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Feedforward Artificial Neural Network (FFANN) Application in Solid Insulation Evaluation Methods for the Prediction of Loss of Life in Oil-Submerged Transformers

Bonginkosi A. Thango

Department of Electrical and Electronic Engineering Technology, University of Johannesburg, Johannesburg 2028, South Africa; bonginkosit@uj.ac.za; Tel.: +27-65-564-7287

Abstract: In this work, the application of a feed-forward artificial neural network (FFANN) in predicting the degree of polymerization (DP) and loss of life (LOL) in oil-submerged transformers by using the solid insulation evaluation method is presented. The solid insulation evaluation method is a reliable technique to assess and predict the DP and LOL as it furnishes bountiful information in examining the transformer condition. Herein, two FFANN models are proposed. The first model is based on predicting the DP when only the 2-Furaldehyde (2FAL) concentration measured from oil samples is available for new and existing transformers. The second FFANN model proposed is based on predicting the transformer LOL when the 2FAL and DP are available to the utility owner, typically for the transformer operating at a site where un-tanking the unit is a daunting and unfeasible task. The development encompasses constructing numerous FFANN designs and picking networks with superlative performance. The training and testing procedures databank is based on the dataset of the 2FAL and DP from a fleet of transformers and measured from laboratory analysis. The correlation coefficient of 0.964 was ascertained when the DP was predicted using the 2FAL measured in oil. In the FFANN model, a correlation coefficient of 0.999 against the practical data where one can make a reliable prediction of transformer LOL concerning 2FAL was generated and the amount of DP present produced. This model can be used to predict the DP and LOL of new and existing transformers at the manufacturer's premises and operating in the field, respectively. To the knowledge of the authors, no research work has been published addressing the methods proposed in this work.

Keywords: 2-furaldehyde (2FAL); feedforward artificial neural network (FFANN); degree of polymerization (DP); loss of life (LOL); transformers

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1. Introduction

Oil-submerged cellulose paper is extensively used as a solid dielectric material in electrical power transformers [1]. During the operational lifetime of the power transformer, cellulose paper progressively decomposes on account of the multi-pronged stresses it is susceptible to [2]. Considering that the insulation condition is a crucial factor to ascertain the reliable operation of power transformers, assessment of the insulation condition has obtained considerable attention from various researchers in the power industry [3]. The effective residual duration of the operation of a power transformer is determined in keeping with the condition of its paper insulation by measuring the degree of polymerization (DP) [4]. According to [5], the earliest DP value of newly manufactured cellulose paper is in the range between 1000 and 1200, which plunges to about 200 to 300 once the cellulose paper attains the end of its lifecycle. Whereas the DP is the most artful indication to examine the decomposition of a cellulose paper insulation, it is seldomly employed by the manufacturing industry due to the intricacy of harvesting the physical paper samples, particularly from hotspot regions of the unit in-service. Intrinsically, considerable research attempts have been performed to associate the DP value with various measurable dissolved-in oil indicators [6–10]. Cellulose is a straight polymer of glucose molecules inextricably linked to glycosidic bonds [5,6]. The cause of towering thermal stresses, hydrogen bonds have the propensity to disintegrate, which is caused by the reduced cellulose molecular chain and the formation of chemical derivatives that are then suspended in the dielectric oil. Furanic compounds and moisture are the principal derivatives of cellulose decomposition [7,8].

In recent times, several DP and LOL models for power transformers have been presented, however, no model has been universally accepted. It is critical to identify the major impediments. Previous reviews in this context have concentrated on a single solution based on specific case studies and alternative routes that can be taken by the manufacturers based on data availability have not been addressed. To corroborate the contribution to the current research, a summary of recent research works is tabulated in Table 1.

Table 1. A summary of recent research works.

