the parameters of the existing model. The moisture (m) of the insulation is signified as the percent by the weight of CSKP, the temperature (T) preserved throughout ageing experimentation is shown in kelvin and the time to failure (t) is in hours. Utilising the proper statistical techniques, the parameters of Equation (1) have been estimated. Firstly, Equation (1) has been linearised by taking logarithms on both sides and hence it follows as:

$$\log t = \log \lambda - a \log m + \frac{B}{T} \tag{2}$$

Assuming $\log t = Z$, $\log m = Y$ and $\frac{1}{T} = X$, the Equation (2) becomes:

$$Z = aY + BX + C \tag{3}$$

where $C = \log \lambda$.

The parameters of Equation (3) in the multiple regression model (MRM) are approximated with a focus on accelerated ageing experiments involving various paper samples immersed in transformer oil. Each paper sample, denoted as 'n' for the number of samples, is subjected to three different temperature and moisture levels, ranging from 90 to 130 °C and moisture levels of 1%–3%. These samples are aged for specific durations during which various ageing indices related to insulation failure, such as DP, 2-FAL, CO_2, and carbon monoxide (CO), are recorded. The MRM is then employed to analyse and estimate the parameters of Equation (3). This process is a key step in understanding the relationship between ageing indices and the conditions under which these samples are exposed to thermal and moisture stresses, providing valuable insights into the degradation of transformer insulation.

$$\sum_{i=1}^{n} Z_i = -a \sum_{i=1}^{n} Y_i + B \sum_{i=1}^{n} X_i + nC \tag{4a}$$

$$\sum_{i=1}^{n} Z_i X_i = -a \sum_{i=1}^{n} Y_i X_i + B \sum_{i=1}^{n} X_i^2 + C \sum_{i=1}^{n} X_i \tag{4b}$$

$$\sum_{i=1}^{n} Y_i Z_i = -a \sum_{i=1}^{n} Y_i^2 + B \sum_{i=1}^{n} Y_i X_i + C \sum_{i=1}^{n} Y_i \tag{4c}$$

3 | METHODOLOGY TO DESIGN AI MODELS BASED ON DIFFERENT FAILURE INDICATORS

The loss of useful service life of LFEPT due to unattended faults is detrimental to its long-time performance. As a result, the CSKP insulation deteriorates much faster and is unable to complete its useful design period. Consequently, the CSKP loses its tensile strength and produces its byproducts into the transformer oil. The DP is said to be the key parameter to determine the extent of the CSKP ageing directly. Also, its byproducts (2-FAL, CO_2, and CO) are used to assess the insulation health. The concentration of these byproducts in the oil directly estimates the condition of the insulating paper. In view of this, the key parameters for determining the useful/residual life of the paper insulation and eventually the power transformers are identified as DP, 2-FAL, CO and CO_2. The value of DP and the concentrations of 2-FAL, CO_2 and CO are taken as the indices of failure to fix the state of the CSKP insulation. These parameters comprehensively provide the amount of degradation that the paper insulation has gone through. The primary objective of the research work presented here is to focus on these four key failure parameters (indicators) along with other factors to assess the insulation lifespan. By analysing these failure indicators, it becomes possible to correctly determine the useful and residual life of a transformer based on the physical state of its solid insulating paper. The proposed work offers the development of four thermo-moisture accelerated ageing models using the artificial neural network (ANN) technique. It is worth mentioning that the data utilised for developing the proposed models are obtained under the laboratory conditions, as outlined and referenced in ref. [13].

3.1 | Development of the proposed NN models to fix the CSKP insulation life

ANNs are an effective network that is employed in a wide range of applications, such as forecasting, prediction, system control, curve fitting, tracking, and so forth. It analyses the information parallelly. ANN has a multi-layered structure where each layer is categorised as either an input, output, or hidden layer. This network structure is made up of layers of connected nodes that allow information to propagate from the inputs to the output. These nodes are basic cognitive structures known as neurons. Every node receives the information parallelly from various inputs and generates an output based on the value that its activation function takes when the argument being used is the weighted average of their inputs. Usually, the network structure along with a set of parameters characterises the ANN. The parameters are the weights applied in each neuron for the aforementioned weighted sums, whereas the structure is the number of interconnected neuron layers, the number of neurons per layer, the connection topology between the neurons, and the type of activation (transfer) function per neuron. In fact, ANNs often have network structures that are predetermined by the designer. The weights are then automatically trained using optimisation algorithms, such as the commonly used back-propagation (BP) algorithm and the Levenberg–Marquardt (LM) optimisation [25, 26]. The BP algorithm's functionality is described by the following set of equations.

