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On the Application of Artificial Neural Network for Classification of Incipient Faults in Dissolved Gas Analysis of Power Transformers

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Abstract: Oil-submerged transformer is one of the inherent instruments in the South African power system. Transformer malfunction or impairment may interpose the operation of the electric power distribution and transmission system, coupled with liability for high overhaul costs. Hence, recognition of inchoate faults in an oil-submerged transformer is indispensable and it has turned into an intriguing subject of interest by utility owners and transformer manufacturers. This work proposes a hybrid implementation of a multi-layer artificial neural network (MLANN) and IEC 60599:2022 gas ratio method in identifying inchoate faults in mineral oil-based submerged transformers by employing the dissolved gas analysis (DGA) method. DGA is a staunch practice to discover inchoate faults as it furnishes comprehensive information in examining the transformer state. In current work, MLANN was established to pigeonhole seven fault types of transformer states predicated on the three International Electrotechnical Commission (IEC) combustible gas ratios. The designs enmesh the development of numerous MLANN algorithms and picking networks with the optimum performance. The gas ratios are in accordance with the IEC 60599:2022 standard whilst an empirical databank comprised of 100 datasets was used in the training and testing activities. The designated MLANN design produces an overall correlation coefficient of 0.998 in the categorization of transformer state with reference to the combustible gas produced.

Keywords: transformer; dissolved gas analysis (DGA); multi-layer artificial neural network (MLANN); IEC 60599:2022 gas ratio method

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1. Introduction

The oil-submerged transformer is one of the inherent instruments in the South African power system. The appropriate operation of electrical transformers is vital to the operation of the national grid. The transformer operating condition unswervingly affects the dependability and stability of the complete grid. Henceforth, it has become particularly significant to identify inchoate transformer faults. Effectual recognition of inchoate fault of oil-submerged transformers can momentously condense the costs coupled with revamping impaired transformers and recovers grid stability and dependability [1–3]. The operation of transformers is generally unremitting and is contingent on thermal and electrical strains. Extreme stresses will bring about the decomposition of the insulating materials which are comprised of cellulose paper and dielectric oil. Hydrocarbons and carbon oxides are produced and disintegrated on account of the decomposition of the insulating materials. The carbon-hydrogen bond (C-H bond) and covalent bonds of the carbons in the dielectric oil will fracture and aforesaid will be conducive to the development of atomic hydrogen and hydrocarbon atoms. These atoms will merge respectively to constitute dissolved gases including Hydrogen (H_2), Carbon Monoxide (CO), Methane (CH_4), Carbon Dioxide (CO_2), Ethylene (C_2H_4), Ethane (C_2H_6), and Acetylene (C_2H_2) [4,5]. These gases can be identified by employing gas chromatography. Classes of inchoate faults that could be engrossed in a transformer are controlled by supervising and scrutinizing the concentration level, production rate, gas ratio, and total level of combustible gases in insulating oil. There are three modes of fault conditions that instigate emancipating of faulty dissolved gases: partial discharge, energy discharge, and thermal expulsion [6–10]. There are numerous chemical and electrical practices existing in supervising insulation state in oil-submerged transformers including Dissolved Gas Analysis (DGA) and Furan Analysis which reveal the Degree of Polymerization of the cellulose paper [11,12]. DGA is one of the most dependable and certified practices to identify an inchoate fault in transformers. DGA can be utilized to evaluate present-day transformer condition, provide forthcoming cautioning of emerging faults, and establish the inopportune usage of transformer for the purpose of offering suitable preparation of maintenance. The procedure generally used within the transformer manufacturing industry to extract transformer oil at the site for DGA in the laboratory is shown in Figure 1.

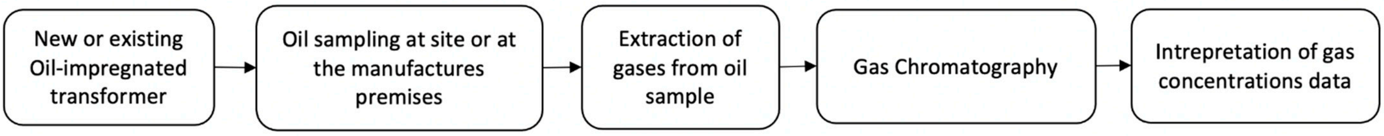

Figure 1. Extraction of transformer oil in the field for DGA.

The recommended DGA practices do not enmesh any mathematical invention and the analysis is based on an experiential technique which may differ based on the knowledge of the laboratory analyst, which results in the erratic analysis [12]. To triumph the shortcoming, numerous computerized models utilizing Artificial Intelligence have been utilized in examining inchoate faults in transformers.