Ref. No	Journal Ranking	Year	Applied Method	Summary
[11]	Q2	2021	Statistical tool (multiple linear regression)	A study of the relationship between the DP and various transformer parameters (DGA, breakdown voltage, furans, oil interfacial tension, moisture content, etc.) is carried out. A strong correlation between the DP and furan was discovered. There was no strong correlation between the DP and other parameters except for furans
[12]	Q2	2021	ANN	The study attempted to predict the DP using methanol, carbon oxides, and hydrogen released in the insulating oil. The classification of the study was, however, tailor-made to the individual maintenance and scheduling strategy of a power utility
[13]	Q1	2021	ANN	The study predicted the furans using the temperature, carbon dioxide, carbon monoxide, and moisture to determine the DP
[14]	Q1	2022	Empirical modeling	The study predicted DP using methanol. The relative error yielded 7%
[15]	Q1	2021	Regression modeling	Prediction of the DP using the furfural indicator at various oil over pressboard ratios and oil change status
[16]	Q1	2021	Frequency domain spectroscopy	The DP was predicted by employing the frequency conditional dielectric modulus technique
[17]	Q2	2020	Fuzzy controller	The DP was predicted using a fuzzy logic controller and considering the furans
[18]	Q1	2019	Adaptive neuro-fuzzy inference system (ANFIS)	DP was predicted using ANFIS and considering furans, carbon dioxide, and carbon monoxide
[19]	Q2	2018	Using Monte Carlo algorithm and ANN	The transformer LOL was predicted considering the loading data, carbon dioxide, breakdown voltage, and acidity
[20]	Q1	2022	Genetic-algorithm optimized support vector machine	The PD was predicted using methanol and ethanol

It can be observed from the most recent works that the methodologies proposed herein have not been reported. It is therefore vital to disseminate the proposed methods to support transformer manufacturers and dielectric laboratories with reliable alternatives to these methods. In this work, the remnant loss of life of the cellulose paper insulation was predicted by proposing two FFANN approaches. The first model is based on predicting the DP when only the 2-furaldehyde (2FAL) concentration measured from the oil samples is available for new and existing transformers. The second FFANN model proposed is based on predicting the transformer LOL when the 2FAL and DP are available to the utility owner.

1.1. Manuscript Contribution

This work presents comprehensive research on developing novel prediction models for loss of life in oil-submerged transformers. The research underpins two models based on FFANN. The contributions of the current research study are as follows:

- A model capable of predicting the DP when only the 2-furaldehyde (2FAL) concentration measured from oil samples is available for new and existing transformers using FFANN was developed
- An FFANN model was developed to predict the transformer LOL when the 2FAL and DP are available to the utility owner, typically for the transformer operating at a site where un-tanking the unit will be an impractical task.

1.2. The Novelty of Current Research

The fundamental goal of this research work was to obtain the loss of life of solid insulation in transformers using different available data alternatively. Even though numerous investigators have worked on the transformer loss of life prediction, as shown in Table 1, no existing research has reported on the application of FFANN to suggest each of the methods proposed in the current study. On the two novel approaches proposed in the current work, the first model was based on predicting the DP when only the 2-furaldehyde (2FAL) concentration measured from the oil samples is available for new and existing transformers. The second FFANN model proposed was based on predicting the transformer LOL when the 2FAL and DP are available to the utility owner, typically for the transformer operating at a site where un-tanking the unit will be a daunting and unfeasible task. These approaches are crucial in the development of prediction techniques for the DP and LOL of new and existing transformers at the manufacturer's premises and operating in the field, respectively.

1.3. The Manuscript Organization

The rest of this manuscript is organized as follows. Section 2 introduces the fundamental principle of artificial neural networks and proposed feedforward artificial neural network. Section 3 presents the results of thee developed models for predicting DP when only 2FAL is available and predicting LOL using the predicted DP and measured 2FAL. Finally, Section 4 presents a detailed conclusion.

2. Materials and Methods

2.1. The Fundamental Principle of Artificial Neural Network

Artificial neural networks (ANNs) are computing techniques motivated by the genetic neural networks that are composed in animal brains [18–20]. An ANN is constructed on an assemblage of coupled nodes so-called artificial neurons, which are essentially archetypal of the neurons in a genetic animal brain. Respective connections such as the synapses in the animal brain can diffuse information to coupled neurons. An artificial neuron obtains information and subsequently processes them and can inform coupled neurons. The "information" at a link is a real number, plus the output of the respective neuron is calculated by a certain non-linear function of the summation of its inputs [18–20]. The links are so-called edges. Generally, neurons and edges are characteristically composed of a weight that adapts as learning progresses. The weight rises or drops the power of the information at a connection. Neurons can have a permissible range in a manner where information is driven exclusively when the total signal intersects that permissible range. Classically, neurons are amassed into layers [18–20]. Distinctive layers can carry out various conversions on the respective inputs. Information travels from the input layer to the output layer, conceivably following crisscrossing the layers numerous times.

