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Ann-Driven Fault Detection Technique in High-Voltage Transmission Lines

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Abstract
This research investigates the application of Artificial Neural Networks (ANNs) for fault detection in high-voltage transmission lines, with a focus on the Onitsha to Enugu transmission power system in Nigeria. The primary objective is to enhance the accuracy and efficiency of fault detection, thereby improving the reliability and stability of power systems. The methodology involves modeling the transmission system using MATLAB/Simulink, generating pre-fault and fault data, and training the ANN using the Levenberg-Marquardt backpropagation algorithm. The ANN's performance is evaluated through various metrics, including error histograms, regression plots, and performance validation plots. Key findings indicate that the ANN-based fault detection scheme can accurately identify and classify different fault types, such as line-to-ground (L-G), line-to-line (L-L), double line-to-ground (L-L-G), and three-phase faults (L-L-L and L-L-L-G). The results demonstrate the ANN's ability to generalize well to new data and adapt to changing system conditions, making it a robust tool for power system protection. The implications of this research are significant, as it offers a viable alternative to conventional protection schemes, addressing their limitations and contributing to the advancement of intelligent fault detection technologies in power systems. This study highlights the potential of ANNs in enhancing power system protection and paves the way for future research to explore the integration of other machine learning techniques and real-time implementation in live power system environments. The findings are relevant to both experts in the field of power systems and general readers, highlighting the transformative impact of artificial intelligence on power system engineering.

Keywords: Artificial Neural Network, Fault Detection, Transmission Lines, Voltage Measurements,

INTRODUCTION

The demand for constant power supply in Nigeria is ever increasing; however, the demand is met with lots of constraint. One of them being system faults. Faults on transmission line in particular is of great interest to the power holding company of Nigeria as more investment is put into restructuring the current infrastructure and also expanding existing ones. The power sector of Nigeria is subdivided into policy, regulations, customers, operations. The operations division brings to light the activities of the transmission company of Nigeria that controls the high voltage delivery of power from generating plants to the substations for transmission to distribution stations. Their focus is to maintain power system stability, reliability and sustainability (Ohajianya, 2014). The protection scheme employed is the distance protection scheme which provides the primary or main protection and back up protection for AC transmission line and distribution line against three faults, phase to phase fault, phase to ground fault and double line to ground fault. The distance protection scheme being predominant suffers from inaccuracy due to restraints of relays on the protection scheme i.e relay settings. The relay cannot fully adapt the fluctuations in the power system conditions especially in parallel line (Tsimtsios et al., 2018).

Among several power system components, transmission line is one of the most important components of the power system network and is mostly affected by several types of faults. Generally, 90% of the fault occurs on the transmission line and the rest of substation equipment and bus bar combined (Tsimtsios et al., 2018). The necessary requirement of all the power system is to maintain reliability of operation which may be done by detecting, classifying and isolating various faults occurring in the system. It is required that a corrective decision should be made by the protective device to minimize the period of trouble and limit outage time, damage and related faults. If any fault or disturbances occurred in the transmission is not detected, located, and eliminated quickly, it may cause instability in the power system and causes significant changes in system quantities like over-current, under or over voltage, power factor, impedance, frequency and power. The three faults occur rarely but if it exists in a system it is quite expensive (Malik et al., 2022).

To improve the accuracy and efficiency of fault detection, classification and location, various methods have been proposed in the literature, such as impedance-based methods, travelling wave methods, artificial intelligence methods, and machine learning methods. Impedance-based methods use the voltage and current measurements at one or both ends of the transmission line to calculate the apparent impedance and compare it with the line impedance to determine the fault type and location (Ghaemi et al., 2021). Travelling wave methods use the high-frequency components of the fault-induced waves that propagate along the transmission line and measure their arrival times and polarities to locate the fault (Gonzalez-Sanchez et al., 2021). Artificial intelligence methods use techniques such as artificial neural networks, fuzzy logic, genetic algorithms, and expert systems to learn from historical or simulated data and classify the fault type and location based on the extracted features (Solanki et al., 2021). Machine learning methods use algorithms such as k-nearest neighbor, support vector machine, decision tree, random forest, and gated graph neural network to perform fault detection, classification and location based on the current and voltage signals of the transmission line (Saiprakash et al., 2024).

This research work brings to view the application of artificial neural network to enhanced power system protection in regards to fault detection, fault location, and application of the adaptive auto reclosure schemes as opposed to conventional approach. Artificial neural networks (ANNs) are computational models that can learn from data and perform tasks such as classification, regression, prediction, and optimization. ANNs have been widely used in various fields of engineering, especially in power systems, due to their ability to handle complex and nonlinear problems. ANNs can also adapt to changing system conditions and learn from new data without requiring explicit programming (Goz et al., 2019). The research focuses on the application of the methods to the Nigeria 330kV network, which is the backbone of the national grid and faces various challenges in power system protection. The research uses both simulation and field data to test the performance of the methods under different fault scenarios and network conditions. The simulation data is generated using MATLAB and the field data is obtained from the Nigerian Electricity Regulatory Commission (NERC).