In the proposed research study, recent related works and their contributions to transformer fault diagnosis have been highlighted and proposed a hybrid MLANN and IEC 60599:2022 gas ratio method for transformer fault diagnosis. Table 1 shows a comparative analysis between the existing recent survey and the proposed hybrid algorithm on transformer fault diagnosis.

Table 1. Summary of recent related works.

Ref.	Year	Method Used	Contribution
[13]	2019	Mean Shift algorithm (MSA), ANN	A MSA-based ANN is proposed. The dissolved gases are IEC 60599: 1999 standard is used to derive the parameters that will be trained by the proposed algorithm. The MSA was employed to satisfactory circumvent the shortcoming of the number of training patterns (data size). Satisfactory results are yielded in the training and validation procedures.
[14]	2018	Dornensburg ratio method, Roger's ratio method, multi-layer artificial neural network perceptron	Fault diagnosis was conducted by proposing a hybrid Dornensburg and Rogers ratio method to select a gas ratio that will train a multi-layer artificial neural network perceptron.
[15]	2018	Weighted DGA, backpropagation ANN	A fault diagnosis method is proposed by considering the energy necessitated to produce dissolved gases (weighting factor). The weighted dissolved gas concentrations were trained to utilize a backpropagation ANN. The IEC-599 standard has been considered in developing the energy-weighted input parameters. The results yield an improvement from the unweighted gases.

Table 1. *Cont.*

Ref.	Year	Method Used	Contribution
[16]	2015	Duval triangle, ANN	A Duval triangle method-based ANN has been proposed for fault diagnosis. The traditional Duval triangle method parameters are used in training the ANN. Results show that the proposed hybrid algorithm has enhanced the traditional Duval triangle method.
[17]	2022	ANFIS, Roger's ratio method	A hybrid Rogers ratio method–based ANFIS was proposed to diagnose transformer faults. The training was performed using the gas ratios recommended in the IEEE C57-104 and the IEC 60599 standards.
[18]	2020	Fuzzy Logic, IEC ratio method	A fuzzy logic- IEC ratio method was proposed for transformer fault diagnoses. The results show improvement from the classical IEC ratio method.
Current research	2022	MLANN, IEC 60599:2022 standard	A hybrid MLANN and IEC 60599:2022 gas ratio method for fault diagnosis is proposed. The proposed algorithm is corroborated by contrasting the presented case studies with the Actual, MLANN-IEC, IEC, and kNN.

Contribution: This research study has presented a brief survey of recent transformer fault diagnoses. The various artificial intelligence-based algorithms using classical DGA methods have been highlighted. The following are the contributions of the proposed research investigation:

- A hybrid MLANN and IEC 60599:2022 gas ratio method for fault diagnosis is proposed that improves the diagnostic reliability and trust between the transformer manufacturer and power utility.
- Case studies on transformer fault diagnosis using the proposed hybrid MLANN and IEC 60599:2022 gas ratio method for fault diagnosis have been presented.

The novelty of current research: The fundamental goal of this research study is to contribute to the field of transformer fault diagnostics. Notwithstanding that several recent research works have worked on transformer fault diagnosis, little and far between research has been reported about the application of a hybrid MLANN and IEC 60599:2022 gas ratio method for fault diagnosis.

The proposed hybrid algorithm is a critical approach for addressing the shortcomings of the IEC gas ration method and developing an efficient fault diagnosis system. The seven fault types which are used in the IEC 60599:2022 standard borne in mind and established that the degree of accuracy of fault diagnosis is not optimal as a result of the restrictions imposed by the gas ratio codes which results in "not detectable" in some case studies. Nevertheless, after applying the proposed hybrid diagnosis algorithm, the diagnosis is on par with the actual fault diagnosis.

The effective ratios of fault diagnosis have also been covered in this research study. The training of the proposed MLANN algorithm is critical. Hence, the DGA dataset used in training the MLANN is composed of samples which address all known types of failures according to the IEC 60599:2022 standard. From this research study, it can be affirmed that the prediction of transformer faults using a hybrid MLANN and IEC 60599:2022 gas ratio method is on equal footing with the actual fault diagnosis and provides enhancement from the IEC 60599:2022 gas ratio method.

Manuscript organization: This manuscript has been methodized as follows: Section 2 covers the materials and methods of the proposed research investigation. Section 3 presents the performance results of the proposed hybrid MLANN and IEC 60599:2022 gas ratio method and numerous case studies have been presented to corroborate the method and benchmark with other techniques. Section 4 provides a conclusion.