2.2. Proposed Feedforward Artificial Neural Network

Two computational schemes based on FFANN were designed to estimate the residual lifespan of oil-submerged transformers. The first model was based on predicting the DP when only the 2-furaldehyde (2FAL) concentration measured from the oil samples is available for new and existing transformers. The second FFANN model proposed was based on predicting the transformer LOL when the 2FAL and DP are available to the utility owner, typically for the transformer operating at a site where un-tanking the unit will be a daunting and unfeasible task.

The choice of inputs, outputs, and network structure in the FFANN prototype is dependent on the efficiency of the FFANN models. The measurements for the gas concentrations concerning the emerging transformer faults were gathered from the real data of a power transformer. In this work, the development of an FFANN was split into four phases: data gathering and processing, FFANN modeling, training, and testing.

2.2.1. Data Gathering and Processing

In the data gathering and processing stage, various transformers from 315 kVA to about 40 MVA 132 kV were considered in the study. These units had been removed from service and were processed in a workshop to diagnose their conditions. The oil sample of individual units was analyzed in the laboratory to attain the 2FAL concentration existing in the oil sample. Concurrently, the sample of the solid insulation material was extracted and analyzed in the laboratory to attain the degree of polymerization. For the respective unit, the lifetime of the unit in-service was collected from the original equipment manufacturer. It follows that the data were divided into two datasets: one contained the measured DP and the measured 2FAL, and in the other dataset, a dataset with column vectors comprising the DP, 2FAL and LOL of the unit was assembled. It should be noted that the LOL is essentially the remnant life of the unit (i.e., the designed services life of the unit minus the lifetime in operation). In processing the datasets, the inputs as well as target data are determined and fed into the ANN matrix for training and validation. In the first model, the 2FAL was specified to be the input, whereas the corresponding DP was specified as the target. In the second proposed model, the transformer remnant life was defined as the target response whereas the available DP and 2FAL dataset were utilized as the inputs. These datasets were classified into three categories: learning, verification, and evaluation. The learning sample comprised 70% of the entire dataset, with the remaining 30% used for verification and evaluation.

2.2.2. ANN Models

In this work, the MATLAB/SIMULINK tool was utilized to execute two ANN models. To identify the optimal ANN model, the learning or training rate (LR) and momentum cost (MC) was changed between 0 to 0.9. However, since all variables were altered iteratively, underfitting as well as overfitting systems remained possible. Overfitting happens whenever a system is proficient in memorizing the system but is unable to extrapolate new input for the system. The early halting approach has been used to achieve an optimized performance to address the overfitting challenge. The termination criteria were obtained by evaluating the mean square error of the learning data during training using data that are limited in size.

2.2.3. Training Phase

A backpropagation approach is a simplified delta function for a feed-forward system with numerous layers that are used during the training phase. This is due to its ability to calculate the slope of each layer, continuously utilizing the chain principle. In practice, quadratic activation functions are utilized to improve performance due to their non-linearity and suitability with a feed-forward backpropagation training (FFBPT) approach. The LM was adopted as the learning classifier in this work because it is a rapid, simple, and stable approach. As a result, the FFBPT approach was chosen as the system structure for the ANN design. The optimal ANN settings with the maximum precision, which is equivalent to R, were obtained by modifying the number of hidden layers, the number of neurons as well as the transfer function. In this work, a three-layer system with 10-hidden layers and a 1-output layer was adopted for both ANN models. While one hidden layer is sufficient for nonlinear modeling, a system with 2-hidden layers outperforms systems with 1- as well as 3-hidden layers in terms of the number of iterations, precision, and sophistication. Furthermore, the 3-layer system helps solve the challenge of slow learning rates.

2.2.4. Testing Phase

An additional batch of data was used to evaluate the trained system. The trained ANN was used to mimic the response output of the additional data batch. The optimal-trained system demonstrates that the modeled output matched the desired output accurately. The efficiency of the trained system was determined utilizing the R correlation value.

Table 2 illustrates a comparative analysis of the ANN types when using the first proposed model dataset. These results justify the selection for the FFANN, which yielded an MSE of 0.324 and an R2 of 0.96431.

Table 2. Comparative analysis of the ANN types.

Parameter	FFANN	RBNN	MPM	RNN
MSE	0.324	2.567	5.876	8.26
R2	0.96431	0.845	0.765	0.56

RBNN—Radial basis neural network, MPM—Multilayer perception model, RNN—Recurrent Neural network, MSE—Mean Square error, R2—correlation coefficient.

