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Original Article

An Artificial Intelligence-Based Novel Strategy for Fault Prognostics in Transformers

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Abstract *- One of the essential components of managing and maintaining power systems is transformer fault diagnostic. This study examines the use of deep learning algorithms, advanced data analytics methods, and other recent advancements in this area. Work has been carried out on fault prognostics in distribution transformers in the power system of the Sultanate of Oman. Based on Duval's Pentagon method, artificial intelligence tools are developed to distinguish the fault types. The fault types identified are partial discharge, thermal fault of temperature T1 < 300°C, thermal fault of temperature T2 < 700°C, thermal fault of temperature T3 > 700°C, low energy discharges - sparking (D1), high energy discharges - arcing (D2), and stray gassing (S). The same has been implemented using the MATLAB Artificial Intelligence Toolbox. Around 150 transformer data in compliance with local utility have been utilized for analysis, from which around 80% have been taken for training and the remaining 20% for testing and validation. One of the significant features of this analysis is that it also highlights the feeble insipient faults. The results obtained from Artificial Intelligence are quite promising, and they could offer insightful information on the significance of transformer fault diagnostics and the part artificial intelligence plays in guaranteeing the dependable operation of the power grid.*

Keywords *- Artificial Intelligence, Condition monitoring, Dissolved gas analysis, Fault types, Transformer.*

1. Introduction

The main objective of condition monitoring of the transformer is to reduce the operational costs of the device in service and extend its utilization period economically through its appropriate maintenance. Generally, there are two kinds of maintenance action plans: proactive and reactive. The proactive maintenance action plan's objectives are to reduce expenses and maintain system performance, whereas a reactive action plan addresses the post-fault diagnostic circumstances and financial losses [1-3]. The utility practices two types of preventive maintenance: Time-Based Maintenance (TBM) and Condition-Based Maintenance (CBM). The CBM is widely accepted as preventive maintenance [4] as it cuts manpower costs. This type of preventive maintenance mainly focuses on applying detailed and comprehensive Condition Monitoring (CM) and diagnostic techniques. The chemical, physical and electrical properties of the transformer oil and the paper insulation of the transformer windings play a key role in evaluating the condition of the transformer. The oil decomposes and releases the various gases [5] due to the high electric and thermal stress within operating transformers developed by the inception of thermal and electrical faults in the transformer windings. These gases dissolve in the oil and decrease its dielectric strength. However, the presence of these gases reveals very useful information and is achieved by the Dissolved Gas Analysis (DGA) method in four steps: (i) Collecting a sample of transformer oil, (ii) Extraction of dissolved gases, (iii) Interpretation of dissolved gases and (iv) Identification of the type of faults. For oil-filled distribution transformers, the DGA is one of the most acceptable methods used to detect incipient and other faults [6-8]. The list of various techniques under the umbrella of DGA is mentioned in Section 2. Many utilities are investing in digital resilience to reduce business risk and fend off fault threats. One example is the Supervisory Control and Data Acquisition (SCADA) system, which is used to monitor transformer parameters in remote areas. In the SCADA system, more sensors are being used, and physical assets are becoming more connected, creating a lot of accessible data useful for condition monitoring. To anticipate abnormalities before they happen, transformer status monitoring and prognostics techniques are gradually shifting toward fuzzy expert and Artificial Intelligence (AI) techniques [9-11]. Since the membership function and diagnostic rules are established through trial-and-error or practical experience, the fuzzy expert system was unable to learn from the prior diagnosis outcomes. To overcome this, the AI can identify the hidden association between fault types and DGA gases through training, which is more significant [12-14].

This paper investigates the application of Artificial Intelligence (AI) for fault prediction in distribution transformers using data from more than 150 units. Oil samples and Dissolved Gas Analysis (DGA) reports were collected from Majan Electricity Company, a local utility in Oman. These samples were analyzed to determine the concentrations of key dissolved gases, and Duval's Pentagon technique was employed to diagnose potential faults.

