POWER CONTROL SYSTEM

Characterization of Artificial Neural Network Based Power Transformer Protection

E. E. Ezema[1], E. B. Ibekwe[1], Ukamaka J. Eze[2]

[1]Department of Electrical Engineering, Enugu State University of Science and Technology, Nigeria
[2]Department of Computer Engineering, Madonna University, Nigeria

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Abstract

This work strives to develop a high-performance power transformer protection system using Artificial Neural Network (ANN). In achieving this, enhanced back propagation algorithm, the calculation ability of Artificial Neural Network (ANN) and its capability to accurately identify non-linear system were harnessed. A combination of two multi-layer neural networks was used in the implementation of the protection system. The first network was used in predicting the transformer oil temperature using the transformer load current as the input. The second ANN network is used in implementing the classification of the power transformer operating conditions which includes normal and fault conditions. This network has the oil temperature, oil level and dielectric strength parameters of the transformer as its input while after identification and classification gives out at its output the transformer dynamic operation condition. These outputs are Normal operation, Overheating, Dielectric degradation and Critical conditions. The critical condition through a trip logic trips off the power transformer. A total of 1500 data from a working 15MVA power transformer were used in the training of the networks. 70% of the data was used in training, 15% was used in validation while the remaining 15% was used in testing the performance. Both ANNs showed remarkable results. The ANN-1(TEMPEST) was able to predict temperature to an accuracy level of 99.99% while the ANN-2(CLASSFAULT) was able to give a 100% operating condition of the power transformer. These results attest to the fact that ANN could be used effectively and efficiently in the protection of power transformers.

Keywords: Power transformer; transformer parameter monitoring; artificial neural network; temperature prediction; fault classification; trip logic

1 Introduction

Electricity is an important energy, silent in nature that has single handedly changed the world in 21st century. Electrical energy formation is subdivided into three categories of Generation, Transmission and Distribution (Grainger and Stevenson, 1994). It is a fact that every sector of the economy depends on a reliable supply of electrical power for its operation. These operations include Industrial processes, commercial activities, communication systems, transportation infrastructure, healthcare facilities, educational institutions and residential consumers. All the aforementioned use electricity that is available continuously and within acceptable limits of voltage and frequency. Consequently, the reliability and stability of an electrical power system depend greatly on the proper operation and protection of its major components (Pansini, 1999). Power transformer is a very important component because of its role in transforming electrical energy between different voltage levels (Harlow, 2012).

Power transformers are used in generating stations, transmission substations and distribution networks. At generating stations, transformers are used to step up the generated voltage to a higher

transmission level in order to reduce transmission losses. At substations, transformers are used to step down voltage levels to values suitable for distribution and utilization (Weedy et al., 2012). A transformer thus becomes an important link between different sections of the power system. Any serious damage of the transformer can consequently affect every aspect of the power supply chain and the transformer itself. Irrespective of their importance, power transformers encounter different electrical, thermal, mechanical and environmental stresses during operation. Some of these stresses occur as a result of abnormal loading conditions, while others may result from abnormal system conditions, ageing, inadequate maintenance, insulation deterioration, excessive loading, poor cooling, moisture contamination, short circuits and other operating abnormalities (Cui and Shin, 1992). Persistent existence of any of these conditions can lead to transformer faults (Kundur, 2003). Depending on their nature and severity, transformer faults may cause overheating, deterioration of insulation, winding damage, oil degradation, internal arcing, fire and, in extreme cases, complete transformer failure. In order to protect the power transformer from getting burnt, traditional monitoring of these parameters is normally carried out using temperature detectors, thermal/heat models, oil level, load variations, fixed thresholds, conventional relays etc. Unfortunately, these approaches fall short of being able to accurately capturing the non-linear relationships between these parameter changes. The relationships between load, ambient temperature, hot-spot temperature, oil level, dielectric strength etc. are basically non-linear in nature and also dynamic. Power transformer protection involves continuously tracking key operating parameters and assessing their status to ensure reliable and efficient operation, prevent failures, and optimize performance. Artificial Neural Networks (ANNs) have attracted considerable attention in engineering applications because of their ability to learn relationships between input variables and desired outputs from representative data (Hopfield, 1982). ANN consists of interconnected processing elements, commonly referred to as neurons, which process information and produce an output based on learned weights and activation functions. During training, the network adjusts its internal parameters so that its output approaches the desired target for the training data (Haykin, 1999).