2. Materials and Methods

2.1. Data Assemblage and Preprocessing

The databank for the combustible gases produced by the dielectric oil samples in the fleet of transformers employed in this work during service is furnished by a local Independent Power Producer (IPP) in South Africa. The databank entails six combustible gases produced in the individual oil samples extracted in the field. The dielectric oil samples were taken to the laboratory for DGA testing to ascertain the kind and concentration level of the dissolved gases generated. Based on the six combustible gases produced in the individual oil samples, three gas ratios are considered using the IEC 60599:2022 standard recommendation [11]. Additionally, seven transformer faults have been utilized as the targeted output for the proposed MLANN algorithm. Table 2 illustrate the gas ratios and the targeted output responses of the MLANN model.

Table 2. Gas input and target response of the proposed MLANN.

Gas Inputs	Targeted Output
	Unit Normal
	Partial Discharge
C_2H_2/C_2H_4	Low energy discharge
CH_2/H_2	High Energy discharge
C_2H_4/C_2H_6	Thermal Fault, $< 300\ ^\circ C$
	Thermal Fault, $300\ ^\circ C$ *to* $700\ ^\circ C$
	Thermal Fault, $> 700\ ^\circ C$

The reading of the databank is in accordance with IEC 60599:2022 standard recommended practice. The latter is widely adopted in the transformer manufacturing industry as a guiding principle in the discrimination of various faults. Table 3 tabularizes the IEC 60599:2022 standard recommendation utilized through the development of the proposed MLANN to understand various fault classes in an oil-submerged transformer. It entails three fundamental combustible gas ratios (FCGR) matching the recommended fault identification. When FCGRs surpass permissible boundaries, inchoate faults can be anticipated in the transformer.

Table 3. IEC 60599:2022 standard fault class.

C_2H_2/C_2H_4	CH_2/H_2	C_2H_4/C_2H_6	Fault Class
< 0.1	< 0.1	< 0.2	Partial Discharge (PD)
> 0.1	0.1 *to* 0.5	> 0.1	Low energy discharge (LED)
0.6 *to* 2.5	0.1 *to* 1	> 2	High Energy discharge (HED)
< 0.1	> 1	< 1	Thermal Fault, $< 300\ ^\circ C$ (T1)
< 0.1	> 1	1 *to* 4	Thermal Fault, $300\ ^\circ C$ *to* $700\ ^\circ C$ (T2)
< 0.1	> 1	> 4	Thermal Fault, $> 700\ ^\circ C$ (T3)

The preprocessing stages are implemented to certify network efficacy. The preprocessing of the gas inputs enmeshes regularization and deregulation of the databank where the gas inputs and targeted response ratios are scaled to a particular range. The regularization is crucial since the concentration level of distinctive gases varies significantly which can potentially ensue in sluggish convergence of the proposed MLANN learning. In the current work, the databank was standardized to a range of -1 to 1.

It is worth noting that based on the above criterion, the gas ratios in practice may provide different combinations that the IEC 60599:2022 standard ratios may not be able to interpret. This can be a challenge to identify faults that fall outside the scope of this method. The application of ANN furnishes an opportunity to gain new insights thereof.

2.2. Proposed MLANN Model

In this work, MLANN models are developed using the MATLAB R2018a software platform. The multilayer feed-forward backpropagation is elected as the network prediction algorithm in view of the fact that it is the most sought-after ANN algorithm and pertinent to the current study.

The backpropagation algorithm implements learning on a multilayer feed-forward ANN. It repetitiously learns a set of weights for prognostication of the class label of tuples. A multilayer feed-forward neural network comprises an input layer, hidden layers, and an output layer. The layers applied in the implementation have a total number of four viz. the input layers, hidden layer 1, hidden layer 2, and an output layer. The number of neurons in the input and output layers are 3 and 1, respectively. Consequently, the number of neurons applied in hidden layers 1 and 2 is 10 and 5, respectively.

In Figure 2, the function block diagram on the proposed MLANN is illustrated for the prognosis of various inchoate transformer faults.