The diagnostic results were subsequently used to train the AI model, enabling accurate and data-driven predictive maintenance of the transformers. This article is divided into five sections. The introduction is developed in section 1, while section 2 describes the techniques used to interpret the DGA. The Artificial Neural Network (ANN) simulation set-up and its training have been discussed in Section 3. The results produced by the AI model and corresponding discussion are presented in Section 4. Finally, the key takeaways of the work in the form of a conclusion and future scope are highlighted in section 5.

2. Techniques to Interpret the DGA

The accurate interpretation of DGA is essential for power and distribution transformers to churn out information on incipient and other faults. There are various techniques proposed by authors in the literature [15-17] for the interpretation of dissolved gases from test results.

For instance, (i) the IEC ratio; (ii) Doernenburg ratio; (iii) Roger ratio; (iv) Muller-Schlesinger and Soldner; (v) Duval triangle and Duval pentagon. Some of these techniques are recommended by professional bodies like IEC 60599-2015 [18, 19] and IEEE C57.104-2019 [20, 21], as the standards for transformer oil samples and their DGA interpretation. To forecast the identification of thermal faults, such as the low energy and partial discharges, the data gathered through interpretation is crucial.

Additionally, the AI system might be trained using these findings. This paper presents a novel approach to include the fault feeble concept using an AI technique based on the interpretation of Duval's Pentagon Method (DPM) as described in section 2.1 to improve the accuracy and consistency. The AI algorithm has been trained to detect the three possibilities of abnormality, like (i) fault existing; (ii) fault not existing and (iii) fault is at a feeble state.

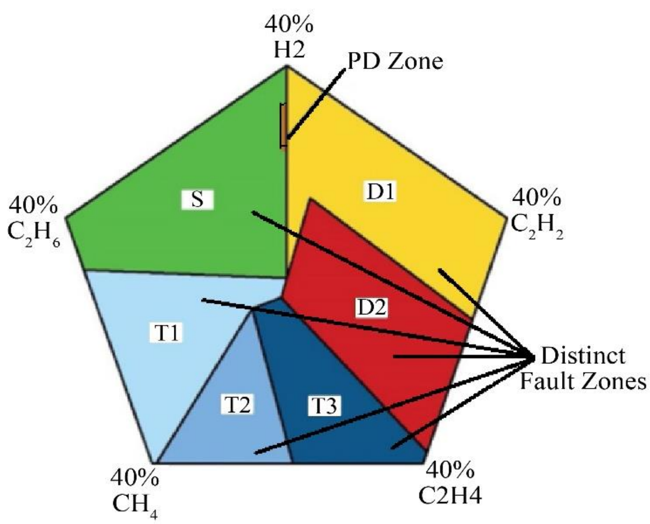


Fig. 1 Duval's pentagon for transformer oil

2.1. Duval Pentagon Method

Michel Duval has proposed the pentagon method, which is a modified and more accepted version of his triangle method. The triangle method uses the three hydrocarbon gases: Methane, Acetylene, and Ethylene. In the pentagon method, two additional gases, like Hydrogen and Ethane, are included, which are beneficial to separate PD phenomena out of the thermal fault at low energy for mineral oil problem investigation [22]. The capacity of the pentagon technique to classify the typical aging state of the insulation used in a transformer has also been enhanced by the introduction of the stray gas zone (S), which is related to the gas generation under normal operation [23]. When compared to alternative techniques, DPM's excellent accuracy in identifying transformer faults is documented by [24]. The midpoint of the pentagon is the beginning point, and its axes span the range from 0 to 100%. Figure 1 illustrates the plotting of the pentagon's centroid on Duval's pentagon [24].

2.2. Data Collection

The DGA and Breakdown Voltage (BDV) results of 150 distribution transformers from a local utility are collected to detect the fault types by DPM. These detected faults are used to train the AI algorithm. As a sample, the data of three DGA reports are shown in Tables 1 and 2. The distribution transformer ratings lie in the 6 to 20 MVA range, at 33/11 kV, 50 Hz, power system network.

2.3. AI in Transformer Fault Diagnosis

The ANN is one of the most significant subfields of artificial intelligence. The biological nerve systems in the human brain served as the model for this information processing paradigm [25]. The neurons are the basic building blocks for gathering information in terms of signals from each other when weighed and connected in a fashion as shown in Figure 2. Earlier, transformer health has long been monitored using traditional methods like Frequency Response Analysis (FRA), Partial Discharge (PD) detection, and DGA.