$$O_j = f(\text{net}_j) = f(x), \text{Thereby } \text{net}_j = \sum_{j}^{i} w_{ji} O_i + \theta_j \tag{5}$$

$$E_p = \frac{1}{2}(t_{pj} - O_{pj})^2 \tag{6a}$$

$$\delta_{pj} = (t_{pj} - O_{pj}) \tag{6b}$$

$$\Delta_p w_{ji} = -\varepsilon \left(\frac{\partial E_p}{\partial w_{ji}}\right) \tag{7a}$$

$$\Delta_p \theta_j = -\varepsilon \left(\frac{\partial E_p}{\partial \theta_j}\right) \tag{7b}$$

Here, j is the layer number and i is the neuron number in that layer. O_j represents the neuron output, net$_j$ is the aggregated weighted sum, the bias θ_j, w_{ji} is the weight of interconnection, ε is the rate of O_{pj} learning, δ_{pj} is showing the value of error in the jth layer, t_{pj} is the target output and is the actual output. E_p refers to be the error for the adopted training pattern p, while the parameter Δp represents the weight and bias updates for a specific pattern p during the back-propagation algorithm. Root mean square (RMS) of the errors in the output layer for the pth sample pattern are calculated using Equation (3). The performance of the NN is evaluated by calculating the mean square error (MSE) of errors between its target outputs and the predicted (actual) outputs for each sample in the dataset. This evaluation reflects that how the NN is learning and approximating the target values. In the context of NN training, the MSE represents the difference between the target output t_{pj} and the actual output O_{pj} for a specific sample. This error measures how far off the NNs prediction is from the correct target value.

The BP algorithm is the most prevalent training algorithm used in the multi-layer NN models. It is employed in two stages. In the first stage, following the application of input vector neurons are fired as per activation functions. The sum of the output of neurons of the layer is scaled by this activation function and forwarded to the next layer. At the output layer, an output vector is generated which is compared with the desired output and an error signal is produced. In the last stage, an error signal is back propagated in the direction opposite to synaptic connections. Then the weights are rescaled to reduce the error between the obtained and desired output. The aforementioned equations represent the same.

This study used four multi-layer feedforward NN models with linear activation functions for the output layer and tangent sigmoid activation functions for the hidden layers. The selection of the proposed model is based on multiple factors, which include the ability to handle complexity in the issues raised, suitability and compatibility with the given problems and the potential to provide a precise prediction. Here, the proposed NN models have the multilayer feedforward architecture that have shown promising performance in cases related to transformer ageing and insulation degradation. This architecture finds its ability to handle complex non-linear correlations within the applied dataset. Since the insulation degradation and its remaining life are often influenced through various interacting components, a multilayer feedforward NN proved to be a suitable choice to model such intricacies. The proposed model takes multiple inputs, including the failure index, moisture, and temperature, to predict the ageing time. Such NNs can efficiently control multivariate inputs and learn complex patterns from them. The parameters of the ANNs were trained using the LM optimisation approach. Each model treats one among DP, 2-FAL, CO_2 and CO as the primary index of failure along with two more inputs, that is, moisture and temperature to express the residual/useful life of CSKP in the power transformers. The dataset for each model has been taken from a series of accelerated thermal ageing experiments that were conducted on electrical-grade cellulosic Kraft papers [13]. During these thermal experiments, the paper insulation (CSKP) was regularly monitored, and data on the values of DP, dissolved gases, and 2-FAL were recorded as a function of ageing time at constant temperature and varying moisture levels. The authors prepared a dataset for the NN models by performing appropriate curve-fitting on the collected data points.

In total, 60 datasets were prepared for training and testing the NN models. For training, 70% of the total dataset was used, while 15% was allocated for the validation, while the remaining 15% for testing the developed models to gage their accuracy. The models were then tested using nine standard data points (samples) presented in Tables 6–9. These data points were selected from the experiments to facilitate a comparison between the outcomes of the developed models and the experimental results, providing a more reliable condition monitoring technique for oil-immersed power transformers.