The pattern-recognition capability of an ANN makes it potentially useful for transformer fault classification. Instead of relying exclusively on manually specified relationships between transformer parameters and faults, the ANN can be trained using examples representing different transformer operating conditions like oil temperature, dielectric strength, oil level etc. After training, the network can receive measured transformer parameters and produce an output corresponding to the condition represented by those inputs (Rumelhart et al., 1986).

In the context of transformer protection, ANN technology can therefore be used to establish a relationship between measurable transformer condition parameters and specific fault categories. The input parameters can be processed simultaneously by the neural network, allowing the system to identify patterns associated with normal and abnormal operating conditions. This approach is particularly relevant where the relationship between the measured variables and the transformer condition is complex or nonlinear.

The application of ANN to transformer protection does not necessarily imply that conventional protective devices must be completely be removed rather it can be considered as an intelligent monitoring and classification layer that complements conventional protection. In a practical protection scheme, established protective devices may continue to provide primary protection, while an intelligent monitoring system can provide additional information and decision support.

Artificial Neural Network (ANN) with its inherent ability in learning and mapping of complex non-linear dynamic relationship from data becomes a very important and reliable tool to be used in protecting power transformers. Its importance cannot be over emphasized as it leads to performance optimization, proactive maintenance, increased reliability, increased transformer lifespan, easier asset management, reduced operation down time etc.

2 Materials and method

2.1 ANN in power transformer protection

The primary objective of transformer protection is to rapidly identify abnormal operating conditions and isolate the transformer before extensive damage occurs. Transformer faults can be classified into Internal Fault that occur within the transformer winding, insulation system, or magnetic core (Inter-turn faults, Winding-to-ground faults, Phase-to-phase faults, Core insulation failures and External Faults that occur outside the transformer protection zone and include(Transmission line faults, Distribution feeder faults, Bus-bar faults, etc. Abnormal Operating Conditions includes Magnetizing inrush current, Over-excitation, Overloading and Current transformer saturation.

Traditional differential relays employ harmonic restraint techniques to distinguish magnetizing inrush currents from genuine internal faults. However, changing system conditions and modern power electronic interfaces have reduced the effectiveness of fixed-threshold harmonic methods.

ANNs optimise these functions through the following processes:

- Protection Algorithm that works as follows; Data Acquisition (the relay continuously samples current and voltage from the primary and secondary sides of the transformer). Pre-processing (the signals are filtered and may undergo transformations like Fourier or Wavelet etc.) to extract relevant harmonics or features. Other data are also normalized.
- An ANN evaluates the sampled waveforms, normalize the data and classifies them into specific categories of normal operation, internal fault, external fault, magnetizing inrush, or over-excitation.
- Unlike traditional harmonic-based relays that may take a full cycle or longer to confirm a fault, ANNs can correctly identify a transient event within a fraction of a cycle (often within 3 to 8 milliseconds).
- ANNs can be trained to distinguish between a genuine fault and other complex, confounding events like Current Transformer (CT) saturation or tap-changer operations. This ability enhances security. The classification output is then integrated with conventional relay logic to generate trip or restraint decisions.

2.2 Development

The proposed system architecture is depicted in Figure 1.

From the block representing the power transformer, three data parameters are taken. These are the oil temperature, oil level and dielectric strength. The transformer load current data in amps forms the input to the TEMPEST ANN(ANN 1). The TEMPEST ANN block output temperature data joins the oil level and dielectric data from the power transformer to form the input to the CLASSFAULT ANN (ANN 2).