3. Results

3.1. Predicting DP When 2FAL Only Is Available

Figure 1 depicts the modeling configuration that predicts DP when only 2FAL is available. The coaching efficiency graph in Figure 2 clearly shows that the learning ability of the ANN is satisfactory. The average mean square error of the trained ANN was less than the predetermined minimum of 0.0001. The mean square error was 692.943 after the coaching of the ANN. As a result, this model was selected as the definitive option for the specified input and output. The trial set error as well as the verification set error had comparable features, and zero notable overfittings transpired after iteration 14. This was the region where the optimum validation result had been achieved.

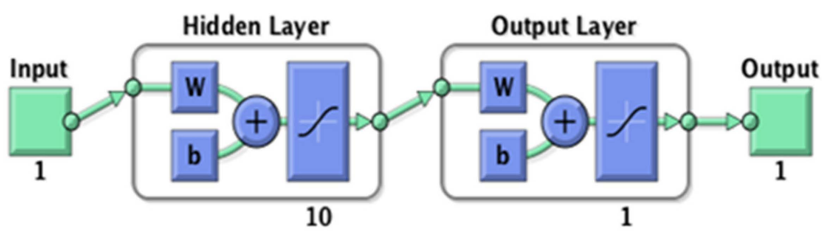

Figure 1. The ANN classifier for the LOL estimation for model one.

Mineral-based oil units were considered. The condition of the oil was taken as is for analysis as it represents the accurate amounts of furans present. The dataset was utilized to train the ANN. Following ANN training, its efficiency was verified by showing the linear regression graph that correlated the targets to the outputs, as illustrated in Figure 3. The correlation coefficient indicates how effectively the ANN's targets may detect changes in outputs. A correlation of 0 means that there is no correlation at all, whereas a correlation of 1 means that there is a complete correlation. A regression result suggests a close relationship between the outputs and targets. The correlation coefficient in this scenario was observed to be 0.964, indicating a high correlation.

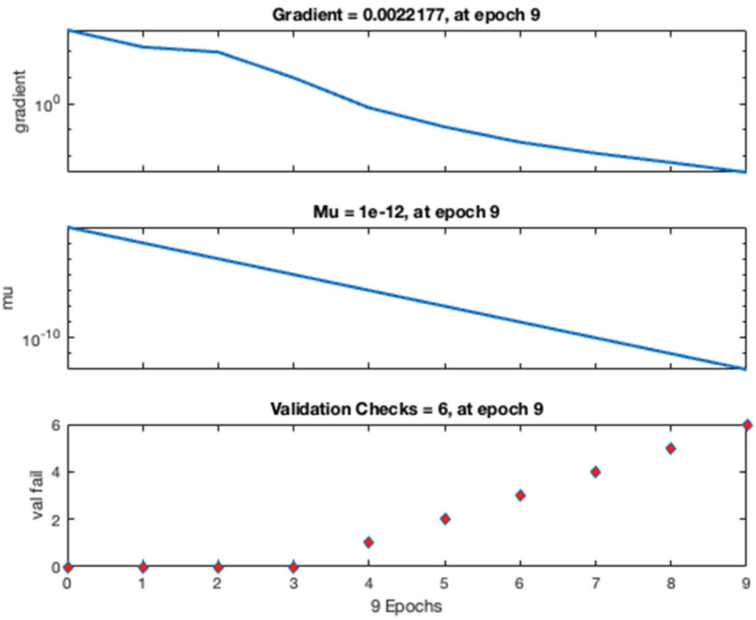

Figure 2. Performance of the training process of model one.