I. Faults in Power System

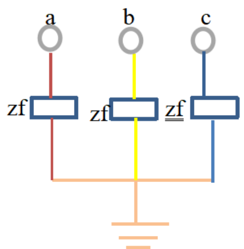
Fault is an unwanted short circuit condition that occurs either between two phases of wires or between a phase of wire and ground. Short circuit is the most risky type of fault as flow of heavy currents can cause overheating or create mechanical forces which may damage equipment and other elements of power system. Faults in power system can also be any abnormal electric current or condition caused by equipment failure such as transformer and rotating machines, human errors and environmental conditions. These faults can cause interruption on electric flow, equipment damages and even cause death of humans, birds and animals (Yadav, 2014).

A. Types of Faults

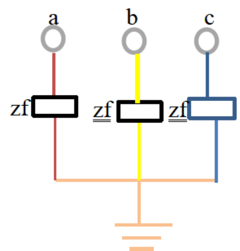
Electrical fault is the deviation of voltages and currents from normal values or states. Under normal operating conditions, power system equipment or line carrying normal voltages and currents which resolves in a safer operation of the system. But when faults occur, it causes excessive high current to flow and this causes damage to equipment and devices. Fault detection and analysis is necessary to select or design suitable switch gear equipment, electromechanical relays, circuit breakers and other protective devices. There are two types of faults namely; symmetrical faults and unsymmetrical faults (Osmani et al., 2023).

a) Symmetrical faults

These faults are very severe and occur infrequently in the power system. They are also called the balanced faults and are of two types namely: line to line to ground fault (L-L-L-G) and line to line to line (L-L-L)



(a) L-L-L-G fault

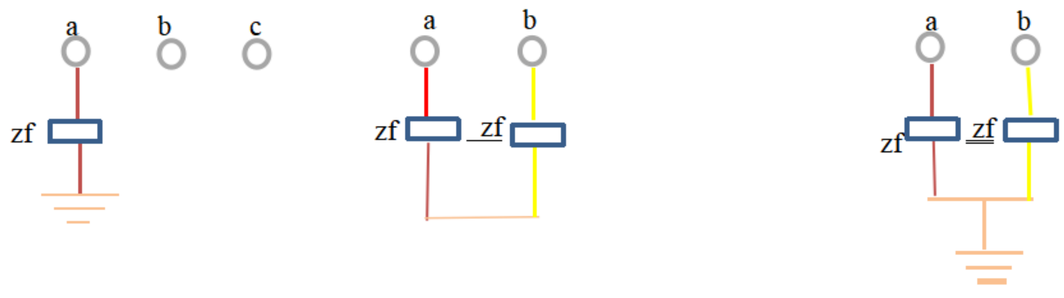


(b) L-L-L-G fault

Only 2.5% of system faults are symmetrical faults if these faults occur, system remains balanced but results in severe damage to the electrical power system equipment. The above figure shows two types of three phase symmetrical faults. Analysis of these faults is easy and usually carried by per phase basis. Three phase analysis is required for selection of set phase relays, rupturing capacity of the circuit breakers and rating of the protective switchgear(Agarwal, 2021).

b) Unsymmetrical faults

The unsymmetrical faults are very common and less severe than the symmetrical faults. The faults are mainly three types namely; line to ground (L-G), line to line (L-L) double line to ground (L-L-G) faults



(a) LG fault (b) LL fault (c) LLG fault

In this case, 60-70% of faults of this type is most common faults of the line to ground fault. This causes the conductors to make contacts with the earth or ground, 15-20% of fault are l-L-G fault and causes the two conductors to make contact with the ground and L-L faults occur when two conductors make contact with each other mainly while swinging of lines due to winds and 5-10% of fault are of this type. The unsymmetrical faults are called the unbalance faults since their occurrence causes unbalance in the system. this means that the impedance values are different in each phase causing unbalance current to flow in the phases and are more difficult to analyse and are carried by par phase basis similar to three phase balance faults (Agarwal, 2021).

II. Research Methodology

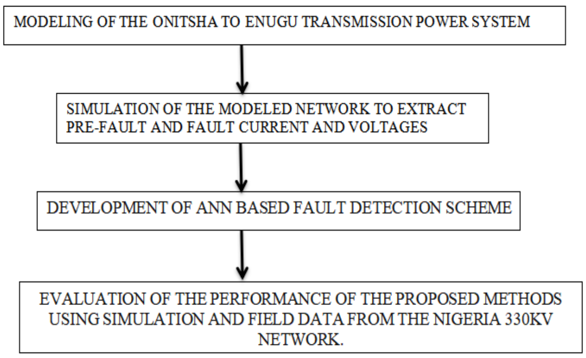


Figure 1: Schematic Representation of the Steps in the Research's Methodological Procedure

1. MODELING OF THE ONITSHA TO ENUGU TRANSMISSION POWER SYSTEM

The system that serves as the foundation for the current investigation is a transmission line that runs from Onitsha to Enugu at 330 kilovolts (KV). The implementation of artificial neural networks (ANNs) as a protection strategy enables the detection and classification of faults to be carried out with the ANN serving as a protection relay. This is how the protection strategy is put into action. Figure 2 depicts Matlab/Simulink Model of Onitsha – Enugu Nigeria Sub Power System Network that was used in the case study. It is made up of the alternating current (AC) source, the transmission line, and the linked electrical loads.