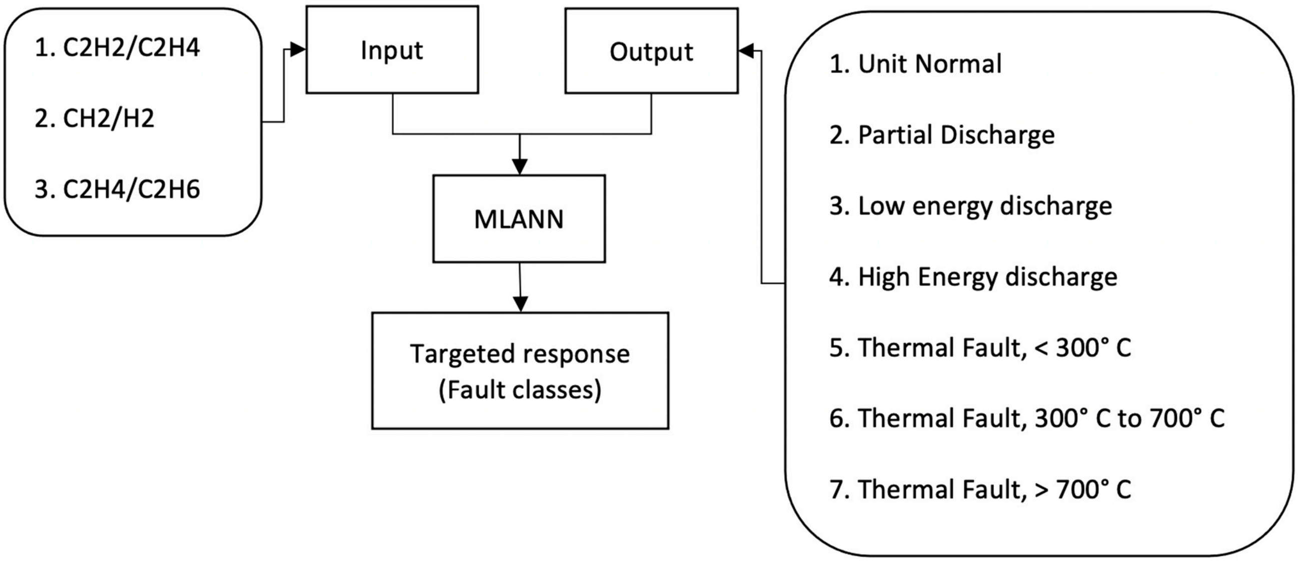

Figure 2. Function block diagram on the proposed MLANN.

The proposed MLANN generate a network response appertaining to gas inputs and targeted fault class output ingested to the network. The development of an ANN model incorporates the selection of the best-performing network training algorithms and parameters. In this work, they are established inductively based on proficiency and network performance.

2.2.1. Training Phase

During the training phase, the network is ingested with data composed of three combustible gas ratios and the transformer state as the focused output. The training phase is the most critical activity in establishing a neural network. Numerous factors can sway the performance of a neural network including network type, training function, adaption learning function, performance function, number of layers, etc. At this stage, the control parameters are diverging inductively. Tribulations that may arise in the course of network training will be underfitting and overfitting. In the case of overfitting, I will ensue when it has the proficiency to learn the network however could not generalize to the different datasets ingested. Primordial stopping is employed in the augmented MLANN as one of the techniques to circumvent overfitting. The dataset for the training phase is apportioned into three datasets viz. training dataset, validation dataset, and testing dataset.

The training dataset is utilized to calculate the gradient and modernize the network's biases and weight whereas the validation dataset is employed to keep under surveillance the state of the training phase. In Figure 3, a comprehensive flowchart of the proposed MLANN model is shown. Largely, the practice of establishing a network is apportioned into two central steps viz. the training and testing stage.

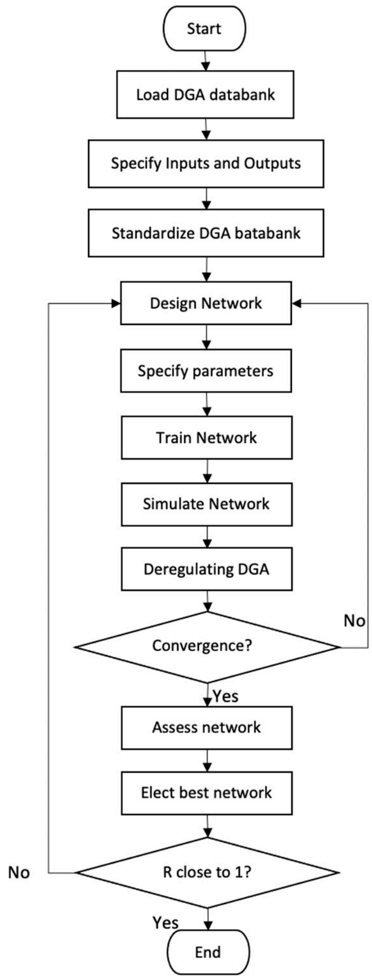

Figure 3. Proposed MLANN flowchart.

The corroboration and training errors customarily decrease at the initial phase of the training stage; nevertheless, when overfitting ensues, the validation error will proliferate.