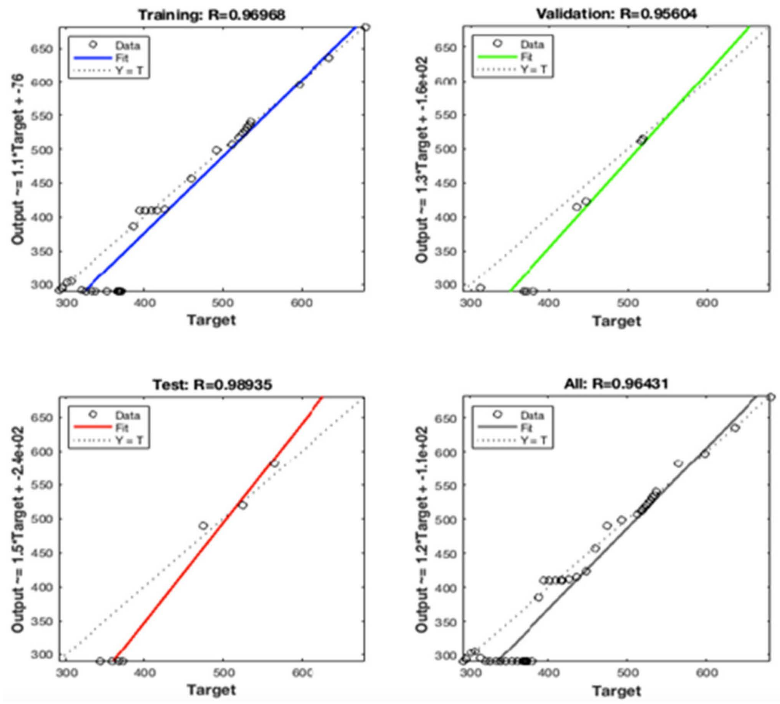

Figure 3. Model linear fitting in training and testing for model one.

Figure 4 depicts the accuracy of the validation checks using the validation set. When the validation error begins to rise, the ANN terminates the learning session, regardless of whether the target has still not been achieved. Therefore, the ANN has a high degree of generalizability. This will halt the learning session when the abstraction performance has reached its maximum. Figure 5 demonstrate the performance parameters of the proposed FFANN.

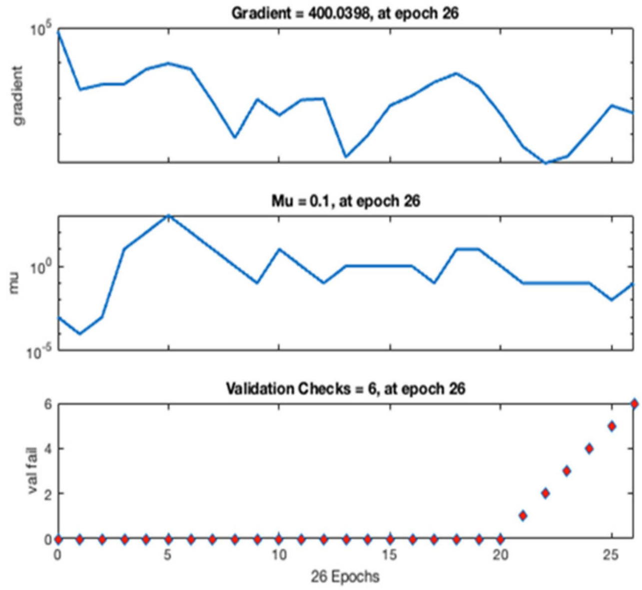

Figure 4. Validation in the training phase of model one.

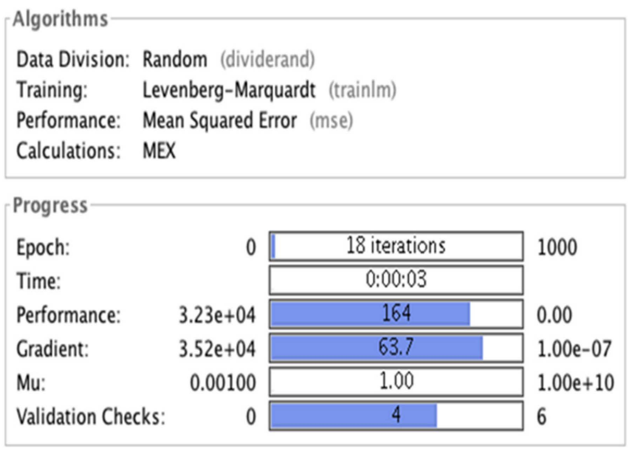

Figure 5. ANN model training of model one.

3.2. Predicting LOL Using Predicted DP and Measured 2FAL

Figure 6 illustrates the model setup for predicting LOL based on the predicted DP and measured 2FAL.

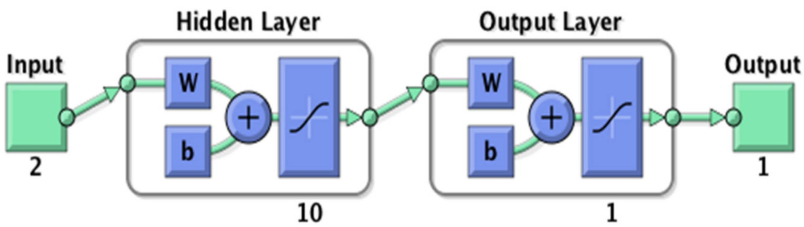

Figure 6. The ANN classifier for LOL estimation for model two.