These methods' efficacy is frequently limited by human interpretation, noise interference, and inconsistent diagnostics [25]. To address the limitations of conventional diagnostic methods, AI and Machine Learning (ML) techniques are increasingly being applied to transformer fault diagnostics.

These models provide a data-driven approach that enhances fault detection accuracy, enables automated fault classification, and supports predictive maintenance strategies, thereby improving the reliability and efficiency of power system operations.

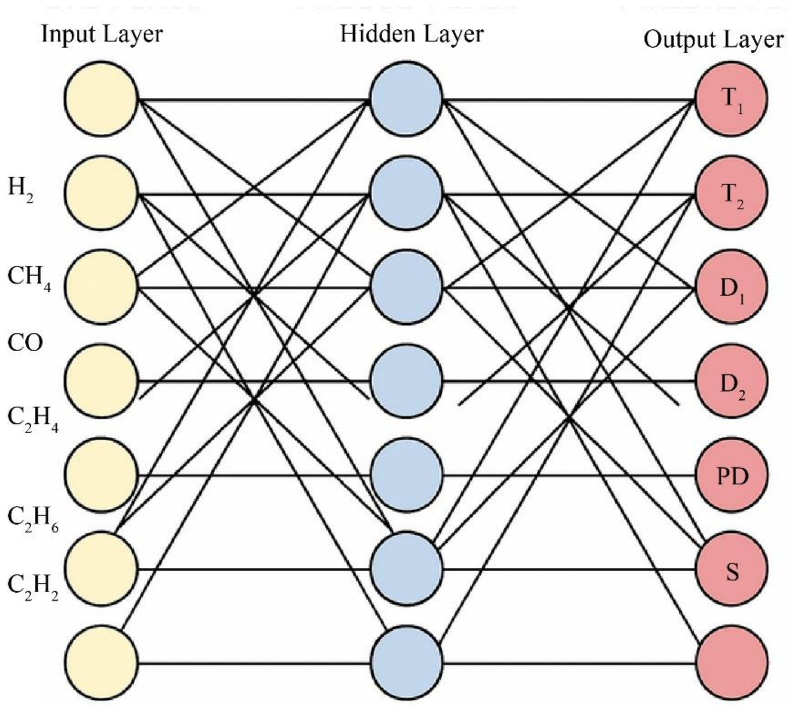


Fig. 2 AI neural structure executed for fault prediction

One way to conceptualize a trained neural network is as an "expert" in the type of data it has been trained to assess. Then, given fresh conditions of interest and response, this expert can be used to generate projections. Two sets of gas concentration measurements are available for the 150 transformers, namely (i) the training set and (ii) the testing set. The data for 120 transformers, or 80% of the total data available, were chosen at random from the 150 transformers' data set. Data for the final 30 transformers, or 20% of the total data set, make up the testing set. A multi-layer perception neural network (MLP) is employed to estimate the kind of transformer failures. Figure 2 displays the MLP. Two hidden layers, one input layer, and one output layer make up the neural network. Seven neurons make up the input layer, and the data from 150 transformers serves as its input. The output layer is made up of a single neuron that represents the transformer's health index.

3. ANN Simulation Set Up

The simulation of the ANN has modelled using MATLAB R2023a with the Neural Network Toolbox. Alternatively, Python 3.10 with TensorFlow and Keras libraries are used for flexible model customization and GPU acceleration. All simulations are performed on a machine with an Intel Core i7 processor, 16GB RAM, and NVIDIA GTX 1660 GPU.