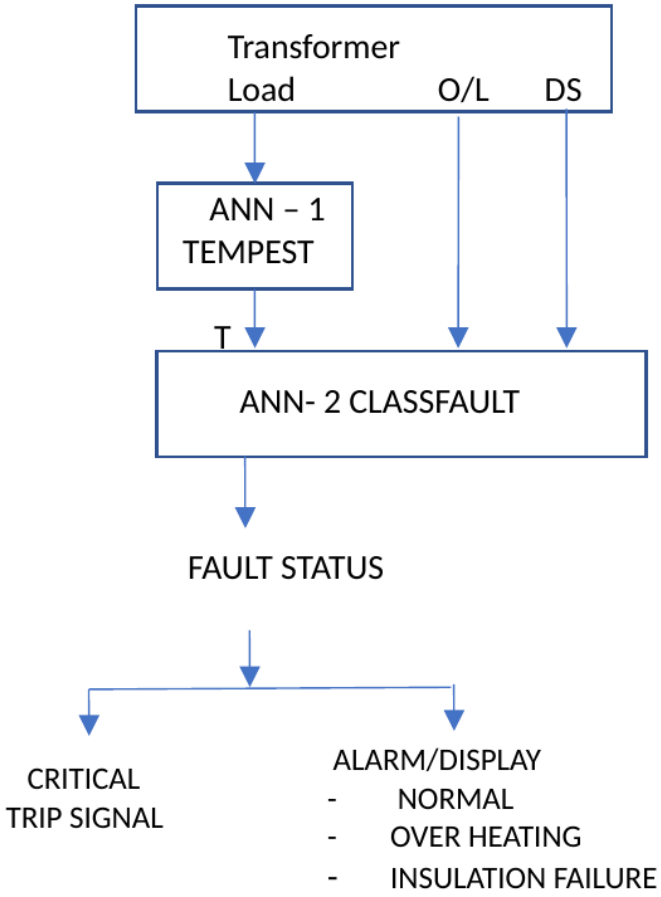


Figure 1. Block diagram of the system architecture.

2.2.1 ANN configuration

The two ANNs are configured as follows:

- TEMPEST ANN has 1 input layer, 10 hidden neuron layers and 1 output neuron layer.
- CLASSFAULT ANN has 3 input layers, 12 hidden layers and 4 output layers.

Their input and output data parameters are as shown in Figure 1.

2.2.2 Data acquisition, preparation, cleaning and normalisation

Data are acquired from an hourly reading from 15 MVA, 11/0.415 transformer at the injection substation. A total of 1500 hourly data covering, the transformer load (A), oil level (%), temperature (°C) and the dielectric strength (kV/mm) were cleaned out, normalized and used in training the ANN-1 (TEMPEST) and ANN-2 (CLASSFAULT) networks. These data are recorded in MS Excel file and saved as TEMPEST_DATASET.xlsx and CLASSFAULT_DATASET.xlsx respectively because of its large size. These data are imported and called into MATLAB environment and coded. In both the TEMPEST and CLASSFAULT ANNs, 70% was used in training, 15% was used in validation while the remaining 15% was used in testing the performance. Each of the two ANN model was generated and coupled with the decision logic protection and other blocks from Neural Network Toolbox to form the complete Simulink model of the power transformer protection system shown in Figure 2.