2.2.2. Testing Phase

In the course of the testing phase, a different dataset is utilized to assess the performance of the trained network. Linear regression analysis is generally employed as a tool to evaluate the performance of a network. The regression correlation coefficient, R, is calculated to examine the relationship between the network input dataset and the targeted outputs. A thoroughly trained network carries off values of R in the vicinity of 1, exhibiting a sturdy association between network input and targeted output. In the light of the proposed network in the current work, the established network is examined by means of the value of R. The optimum network is elected predicated on the closest value to 1.

3. Results

3.1. Network Performance

The developed MLANN was trained using a databank comprised of 120 transformer oil samples where 80 of the samples are utilized for the training stage and 40 samples were utilized for the testing phase. The training function employed in the training network is the Levenberg–Marquardt backpropagation (TRAINLM). TRAINLM is in many cases the quickest backpropagation algorithm in the MATLAB toolbox and is largely suggested as a forerunner supervised algorithm, notwithstanding that it does necessitate more storage compared with other algorithms. Figure 4 shows the training phase performance of the proposed MLANN.

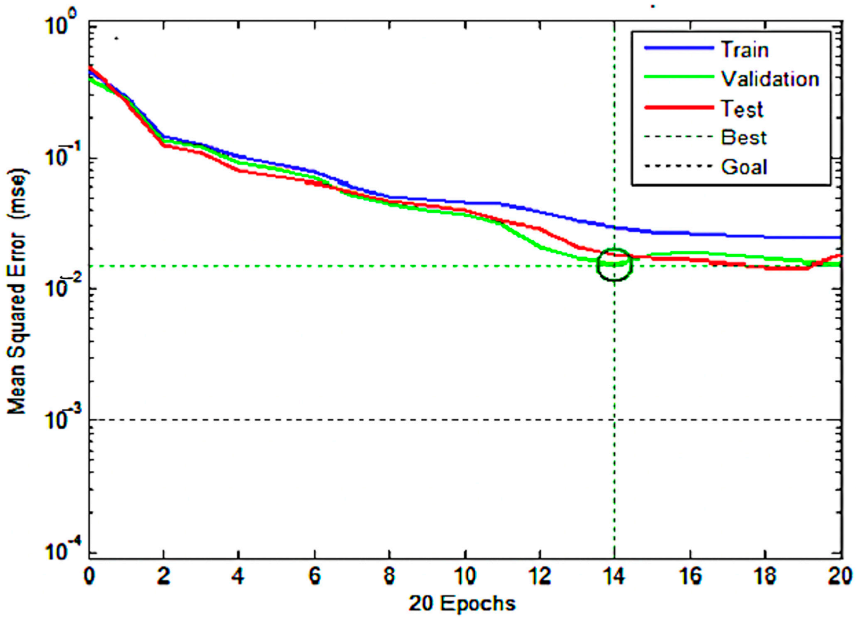

Figure 4. Training Phase performance of the proposed MLANN.

It can be observed that the testing dataset error and the validation dataset error have comparable features and there is no indication of overfitting. It can be iterated that the early stopping technique (EST) was used in the network to increase simplification.

EST is a normalization method for deep neural networks that halts the training process once the parameter updates at no time start to produce enhancement on a validation dataset. Fundamentally, the current optimal parameters are stored and updated during training, and when parameter updates in no case produce an enhancement, the training is stopped and employs the last optimal parameters. EST regularizes by constraining the optimization process to a reduced volume of parameter space. The effect of EST before and after can be illustrated in Figure 5. It can be observed that before the EST is applied, the error is no longer decreasing with the number of iterations. A point after the EST can be observed to yield an increasing error in the validation set.

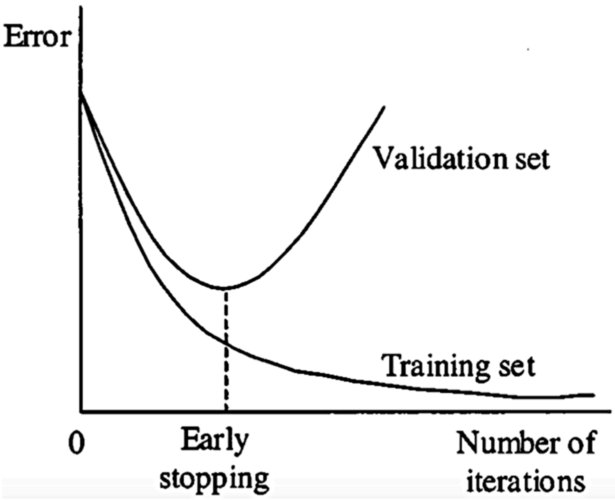

Figure 5. Principle of early stopping on proposed MLANN.