3.1. Input and Output Data

The input dataset used for training the ANN model is constructed based on key gases measured through DGA and is aligned with the principles of the DPM. The gases involved in this method are as follows:

- H_2 (Hydrogen)
- CH_4 (Methane)
- CO (Carbon Monoxide)
- CO_2 (Carbon Dioxide)
- C_2H_4 (Ethylene)
- C_2H_6 (Ethane)
- C_2H_2 (Acetylene)

These seven gases that form the input feature vector are chosen due to their diagnostic relevance in transformer fault identification. The DPM has an advantage over the classic Duval Triangle. It introduces Hydrogen (H_2) and Ethane (C_2H_6) to enhance the separation of Partial Discharge (PD) phenomena from low-energy thermal faults, thereby improving classification accuracy. Furthermore, including a stray gas zone (S) that reflects gas behaviour under normal operating conditions extends the DPM's capability to detect insulation aging and distinguish non-faulty states. The output vector is represented by binary indicators, each corresponding to a specific fault type or condition derived from the DPM classification:

- T_1, T_2, T_3 - Thermal faults (classified by temperature severity)
- D_1, D_2 - Discharge faults (arcing-related events)
- PD - Partial Discharge
- S - Stray gas zone, indicating normal operational gas patterns

The dataset used for training and testing the ANN model is shown in Table 3. The fault conditions are represented using discrete integer values (0, 1, or 2) to indicate the status of each fault type. The interpretation of these values is as follows:

- 0 → Fault is not present.
- 1 → Fault is present at a normal level or lower severity.
- 2 → Fault is present in a feeble state

Each sample in the dataset may have multiple types of faults existing simultaneously (multi-label), reflecting real-world transformer behaviour. Each row in the dataset consists of the gas concentration inputs in parts per million (ppm) and the corresponding fault classification outputs based on the DPM.

This structure allows the ANN model to learn from complex gas patterns and accurately predict diverse fault scenarios as categorized by the DPM framework.

3.2. Architecture and Parameters

The Artificial Neural Network (ANN) model employed in this study is structured as a feedforward backpropagation network, as shown in Figure 4, to optimized for the multi-class classification of transformer faults.

The architectural and training parameters are as follows:

- Input Layer: Comprised of 7 neurons, each representing one of the dissolved gas inputs: H_2, CH_4, CO, CO_2, C_2H_4, C_2H_6, and C_2H_2.
- Hidden Layers: The network contains two hidden layers to capture complex nonlinear relationships:
    - First hidden layer: 25 neurons
    - Second hidden layer: 15 neurons
- Activation Functions: TANSIG (Hyperbolic Tangent Sigmoid) is used across all layers to introduce non-linearity and enable fine-grained mapping.
- Output Layer: Contains 7 neurons, each corresponding to a distinct output class derived from the DPM (i.e., T1, T2, T3, D1, D2, PD, S). This enables multi-label classification, where multiple fault types can be identified for a single input.
- Training Function: The network is trained using TRAINBR (Bayesian Regularization backpropagation), which enhances generalization by reducing overfitting, especially in smaller datasets.
- Training Samples: Around 150 training samples were used to train the ANN model, the majority of which were collected from real-world transformer fault cases in cooperation with a local utility. These samples represent typical fault conditions encountered in the industry, ensuring that the network is trained on realistic and practical scenarios.

3.3. Training Performance and Validation

To assess the efficacy of the proposed ANN model in transformer fault diagnosis, a comprehensive evaluation was conducted through training performance, regression analysis, and training state assessment.

The training performance plot demonstrates a rapid and smooth convergence of the network's Mean Squared Error (MSE) as shown in Figure 3, with minimal overfitting observed. This indicates that the model effectively generalized from the training data without suffering from noise or imbalance in the dataset.

The training regression plot, as shown in Figure 5, exhibits a high degree of correlation between the predicted and actual output targets, with regression values (R) approaching 1.0 across the training, validation, and testing phases. This highlights the network’s excellent ability to accurately classify multiple fault conditions based on dissolved gas concentrations.