The cumulative mean square deviation of the generated ANN was 0.0006684, and Figure 7 illustrates that the testing and verification curves had comparable properties, indicating efficient training. The trial set error and the verification set error had similar characteristics, and no significant overfitting occurred after iteration 13. The correlation coefficient represents how successfully the ANN's goals can make corrections in outputs, with 0 representing no correlation at all, while 1 represents perfect correlation. The function of the trained ANN was evaluated in two methods. Initially, the linear regression that ties the goals to the outputs is illustrated in Figure 8. The correlation coefficient in this scenario was observed to be 0.999, indicating a strong correlation.

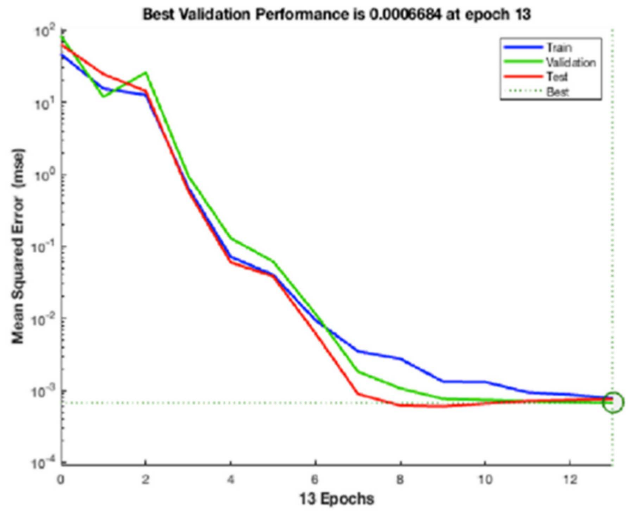

Figure 7. Performance of the training process for model two.

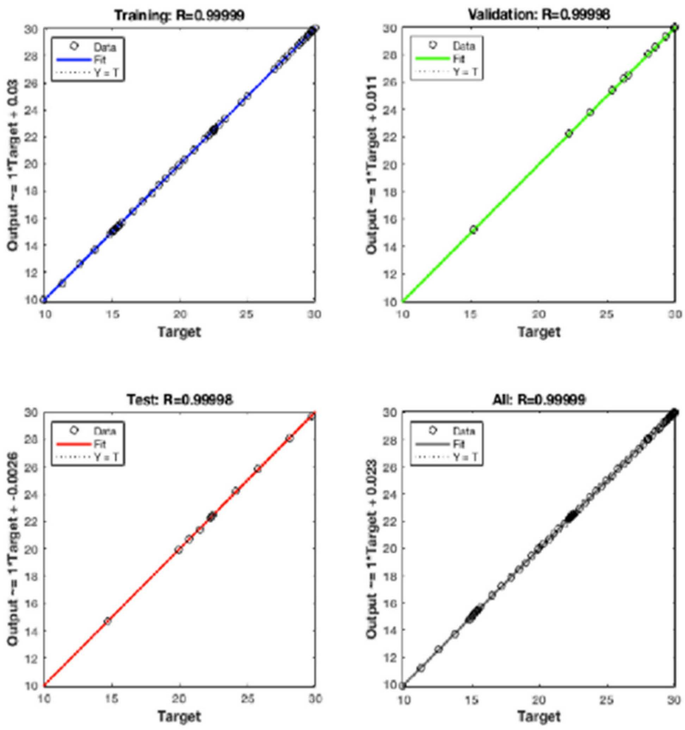

Figure 8. Model linear fitting in training and testing model two.

It was observed that the model could be used to predict the DP and LOL of new and existing transformers at the manufacturer's premises and operating in the field, respectively.

In Figure 9, the Gradient, mu (i.e., control parameter for the algorithm used to train the neural network) and validation failure (val fail) results are presented.