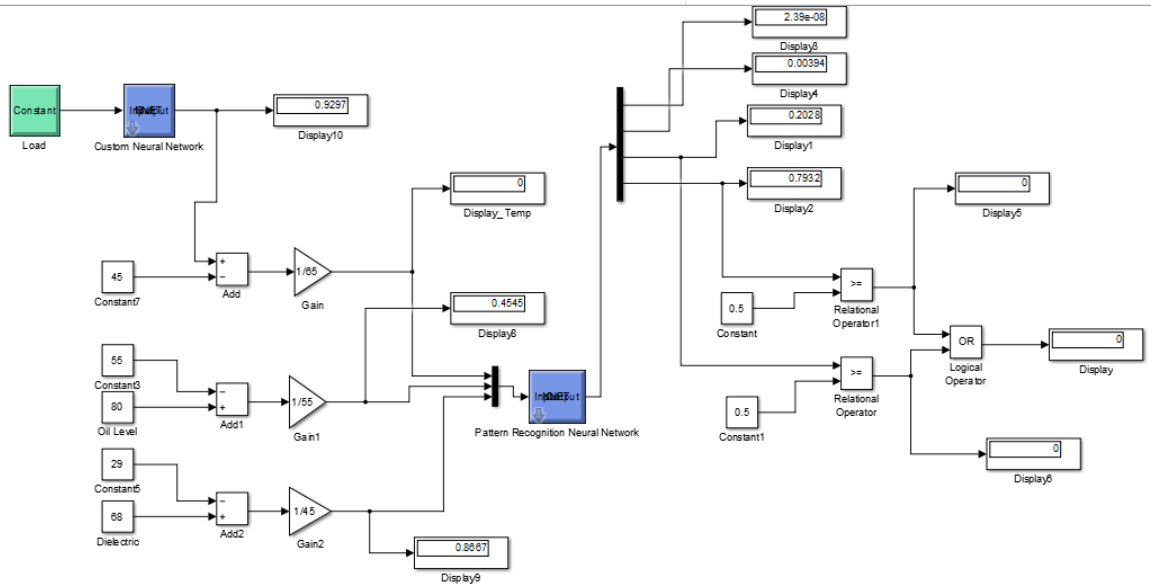


Figure 2. Complete ANN power transformer protection system in Simulink.

3 Results and discussion

The regression plot, the actual versus predicted temperature plot and the error plot of the TEMPEST ANN output are shown in Figure 3, Figure 4 and Figure 5, respectively. It is seen in Figure 3 that the TEMPEST ANN had a prediction accuracy of 99.99%.

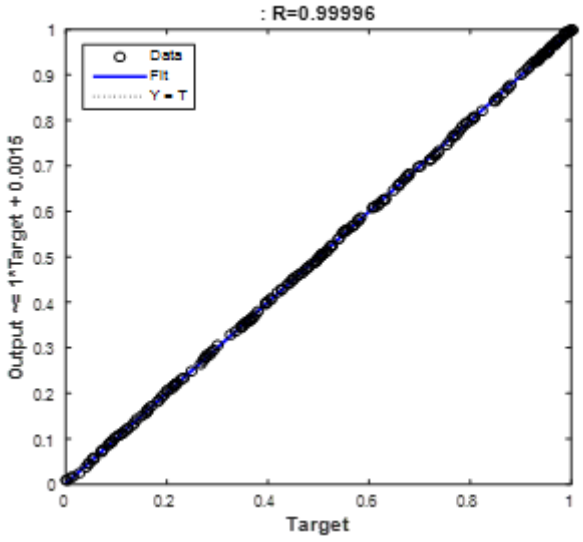


Figure 3. Regression plot of the TEMPEST ANN.

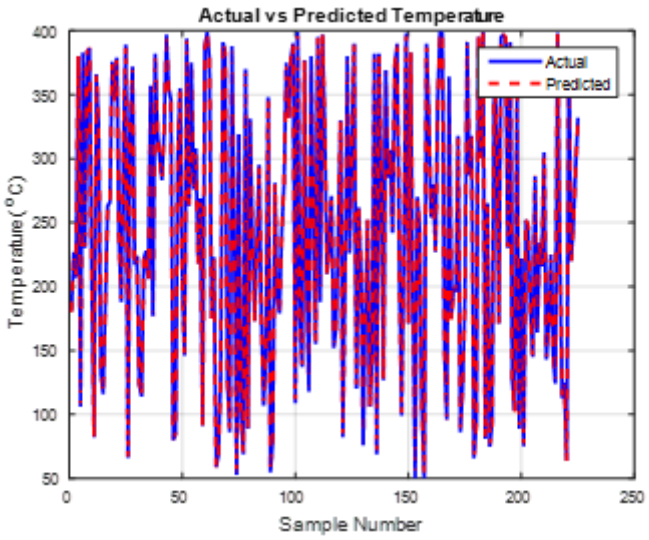


Figure 4. Actual versus predicted temperatures.