The developed models have been trained using the prepared experimental dataset and establishing the correlation between failure indices taken one at a time, moisture and temperature to estimate the useful life of transformer insulation. The correlation established resembles the modified Arrhenius equation as given in Equation (1). Each training set consists of three input vectors, that is, a failure index, a moisture level and a constant temperature, and a single output vector which gives the time to failure of CSKP insulation for the four NN models. One of the significant advantages of NN-based RLA of paper insulation is its ability to learn directly from the training samples and the knowledge updation whenever required. Figures 2 and 3 shows the schematic and the internal architecture of the proposed system for measurement of the useful insulation life. In Figure 2, I_1, and I_3 represent input vectors and O is the output vector. In Figure 3, I_2 and I_3 represent temperature and moisture level whereas I_1 is the variable input vector and can take the values of DP or the concentrations of 2-FAL or carbon oxides or CO.

3.2 | Optimal NN configuration system

The optimal configuration of the NN models can be achieved following two steps. First by varying the number of hidden layers and second by changing the number of neurons in the hidden layer. The work carried out here to outline the useful life of CSKP insulation using NN models have been trained by changing the number of neurons in the hidden layer. This approach finds simply to reach an optimal configuration of the NN architectures. During the training process, the summation of the output of each neuron of the hidden layer generates the output vector. This output vector is subtracted from desired output vector and the error signal is obtained. The 'trainlm' is a network training function in the MATLAB environment that continuously updates the weight and the bias value as per the LM optimisation technique. Training is carried out in accordance with the parameters set by trainlm, including the maximum number of epochs, the performance target, validation failure, performance gradient, and the maximum training duration (s). The LM technique, designed to expedite second-order training, sidesteps the need for Hessian matrix computation, akin to quasi-Newton methods. When the performance function adopts a sum-of-squares structure, estimating the Hessian matrix involves specific techniques. This strategic approach streamlines optimisation, enhancing efficiency in

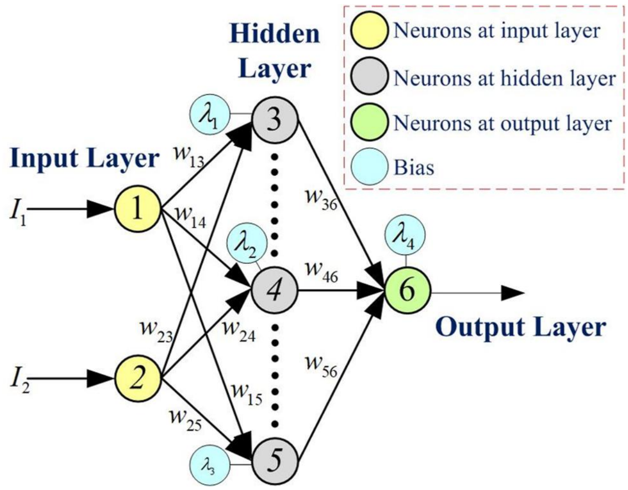

FIGURE 2 Architecture of ANN model formulation.

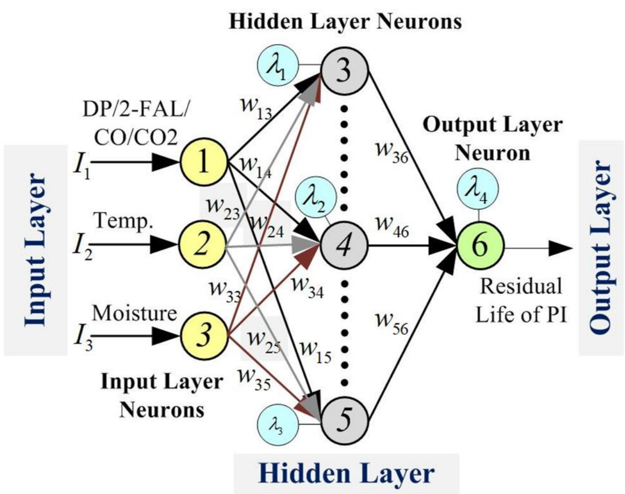

FIGURE 3 Internal architecture of the system estimating the insulation life.

second-order training without the computational overhead of directly calculating the Hessian matrix.

$$H = J^T J \tag{8}$$

and the gradient's computed as follows:

$$g = J^T E \tag{9}$$

here E is a vector of network errors and J is the Jacobian matrix containing the first derivatives of the network errors with respect to the weights and biases. The computation of the Jacobian matrix is substantially simpler than that of the Hessian matrix and may be done using a conventional back-propagation method. The LM uses this computation to the Hessian matrix in order to obtain the following Newton-like update:

$$x_{k+1} = x_k - \left[J^T J + \mu I \right]^{-1} J^T E \tag{10}$$

where μ is the scalar and when it is zero, it simply represents Newton's method. As the μ approaches to a larger value, it would become a gradient step following a small step-size. Using LM to train NNs looks to be the quickest way to build feedforward NNs of a reasonable size as compared to other NN algorithms such as Bayesian regularisation (BR) or scaled conjugate (SCG).