Figure 6 shows the validation check performance by the validation dataset. After the validation error is initiated to increase, the network ends the training procedure even though the goal is hitherto attained. The network has the capability to simplify optimally. It will end the training procedure at the optimal simplification capability.

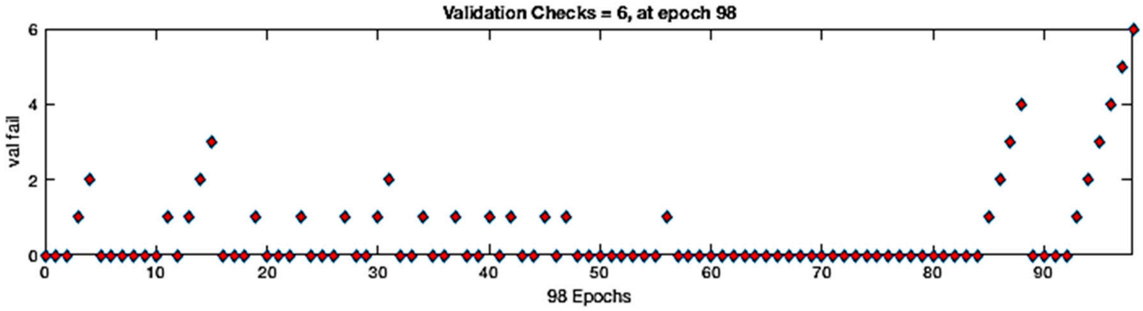

Figure 6. Training validation checks of proposed MLANN.

During the testing phase, the performance of the trained MLANN was therefore tested by ingesting the testing dataset. Figure 7 illustrates the regression model of MLANN at the testing stage. It can be observed that the correlation coefficient is 0.95495.

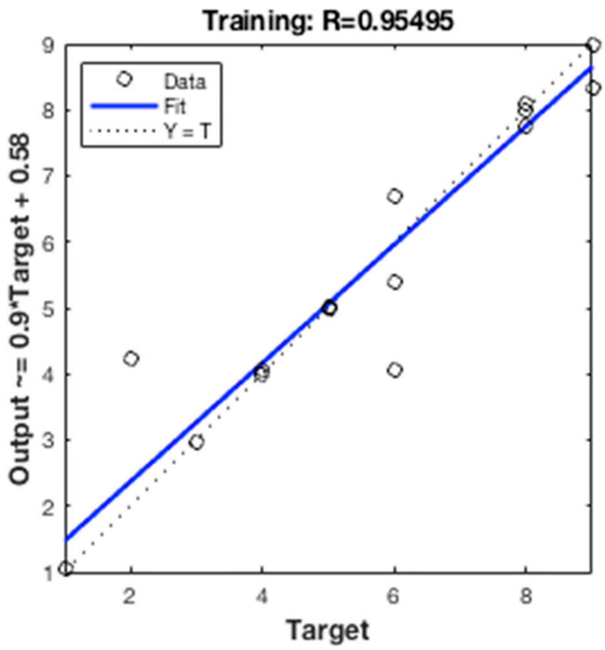

Figure 7. Regression outcomes in the training phase of the proposed MLANN.

Additionally, Figure 8 shows the performance of the proposed MLANN during the validation phase. It can be observed that the correlation coefficient is 0.99989.

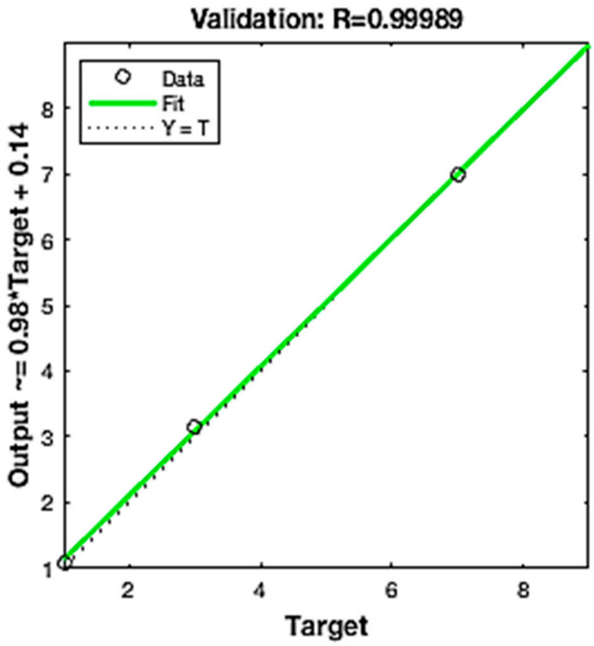

Figure 8. Regression outcomes in the validation phase of the proposed MLANN.