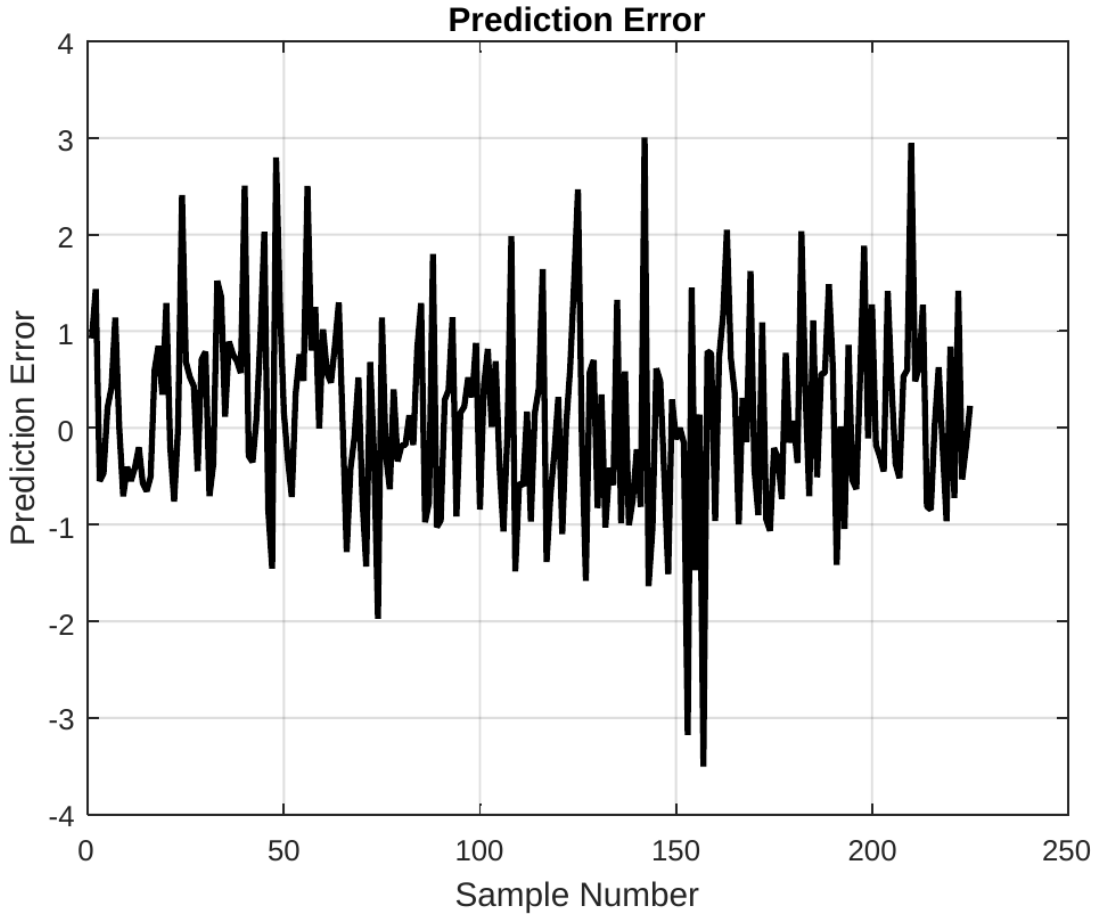


Figure 5. Prediction error plot.

The TEMPEST ANN demonstrated excellent performance based on the obtained evaluation metrics. The validation and testing MSE values were 0.000007 and 0.000008, respectively. The RMSE and MAE were 1.003478 and 0.786408, while the R-Squared value was 0.999914. The overall accuracy was 99.99%. These results indicate that the developed ANN was able to learn the required input-output relationship with very high accuracy.

The confusion matrix and the receiver operating characteristics of the CLASSFAULT ANN are shown in Figure 6 and Figure 7.