The optimal insulation life estimation models with different failure indices have been obtained by studying the effect of change in the number of hidden layer neurons on MSE. The MSE of each model for different hidden layer configurations has been recorded and optimal configuration has been identified. The variation of the mean square in errors with the number of hidden layer neurons in the life estimation NN models have been plotted in Figures 4–7.

Table 1 is listed with the least MSE for every NN model based on one failure index (i.e. one among DP, 2-FAL, CO_2 or CO) against a particular number of neurons in the hidden layer. With 35 hidden layer neurons, DP failure index model shows

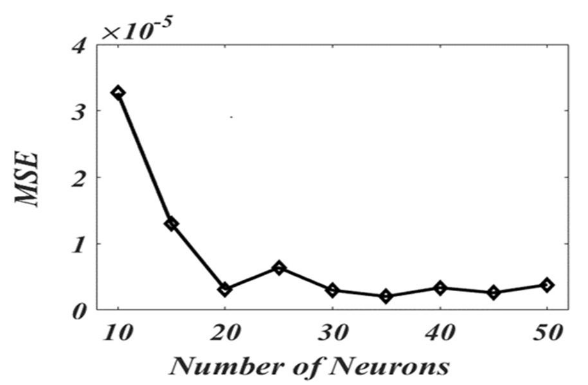

FIGURE 4 Variation in MSE for NN model treating DP as a failure index.

least MSE error. For 2-FAL and CO_2 as failure indices, the best model architecture has 50 hidden layer neurons and hidden layer with 25 neurons shows best prediction accuracy in case of CO-based NN model.

Equations (11)–(14) represent the basic fit equations for the performance plots of Figures 4–7, respectively. The best fit for all the models has been achieved at the third-order polynomial. Also, Tables 2–5 list the values of different statistical parameters of the characteristic curves of the performance plots.

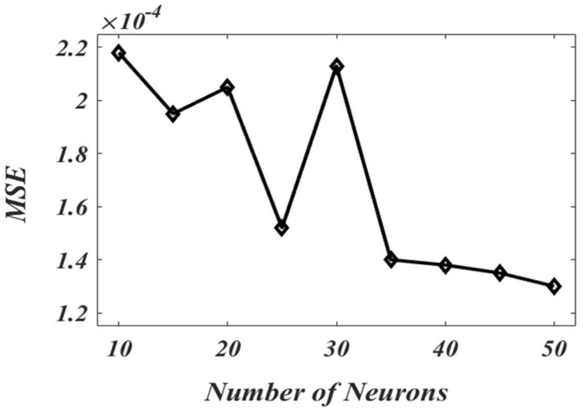

FIGURE 5 Variation in MSE for NN model treating 2-FAL as a failure index.

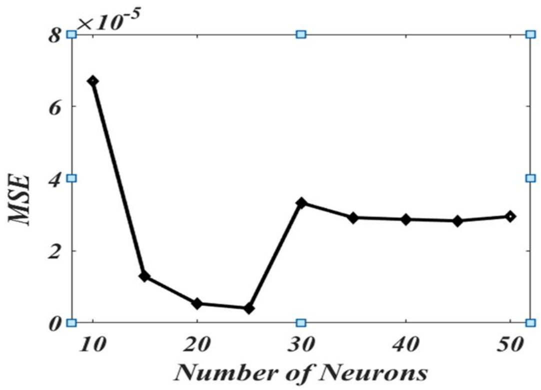

FIGURE 6 Variation in MSE for NN model treating CO as a failure index.

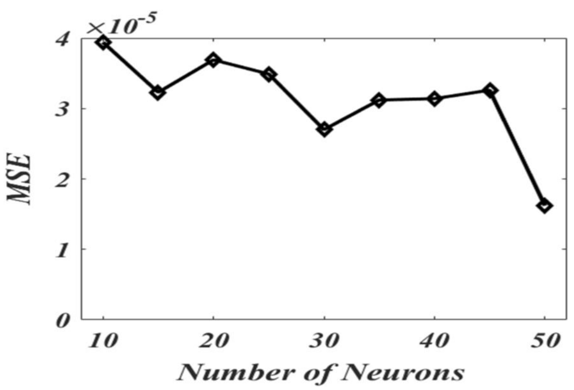

FIGURE 7 Variation in MSE for NN model treating CO_2 as a failure index.