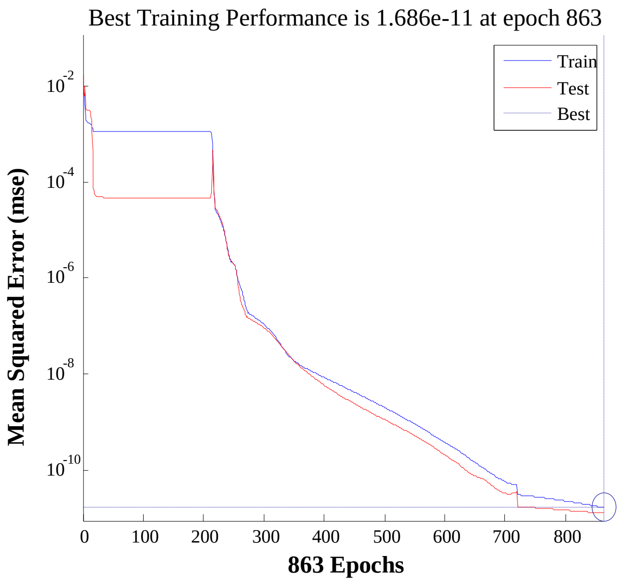


Fig. 3 Training performance

Furthermore, the training state, as shown in Figure 6, displays the evolution of the gradient, Mu (damping factor), and the number of successive validation failures (ssX), confirming the stability of the learning process. The gradient showed a consistent decrease, indicating effective convergence, while Mu remained within stable bounds throughout training. The ssX values stayed within an acceptable range, ensuring that the early stopping mechanism was not prematurely triggered. These results demonstrate that the Bayesian regularization algorithm (trainbr) successfully minimized the error while maintaining high generalization capability and robustness. These results collectively validate the reliability and high performance of the ANN-based approach in transformer condition monitoring and fault prediction, thereby proving the applicability of AI-based methodologies for transformer condition monitoring.

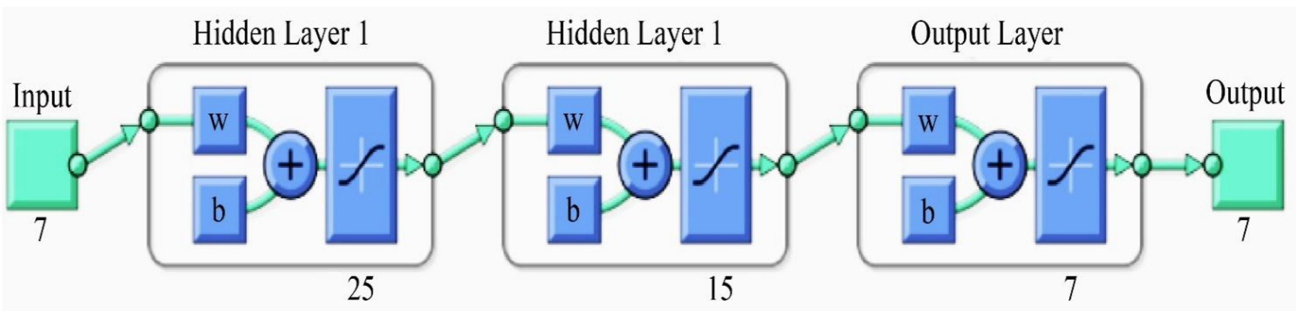


Fig. 4 Proposed AI architecture

Table 1. DGA test report as per IEEE C57-104 standard

Sr	**Capacity (MVA)**	**Oil temp At site(^{0}C)**	**DGA Test Results (ppm)**							
			H_2	CH_4	CO	CO_2	C_2H_4	C_2H_6	C_2H_2	TDCG
1	6	50	107.63	4.10	879.25	1382.05	0.69	0.93	0.00	992.60
2	10	62	13.94	2.49	578.21	2969.43	40.85	0.18	0.00	635.67
3	20	42	15.23	18.36	1452.56	6635.01	1.63	1.64	0.00	1489.42

Table 2. BDV Test Result as per IEC 60156 standard

Sr	Capacity (MVA)	Breakdown Voltage (kV)						
		Test1	Test2	Test3	Test4	Test5	Test6	Avg Voltage
1	6	87.4	82.4	83.0	93.8	80.7	87.8	85.8
2	10	65.3	71.1	65.8	66.3	81.3	88.2	73.0
3	20	62.0	57.7	67.5	94.1	92.7	97.5	78.6

Table 3. Sample dataset demonstrating input gas concentrations and the corresponding fault categories (T_1, T_2, T_3, D_1, D_2, PD, S) derived based on the DPM