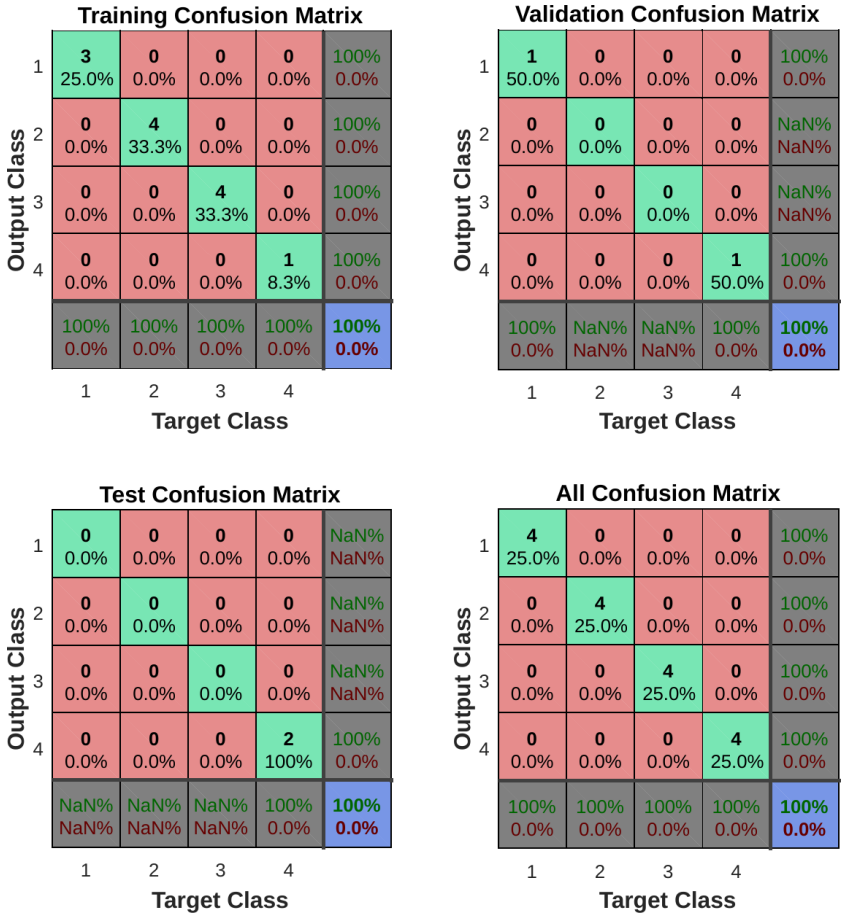


Figure 6. Confusion matrix of the CLASSFAULT ANN.