TABLE 1 Least MSE at a particular number of neuron for NN models based on four failure indices.

Failure index	Number of hidden layer neurons	Mean square error (MSE)
DP	35	2.06×10^{-6}
2-FAL	50	1.30×10^{-4}
CO	25	4.07×10^{-6}
CO_2	50	1.62×10^{-5}

TABLE 2 Statistical parameters for the performance model treating DP as the failure index.

	X	*Y*
Min	10	2.06×10^{-6}
Max	50	3.27×10^{-5}
Mean	30	7.787×10^{-6}
Median	30	3.37×10^{-6}
Mode	10	2.06×10^{-6}
Std	13.69	9.932×10^{-6}
Range	40	3.064×10^{-5}

TABLE 3 Statistical parameters for the performance model treating 2-FAL as the failure index.

	X	*Y*
Min	10	0.00013
Max	50	0.000218
Mean	30	0.000169
Median	30	0.000152
Mode	10	0.00013
Std	13.69	3.721×10^{-5}
Range	40	8.8×10^{-5}

TABLE 4 Statistical parameters for the performance model treating CO as the failure index.

	X	*Y*
Min	10	4.07×10^{-6}
Max	50	6.71×10^{-5}
Mean	30	2.65×10^{-5}
Median	30	2.87×10^{-5}
Mode	10	4.07×10^{-6}
Std	13.69	1.888×10^{-5}
Range	40	6.303×10^{-5}

$$y = -\left(1.99 \times 10^{-9}\right) x^3 + \left(2.17 \times 10^{-7}\right) x^2 - \left(7.56 \times 10^{-6}\right) x + 8.68 \times 10^{-5} \tag{11}$$

$$y = \left(1.1 \times 10^{-9}\right)x^3 - \left(9.7 \times 10^{-8}\right) x^2 + \left(2.2 \times 10^{-7}\right) x + 0.00022 \tag{12}$$

$$y = -\left(7.8 \times 10^{-9}\right)x^3 + \left(7.7 \times 10^{-7}\right) x^2 - \left(2.3 \times 10^{-5}\right) x + 0.00022 \tag{13}$$

$$y = -\left(1.5 \times 10^{-9}\right)x^3 + \left(1.3 \times 10^{-7}\right) x^2 - \left(3.4 \times 10^{-6}\right) x + 6.3 \times 10^{-5} \tag{14}$$

TABLE 5 Statistical parameters for the performance model treating CO_2 as the failure index.

	X	*Y*
Min	10	1.62×10^{-5}
Max	50	3.94×10^{-5}
Mean	30	3.132×10^{-5}
Median	30	3.23×10^{-5}
Mode	10	1.62×10^{-5}
Std	13.69	6.7×10^{-6}
Range	40	2.32×10^{-5}

4 | RESULT AND DISCUSSION

The proposed CSKP insulation health assessment models have been optimally configured by fine-tuning the number of hidden layer neurons. The optimal configurations thus achieved have been validated and tested for various moisture and temperature levels for real-time samples with known DP values and remaining life. The testing data has been prepared fixing the temperature and varying moisture levels for the pre-tested samples. Then, the moisture level is kept constant and temperature is varied. In order to validate the authenticity of models they have been tested using developed data set. The

TABLE 6 Comparison of measured life evaluated using NN and mathematical actual model by treating DP as a failure of index.

		Measured insulation life				
Temp. (°C)	**Moisture (%)**	**Actual**	**Using neural network**	$t = \lambda m^{-a} e^{\frac{B}{T}}$	**Error (%) calculated in [13]**	**Error (%)**
90	1	64,000	64,041	74,473	−16	−16
90	2	27,500	27,480	27,284	1	0.71
90	3	17,300	17,334	15,164	12	12.5
110	1	16,000	16,142	15,396	4	4.6
110	2	5800	5778	5640	3	2.38
110	3	3000	3025	3135	−4	−3.6
130	1	4100	4054	3722	9	8
130	2	1375	1384	1364	1	1.4
130	3	675	675	758	−12	−12

TABLE 7 Comparison of measured life evaluated using NN and mathematical actual model by treating 2-FAL as a failure of index.

		Measured insulation life				
Temp. (°C)	**Moisture (%)**	**Actual**	**Using neural network**	$t = \lambda m^{-a} e^{\frac{B}{T}}$	**Error (%) calculated in [13]**	**Error (%)**
90	1	45,200	45,294	71,224	−58	−57
90	2	39,811	39,768	28,569	28	28
90	3	18,000	17,747	16,742	7	5
110	1	16,800	16,318	14,079	16	13
110	2	5754	5755	5647	2	1.87
110	3	3020	002	3310	−10	−10
130	1	3981	3983	3269	18	18
130	2	1150	1142	1311	−14	−14
130	3	682	703	768	−13	−9

TABLE 8 Comparison of measured life evaluated using NN and mathematical actual model by treating CO as a failure of index.