Consequently, Figure 9 shows the performance of the proposed MLANN during the testing phase. It can be observed that the correlation coefficient is 0.90087.

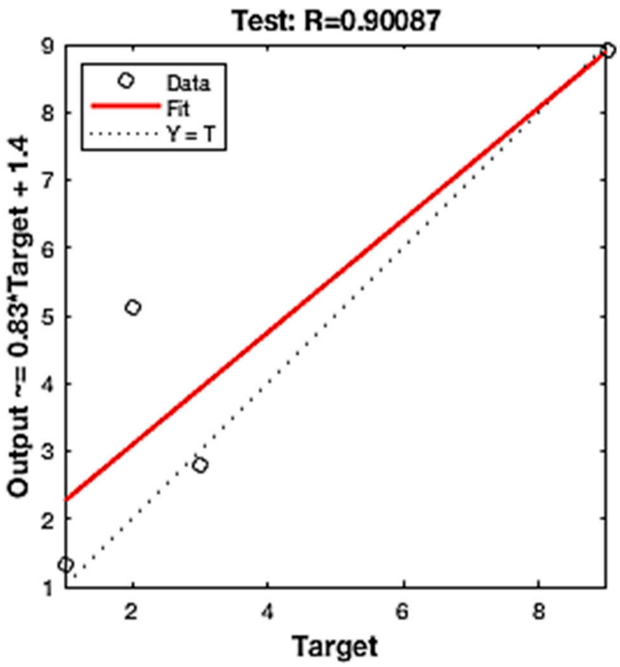

Figure 9. Regression outcomes in the testing phase of the proposed MLANN.

Finally, Figure 10 shows the overall performance of the proposed MLANN. It can be observed that the correlation coefficient is 0.94916.

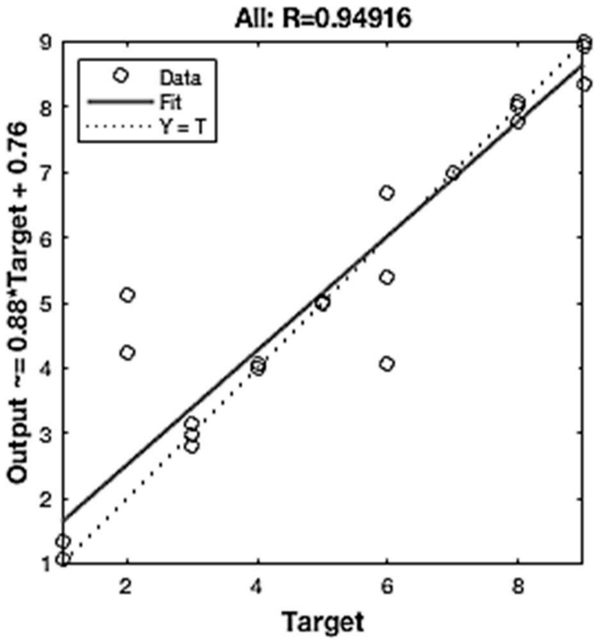

Figure 10. Overall regression outcomes of the proposed MLANN.

The regression plot in Figures 7–10 indicates how close the output response of the developed model is compared to the actual target responses.

After inductively training and testing the neural network, the best-performing network was elected. The optimum neural network that can be utilized to envisage inchoate fault in oil-submerged transformers is a two-layer feed-forward backpropagation network with structure [1,6,8] with a hyperbolic tangent sigmoid transfer function (Tansig), Log-sigmoid transfer function (logsig), and linear transfer function (purelin) by means of the Levenberg–Marquardt training algorithm.

3.2. Benchmarking of the Proposed Method with K-Nearest Neighbors (kNN)

In the previous subsection, the study presented an extremely efficacious pre-processing approach to classifying incipient transformer faults based on the DGA dataset. The preprocessing approach was highly efficacious in stopping the training process once the parameter updates at no time started to produce enhancements on a validation dataset. The degree of accuracy in classification and sensitivity parameters is also first-class. The performance of the DGA input data is then now evaluated by benchmarking the proposed MLANN and kNN classifier.

By adopting the DGA dataset considered for the proposed MLANN, the classification accuracy compared to kNN was carried out. MLANN technique yield 99.98% accuracy, when compared to the kNN technique, which yields 95.05%. The enhanced accuracy could be enumerated since the proposed MLANN technique enhances the learning rates, by updating the weights, by way of keeping to a minimum the misclassification error. Additionally, the sigmoid activation function matches a smooth surface, which supports classification accuracy.