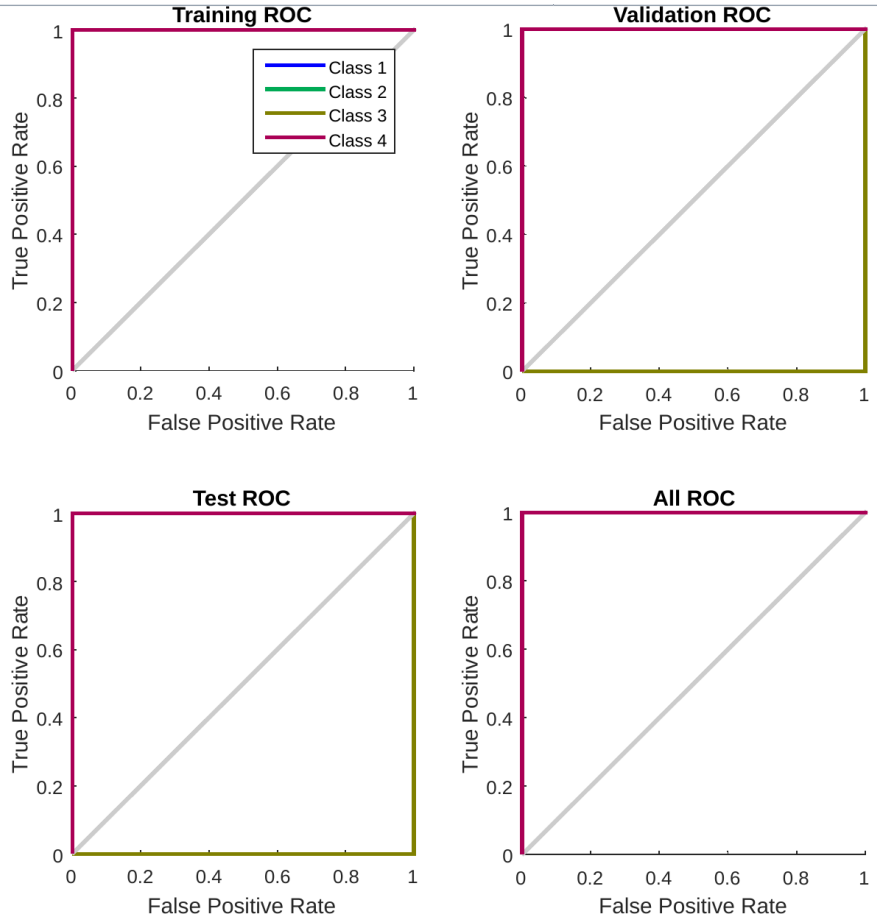


Figure 7. Receiver operating characteristics of the CLASSFAULT ANN.

The CLASSFAULT ANN results demonstrate excellent classification performance for the test dataset as shown in Figure 6 and Figure 7. The network achieved 100% classification accuracy, with all 16 actual conditions correctly reproduced by the predicted conditions. No classification error was observed among the tested samples. This means that there were no false classifications within the 16-sample evaluation. The results therefore confirm that CLASSFAULT ANN successfully performs the intended fault-classification function and provides an appropriate input to the transformer protection decision stage.

4 Conclusion

This treatise is finding an alternate and optimal approach to power transformer protection other than the traditional approaches which falls short of the required efficiency. The chosen approach was ANN. From the results seen above, ANN proved to be very effective and efficient. Both ANNs showed remarkable results. The ANN-1(TEMPEST) was able to predict temperature to an accuracy level of 99.99% while the ANN-2(CLASSFAULT) was able to give a 100% classification of operating condition of the power transformer data used in the data training set. These results attest to the fact that ANN could be used effectively and efficiently in the protection of power transformers. This does not suggest a complete removal of the existing protection system rather it can be considered as an intelligent monitoring and classification layer that complements conventional protection. In a practical protection scheme, established protective devices may continue to provide primary protection, while an intelligent monitoring system can provide additional information and decision support.

References

[1] Cui X, Shin KG (1992). Application of neural networks to temperature control in thermal power plants. *Engineering Applications of Artificial Intelligence*, 5(6), 527–538.

[2] Grainger JJ, Stevenson WD Jr (1994). Power system analysis. *McGraw-Hill*, New York.

[3] Harlow JH (ed.) (2012). Electric power transformer engineering, 3rd ed. *CRC Press*, Boca Raton, FL.

[4] Haykin SS (1999). Neural networks: A comprehensive foundation, 2nd ed. *Prentice Hall*, Upper Saddle River, NJ.

[5] Hopfield JJ (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences of the USA*, 79(8), 2554–2558. https://doi.org/10.1073/pnas.79.8.2554

[6] Kundur P (2003). Power system stability and control. *McGraw-Hill*, New York.

[7] Pansini AJ (1999). Electrical transformers and power equipment, 3rd ed. *Fairmont Press*, Lilburn, GA.

[8] Rumelhart DE, Hinton GE, Williams RJ (1986). Learning representations by back-propagating errors. *Nature*, 323, 533–536. https://doi.org/10.1038/323533a0

[9] Weedy BM, Cory BJ, Jenkins N, Ekanayake JB, Strbac G (2012). Electric power systems, 5th ed. *Wiley*, Chichester.