		Measured insulation life				
Temp. (°C)	**Moisture (%)**	**Actual**	**Using neural network**	$t = \lambda m^{-a} e^{\frac{B}{T}}$	**Error (%) calculated in [13]**	**Error (%)**
90	1	49,164	49,166	57,771	−18	−17
90	2	18,989	19,376	21,074	−11	−8.76
90	3	13,313	13,345	11,683	12	12
110	1	13,892	13,804	13,111	6	5
110	2	5180	5240	4783	8	8.72
110	3	3064	3062	2651	13	13
130	1	3963	3963	3447	13	13
130	2	1169	1159	1258	−8	−8.5
130	3	563	565	697	−24	−23

TABLE 9 Comparison of measured life evaluated using NN and mathematical Actual model by treating CO_2 as a failure of index.

		Measured insulation life				
Temp. (°C)	**Moisture (%)**	**Actual**	**Using neural network**	$t = \lambda m^{-a} e^{\frac{B}{T}}$	**Error (%) calculated in [13]**	**Error (%)**
90	1	34,161	34,160	58,306	−71	−71
90	2	31,876	31,880	22,539	29	29
90	3	15,679	15,831	12,926	18	18
110	1	14,550	13,669	12,614	13	8
110	2	4394	4347	4876	−11	−12
110	3	2655	2647	2796	−5	−5
130	1	4280	4300	3177	26	26
130	2	1242	1237	1228	1	1
130	3	521	523	704	−35	−35

output of the models has been compared with the known output and lifetime estimated using empirical model.

In the Tables 6–9, the CSKP insulation life is estimated using the NN and have compared with evaluated insulation life using the empirical model represented by the Equation (1) for numerous moisture and temperatures. An intense observation on these results seem to follow that the differences between the life evaluated by NN model and those obtained mathematically, both cantered on DP (Table 6) is least. It is also known truth that any failure index measured through a destructive test is always preferable to one measured by diagnostic test. Hence, the DP finds to be a precise indicator of the physical tensile strength of the insulating paper and, thereby, the state of its ageing. Given this, estimated life utilising DP as a failure index offers a more trustworthy measurement (least error) as validated by the proposed NN model (Table 6).

A parallel comparison is made for the results listed in Tables 7–9 which show relatively large but not unreasonable errors. It is also revealed here that the measured life of insulation for all the NN models is quite closer to what it obtained experimentally. It might also be seen in Tables 6–9 that the estimation of the measured life differs, subjected to the index applied to outline the failure of the insulation.

There should be skilled judgements to agree with or refuse to the predictable life depending upon any of the indexes. The DP measures directly the physical tensile strength of the paper and hence the state of the CSKP ageing. Taking this into account, the assessed useful/residual life considering DP as an index of failure offers a more reliable diagnostic test.

The data in Tables 6–9 is represented in Figures 8–11, displaying how moisture levels affect insulation life at constant temperatures. The graphs clearly validate that moisture content has a significant impact on insulation decomposition. Moisture indeed plays a pivotal role in the ageing of insulation when coupled with temperature and electrical stresses, as elucidated by our findings. Our research underscores a clear relationship between moisture content and insulation life, where an increase in moisture content corresponds to a decrease in insulation longevity, even with a minor temperature fluctuation between 110 and 130 °C. Notably, a mere 3% moisture content leads to a substantial reduction in insulation life across all examined failure indices. The linear correlation between moisture content

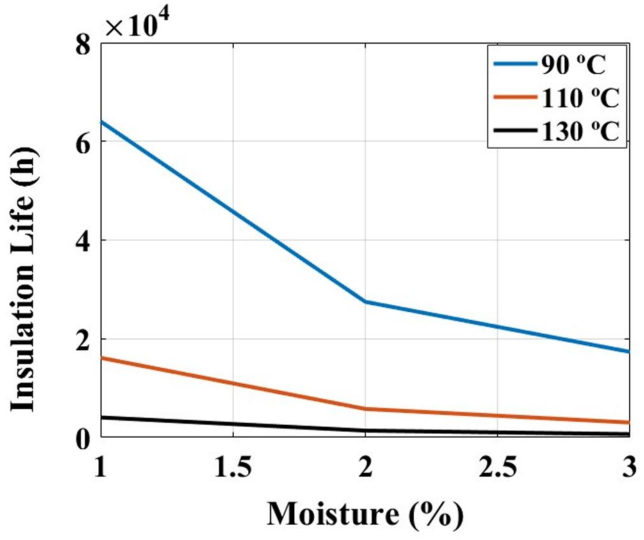

FIGURE 8 Insulation life changes in response to different moisture level and constant temperature considering DP as the failure index.