3.3. Experimental Data

In this subsection, the experimental data of 10 transformers are introduced to evaluate the prediction accuracy of the proposed MLANN-IEC. The transformer is impregnated with mineral oil and ranges from 15 MVA to 40 MVA with a high voltage from 11 kV to 132 kV on the high voltage side. The data was furnished by a local South African independent power utility and a comparison of the actual, MLANN-IEC with early stopping effect and the classical IEC method is tabulated in Table 4.

Table 4. Transformer case studies.

Case No.	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6	**Actual Fault**	**MLANN-IEC**	**IEC**	**kNN**
1	0.022	2.685	0.476	PD	PD	ND	LED
2	0.001	0.077	5.919	LED	LED	LED	LED
3	0.158	0.704	6.989	HED	HED	HED	HED
4	6.236×10^{-4}	13.866	5.384	T3	T3	T3	T3
5	3.611	0.252	0.72	LED	LED	ND	LED
6	4.137	0.277	4.846	LED	LED	LED	LED
7	0.112	0.092	0.971	HED	HED	HED	HED
8	0.096	6.662	0.135	T2	T2	T2	T1
9	0.111	39	0.25	NF	NF	ND	LED
10	0.002	7.274	0.067	T2	T2	T2	T2
11	0.016	0.142	1.218	T1	T1	T1	T1
12	0.001	0.094	4.721	LED	LED	LED	LED

ND—Not Detectable, NF—No-Fault.

Based on the experimental results above, it can be observed that case numbers 1, 5, and 9 were not detectable by the classical IEC method because of the deficits the method has when the gas ratio codes are not described on the standard criterion. The results in a "ND" condition of the transformer oil samples. The proposed network has, however, maintained consistency with the actual transformer diagnosis. In practice, the prediction of the neural networks may differ due to the data size, minimal MSE, and optimal early stopping of the network that furnishes a high correlation of the training, validation, testing, and the overall network performance.

In Table 5, a comparison between the proposed hybrid method and other methods has been tabulated to highlight the merits of the proposed approach. The number of samples of all fault types has been presented including the correct and incorrect diagnosis of each method. The accuracy of the respective method in diagnosing a specific fault type and overall accuracy has been provided.

Table 5. Case study accuracy analysis.

Method	**No. of Samples**	**Correct Diagnosis**			**Incorrect Diagnosis**			**Accuracy**		
		Proposed	**IEC**	**kNN**	**Proposed**	**IEC**	**kNN**	**Proposed**	**IEC**	**kNN**
PD	1	1	0	0	0	0	0	100%	0%	0%
LED	4	4	3	4	0	1	0	100%	75%	100%
HED	2	2	2	2	0	0	0	100%	100%	100%
T3	1	1	1	1	0	0	0	100%	100%	100%
T2	2	2	2	1	0	0	1	100%	100%	50%
T1	1	1	1	1	0	0	0	100%	100%	100%
NF	1	1	0	0	0	1	1	100%	50%	50%
Total	12	12	9	9	0	2	3	100%	75%	71.42%

NB: Proposed—MLANN-IEC.

The performance of MLANN-IEC, IEC, and kNN in diagnosing transformer faults of 12 samples is contrasted by utilizing the same gas ratio data and the corresponding percentage accuracy is tabulated in Table 5. The proposed algorithm is proposed to circumvent the limitations of the IEC ratio method. This shows that the merit of choosing ANN is corroborated by adopting kNN for comparison with another artificial intelligence technique. It is evident from Table 5 that the performance of the proposed hybrid method is superior to the IEC and kNN methods.

4. Conclusions

In this work, an artificial neural network (ANN) model based on the multilayer feed-forward back-propagation has been designed to prognosticate inchoate fault in a mineral oil-submerged transformer designed according to a South African technical specification using three gas ratios of dissolved gases premised on the IEC 60599:2022 standard. A fit and simplified network are established by employing the early stopping technique. The vigour of the established network is corroborated by testing the network by employing a new dataset comprising 30 transformer oil samples in the testing phase. Henceforth, the prognostication of the inchoate fault of a transformer can be efficaciously carried out by employing a developed network. The proposed algorithm can be pragmatic to identify inchoate faults in transformers where the laboratory results of the oil samples have been attained by the manufacturer.

The proposed hybrid algorithm is a critical approach for addressing the shortcomings of the IEC gas ration method and developing an efficient fault diagnosis system. The seven fault types which are used in the IEC 60599:2022 standard borne in mind and established that the degree of accuracy of fault diagnosis is not optimal as a result of the restrictions imposed by the gas ratio codes which results in "not detectable" in some case studies. Nevertheless, after applying the proposed hybrid diagnosis algorithm the diagnosis is on par with the actual fault diagnosis.

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