Sr No.	Inputs measured in parts per million (ppm)							Condition and Type of Fault						
	H_2	CH_4	CO	CO_2	C_2H_4	C_2H_6	C_2H_2	T_1	T_2	T_3	D_1	D_2	PD	S
1	107.63	4.1	879.25	1382.05	0.69	0.93	0	0	0	0	1	0	1	1
2	13.94	2.49	578.21	2969.43	40.85	0.18	0	0	0	1	0	1	0	0
3	36.73	3.38	541.07	5533.24	17.49	7.19	0	0	0	0	1	2	0	1
4	15.23	18.36	1452.6	6635.01	1.63	1.64	0	1	1	1	0	0	0	0
5	33.09	1.87	289.32	6546.51	15.45	1.02	0	0	0	0	1	1	0	1
6	67.46	2.46	1089.76	184.87	8.07	7.26	0	0	0	0	1	1	0	1
7	61.4	1.36	1020.99	4946.73	2.73	8.32	0	0	0	0	1	0	0	1
8	80.04	2.61	770.84	3056.99	15.99	2.81	0	0	0	0	1	1	0	1

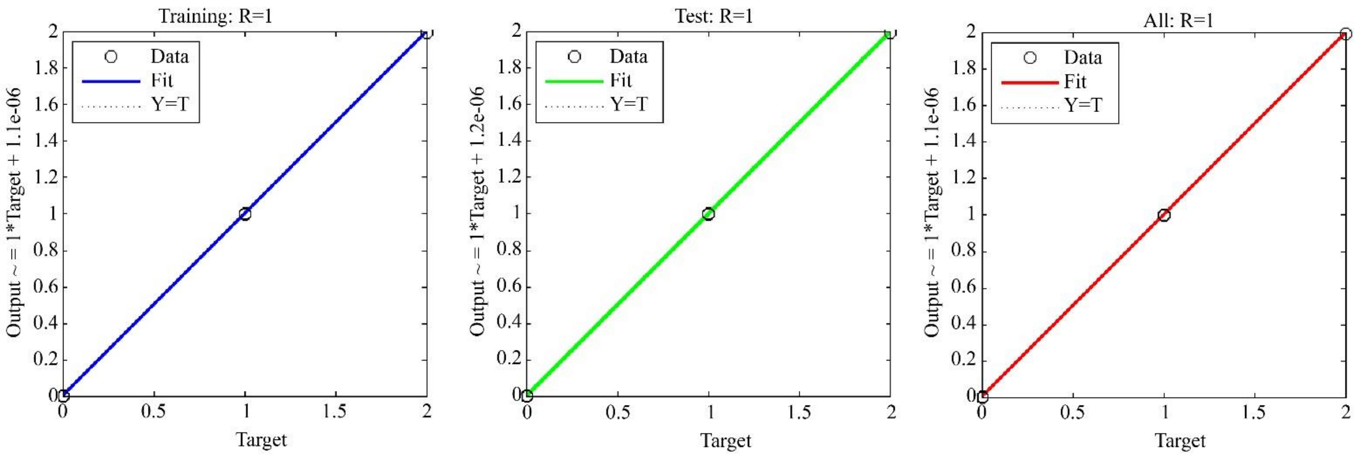


Fig. 5 Training regression

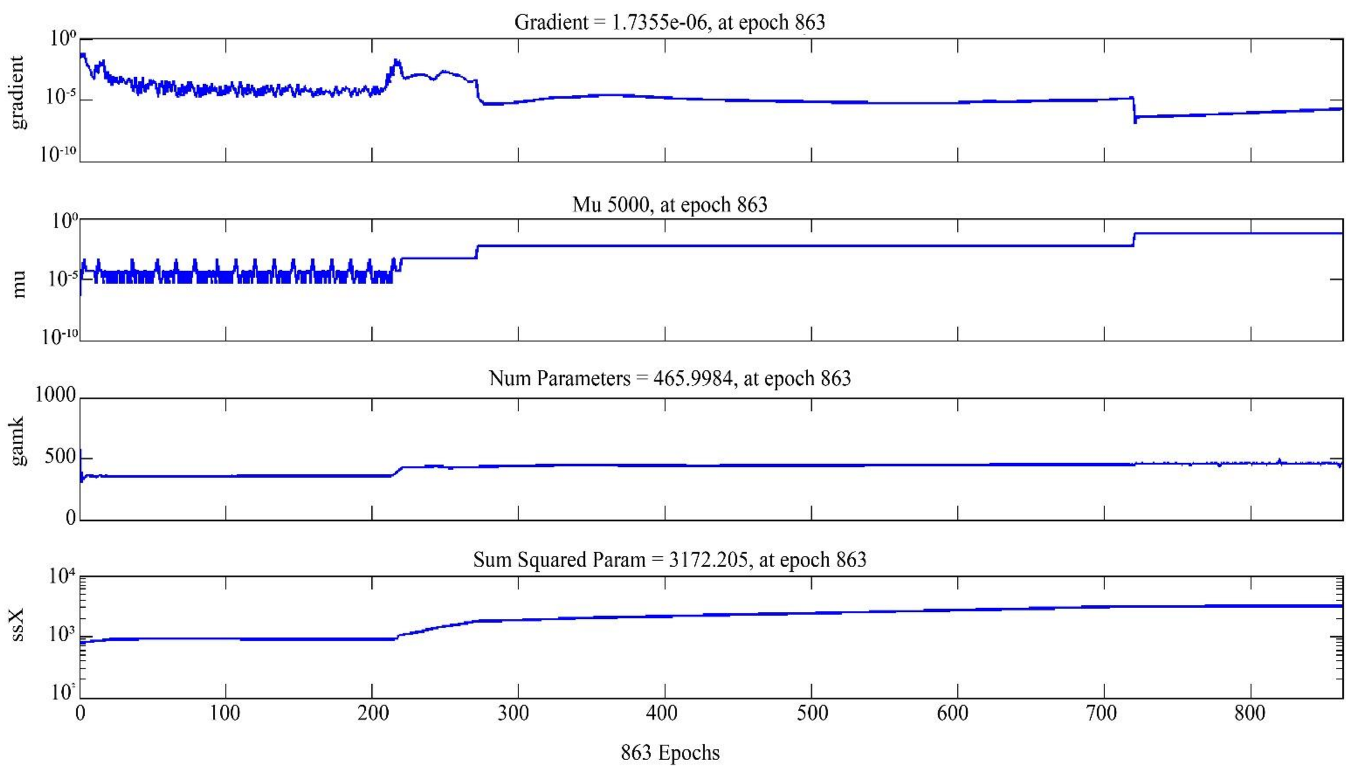


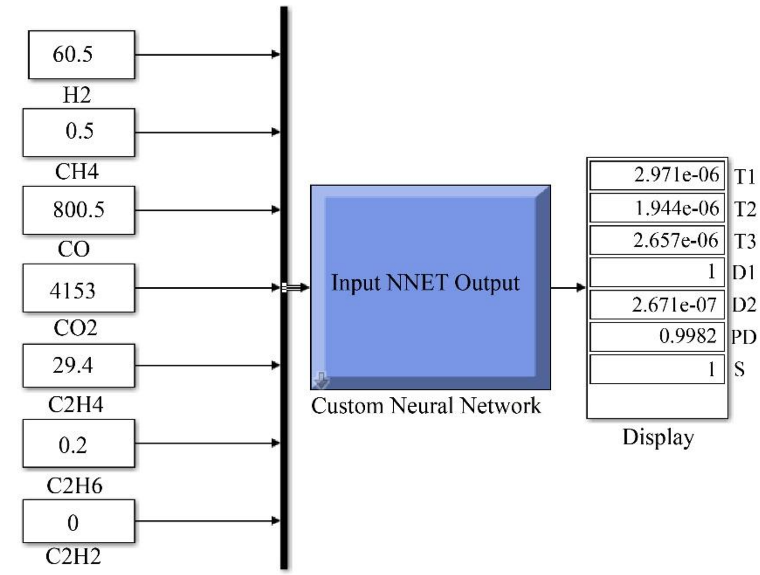
Fig. 6 Training state

4. Results and Discussions

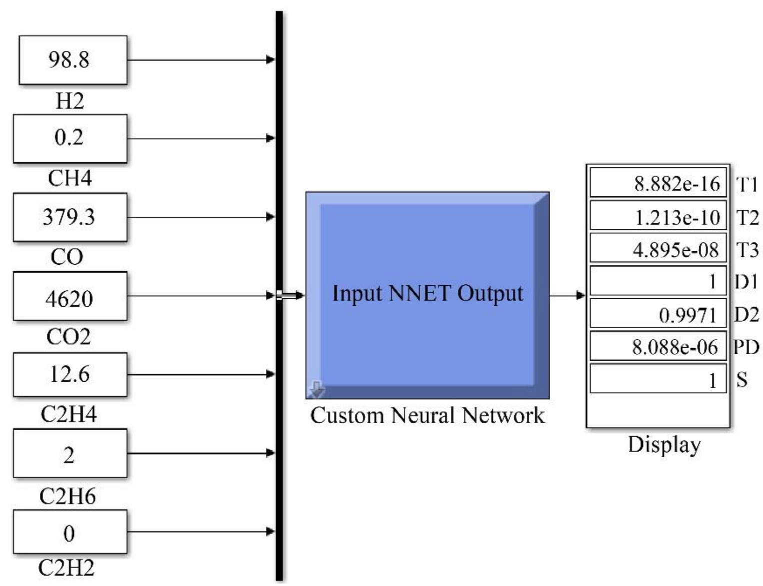
The proposed Artificial Neural Network (ANN) model achieved excellent performance in classifying transformer fault conditions using Dissolved Gas Analysis (DGA) inputs. Approximately 150 training samples representing typical industrial fault scenarios, obtained in collaboration with a local utility, were used to develop the model.

A corresponding Simulink model was also created to simulate the trained ANN structure, enabling real-time fault detection. The model was tested with various unseen input samples, as illustrated in Figure 7 (a) and Figure 7(b), demonstrating high accuracy and consistency across both training and testing phases. The model's strong predictive capability and robustness support its practical deployment for transformer condition monitoring.