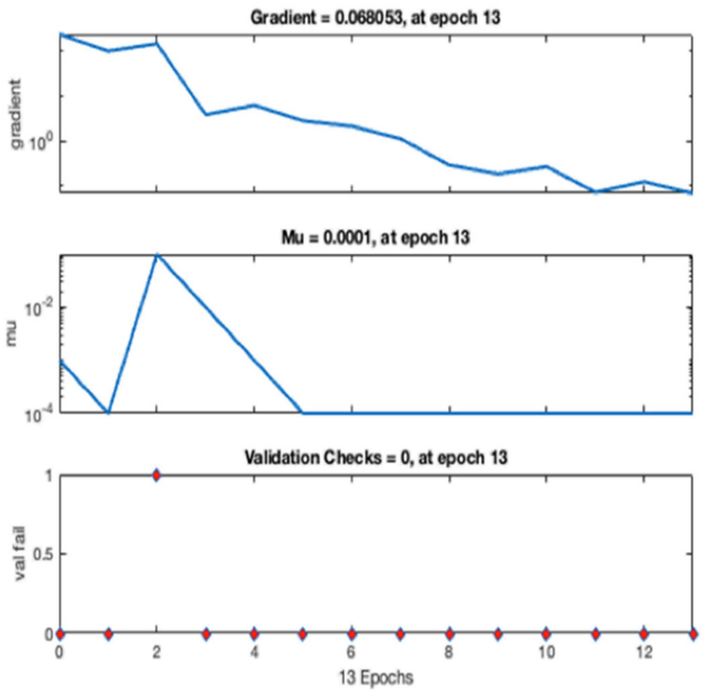

Figure 9. Validation in the training phase of model two.

The output parameters of the training model for model two are illustrated in Figure 10.

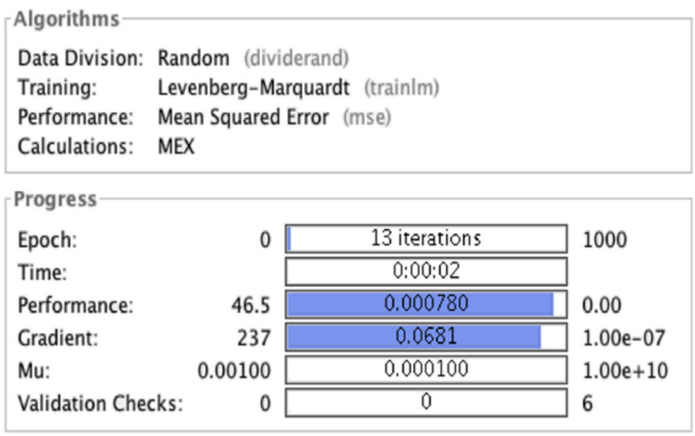

Figure 10. ANN model training of model two.

4. Conclusions

Several publications have suggested that power transformers erected in the 1980s are still in service and that some of these transformers are in an acceptable state based on the data analyses such as DP, furan, CO_2, and others. The service durability of these transformers exceeds 21 years, although the conventional technique predicts 21 years. This sustained efficiency is dependent on operational situations. These transformers are most likely to be used within the manufacturers' specified thresholds. Furthermore, the residual lifespan of the insulation is dependent on the transformer overloading cases and may be evaluated utilizing software iterations, considering the variance of overloading and LOL in the past years.

In this work, we proposed an approach for estimating the lifespan reduction and expansion of transformers. To acquire better consistent results, it is preferable to adopt a knowledge-based technique that accommodates all sets of data to accurately estimate the LOL of transformers. The ANN was applied to predict the DP and LOL in oil-submerged transformers by using the solid insulation evaluation. The proposed approach makes it simple to ascertain the extent of lifetime reduction and expansion for transformers, providing for improved accurate prediction of residual serviceability.

In this work, two ANN models were proposed. The first model was based on predicting the DP when only the 2FAL concentration measured from oil samples is available for new and existing transformers. The second ANN model proposed was based on predicting the transformer LOL when the 2FAL and DP are available to the utility owner, typically for the transformer operating at the site where un-tanking the unit will be a daunting and unfeasible task. The training and testing procedures databank was based on the dataset of the 2FAL and DP from a fleet of transformers and measured from laboratory analysis. The correlation coefficient of 0.964 was ascertained when the DP was predicted using the 2FAL measured in oil. On the ANN model, a correlation coefficient of 0.999 was obtained, against the practical data where one can make a reliable prediction of transformer LOL concerning the 2FAL generated and the amount of DP present produced. It was found that this model can be used to predict the DP and LOL of new and existing transformers at the manufacturer's premises and operating in the field, respectively.

This work provides critical knowledge for the electrical energy industry as well as beneficial attributes for future preparation. Operational planning for electrical generation, transmission, and distribution networks can perhaps be designed with greater reliability.

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