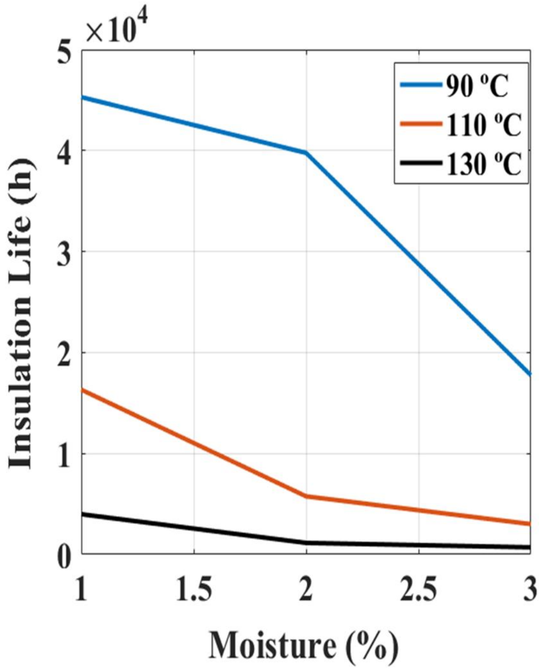

FIGURE 9 Insulation life changes in response to different moisture level and constant temperature considering 2-FAL as the failure index.

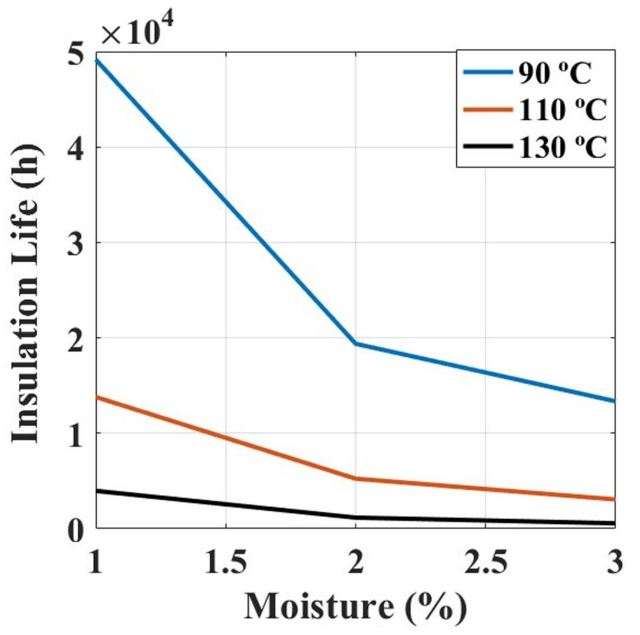

FIGURE 10 Insulation life changes in response to different moisture level and constant temperature considering CO as the failure index.

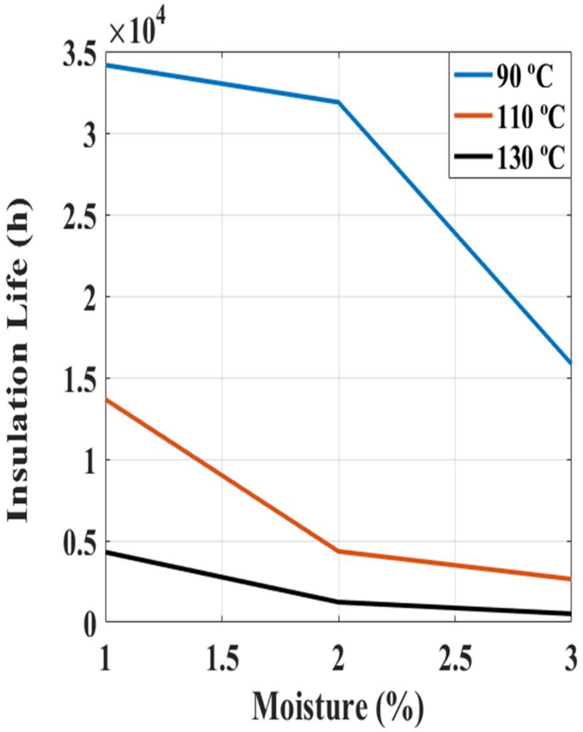

FIGURE 11 Insulation life changes in response to different moisture level and constant temperature considering CO_2 as the failure index.

and insulation life demonstrates a proportional decline in residual life with rising moisture levels. This phenomenon clearly establishes moisture's role as a catalyst, intensifying the ageing process of insulation when it interacts with temperature and electrical stresses.