Its ability to deliver fast, automated, and reliable fault diagnosis contributes significantly to predictive maintenance strategies, ultimately minimizing downtime and reducing the risk of unanticipated transformer failures in the power systems network. Even though the proposed strategy has a lot of merits, there exist some limitations, such as the AI method's sensitivity to the quality of training and the data quality. In addition, the methodology has a limitation: whenever a new type of problem manifests, it is taken as an existing fault based on the previous training set, which may lead to considerable deterioration of diagnostic accuracy.



(a) Input 1



(b) Input 2

Fig. 7 Simulink model at different inputs

5. Conclusion and Future Scope

This study presents a robust ANN-based methodology for precise fault classification in power transformers using DGA data. The ANN was trained on real-world industrial samples obtained in collaboration with a local utility. The MATLAB/Simulink model uses a feedforward backpropagation network with Bayesian regularization, showing strong accuracy on both training and testing datasets. The simulation results have confirmed the ANN's effectiveness in accurately detecting and classifying various types of transformer faults, including thermal faults, partial discharges, and stray gassing, with high precision and reliability. The integration of the ANN within the Simulink environment further enhances its potential for real-time fault monitoring and intelligent decision support in power system operations.

5.1. Limitations and Future Scope

This study was limited to DGA-based results with a relatively small dataset, so the model may not fully capture the diversity of transformer operating conditions. Its performance is sensitive to data quality, and rare or unseen fault types may be misclassified, reducing diagnostic accuracy. Future research should resolve these challenges by incorporating greater and more assorted datasets and extending the model to handle complex multi-fault scenarios. Integration with real-time data streams from SCADA systems or IoT-enabled sensors could enable continuous online monitoring and adaptive diagnostic capabilities.

Furthermore, adopting hybrid AI techniques, such as combining ANN with fuzzy logic, genetic algorithms, or ensemble methods, may enhance robustness and interpretability. Finally, developing a lightweight, user-friendly graphical interface would support practical field deployment and promote wider adoption in the power industry.

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