The combined influence of these ageing parameters significantly accelerates the deterioration of insulating paper (CSKP), resulting in premature failures. To ensure the reliability and longevity of electrical systems, it is imperative to meticulously manage and control moisture levels within the CSKP insulation. The preservation of optimal insulation materials and the implementation of effective measures to safeguard against moisture infiltration are critical for the dependable operation of electrical equipment. In essence, our research underscores the critical significance of moisture in insulation degradation and its synergistic effect with temperature and electrical stress, which together expedite the ageing process and lead to premature failures. This insight serves as a valuable contribution to the field of electrical engineering and underscores the importance of moisture control in ensuring the sustained performance of electrical systems.

5 | CONCLUSION

The objective of this work is to draw attention to a potential approach for calculating the RUL of insulating paper in power transformers. It has been demonstrated here that the estimating process depends significantly on the insulation failure index employed. Estimating the useful/residual life of CSKP insulation gives a significant aspect for improving the conditional awareness at the transformer flawless operation level. The paper introduces four NN models as an innovative approach to estimate the remaining life of transformer insulation. These models utilise key input parameters, including the failure index, moisture levels, and temperature, to diagnose the impact of moisture on CSKP insulation. Each NN model is specifically tailored to address one of the following failure indices: DP, 2-FAL, and carbon oxides (CO and CO_2). The process involves training and testing these models to achieve optimal configurations in terms of the number of neurons in the hidden layer, ultimately enhancing prediction accuracy. These NN models are validated using pre-tested samples, ensuring their real-world applicability. To evaluate the effectiveness of the models, the estimated insulation life is compared with values obtained through inspection and mathematical calculations based on the modified Arrhenius equation. This comparative analysis enables a comprehensive assessment of the models' performance and their potential as a reliable means of estimating the remaining useful life of transformer insulation. The error percentage is found to be in close approximation to the mathematical model with minimal discrepancies in predicted insulation life. Further it is revealed that using DP as an index of failure, the life of transformer can be predicted more accurately.

AUTHOR CONTRIBUTIONS

Md. Manzar Nezami: Conceptualiszation; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Validation; Visualiszation. **Md. Danish Equbal**: Investigation; Methodology; Resources; Software; Validation; Visualiszation; Writing – review & editing. **Md. Fahim Ansari**: Conceptualiszation; Data curation; Project administration; Supervision; Validation; Visualiszation; Writing – review & editing. **Majed A. Alotaibi**: Conceptualiszation; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Supervision; Writing – original draft. **Hasmat Malik**: Conceptualiszation; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Writing – original draft. **Fausto Pedro García Márquez**: Conceneptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Supervision; Validation; Visualization; Writting – original draft. **Mohammad Asef Hossaini**: Conceneptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Supervision; Validation; Visualization; Writting – original draft.

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NOMENCLATURE

2-FAL	2-furfuraldehyde
AI	artificial intelligence
ANFIS	adaptive neuro-fuzzy inference system
ANN	artificial neural network
BP	back propagation
BR	Bayesian regularisation
CO	carbon monoxide
CO_2	carbon dioxide
CSKP	cellulosic solid Kraft paper
DGA	dissolved gas analysis
DP	degree of polymerisation
E_p	error for the adopted training pattern p
FIS	fuzzy inference system
HI	health index
i	neuron number in that layer
j	layer number
LFEPT	liquid filled electrical power transformers
LM	Levenberg–Marquardt
ML	machine learning
MO	mineral oil
MRM	multiple regression model
net_j	aggregated weighted sum
NN	neural network
O_j	neuron output
O_{pj}	actual output
RL	residual/useful life
RLA	residual life assessment
RMS	root mean square
RMSE	root mean square error
RUL	residual useable life
SCG	scaled conjugate
SVM	support vector machine
t_{pj}	target output
w_{ji}	weight of interconnection
Δ_p	weight and bias update for a specific pattern p
δ_{pj}	value of error in jth layer
ε	rate of learning
θ_j	bias

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data will be provided on request.

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