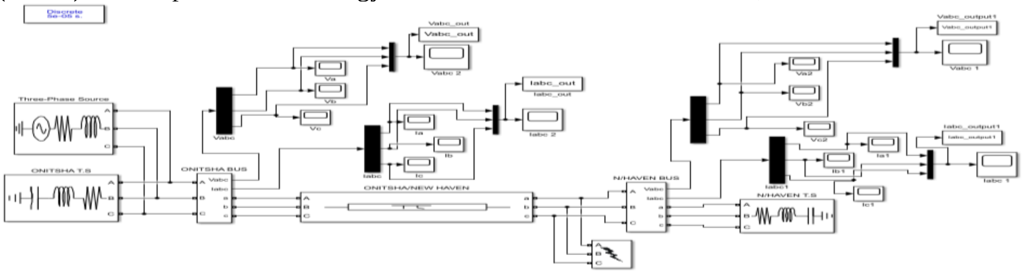


Figure 2: A Matlab/Simulink Modeled of Onitsha – Enugu Nigeria Sub Power System Network

2. SIMULATION OF THE MODELED NETWORK TO EXTRACT PRE-FAULT AND FAULT CURRENT AND VOLTAGES

Three – phase voltage and current signals of the transmission line are represented by equations 3 to 6.

$$v_a = V_p \sin(\theta + \emptyset) \quad (1)$$

$$v_b = V_p \sin(\theta + \emptyset) \quad (2)$$

$$v_C = V_p \sin(\theta + \emptyset) \quad (3)$$

$$i_a = I_p \sin(\theta + \varphi) \quad (4)$$

$$i_b = I_p \sin(\theta + \varphi) \quad (5)$$

$$i_C = I_p \sin(\theta + \varphi) \quad (6)$$

The relationship between the voltage and currents at the transmitting end and the receiving end may be expressed mathematically as follows:

$$\begin{bmatrix} V_S \\ I_S \end{bmatrix} = \begin{bmatrix} 1 & Z \\ 0 & 1 \end{bmatrix} \begin{bmatrix} V_R \\ I_R \end{bmatrix} \quad (8)$$

Thus,

$$|V_S| = [\,(\,|V_R|\cos\emptyset_R + |I|R)^2 + (\,|V_R|\sin\emptyset_R + |I|X_L)^2]^{\frac{1}{2}} \quad (9)$$

$$|V_S| = [\,(\,|V_R|^2 + |I|^2(R + X_L)^2 + 2(\,|V_R||I|(R\cos\emptyset_R + X_L\sin\emptyset_R)]^{\frac{1}{2}} \quad (10)$$

$$|V_S| = |V_R|[1 + \frac{2|I|R\cos\emptyset_R}{|V_R|} + \frac{2|I|X_L\sin\emptyset_R}{|V_R|} + \frac{2|I|^2X_L(R^2 + X_L{}^2)}{|V_R|^2}]^{\frac{1}{2}} \quad (11)$$

$$\frac{2|I|^2X_L(R^2 + X_L{}^2)}{|V_R|^2} \cong 0 \quad (12)$$

Then,

$$|V_S| = |V_R|[1 + \frac{2|I|R\cos\emptyset_R}{|V_R|} + \frac{2|I|X_L\sin\emptyset_R}{|V_R|}]^{\frac{1}{2}} \quad (13)$$

However, by binomial expansion, and retaining first order terms, we obtain that,

$$|V_S| = |V_R|[1 + \frac{2|I|R\cos\emptyset_R}{|V_R|} + \frac{2|I|X_L\sin\emptyset_R}{|V_R|}]^{\frac{1}{2}} \quad (14)$$

$$|V_S| = |V_R| + |I|(R\cos\emptyset_R + X_L\sin\emptyset_R) \quad (15)$$

3. DEVELOPMENT OF ANN BASED FAULT DETECTION SCHEME

The ANN being employed in this circumstance is divided into three stages: detection, classification, and isolation. Each phase involves the selection of an ANN, which is subsequently trained for the specific purpose. The three phase currents (I = Ia Ib Ic) and voltages (V = Va Vb Vc) of the Power system blockset line serve as the inputs for each network (simpowersystem).

The three tasks that a full fault diagnosis technique for transmission line systems must fulfill are as follows:

1) fault Identification: The goal of this stage is to identify whether or not a fault has occurred in the transmission line.

2) Fault classification: This is the step at which the different types of faults are discovered.

3) Identifying the fault: This phase entails determining the zone in which the troublesome line is located.

a) Choosing the most suitable network

While supervised learning is the preferred way for training a network to approximate functions, multilayer perceptual networks produce the most accurate and acceptable function approximations. The back-propagation learning method is also used for generalisation. However, this strategy requires a long training period and has the potential to limit coverage to inconsequential levels (Obi et al, 2024).

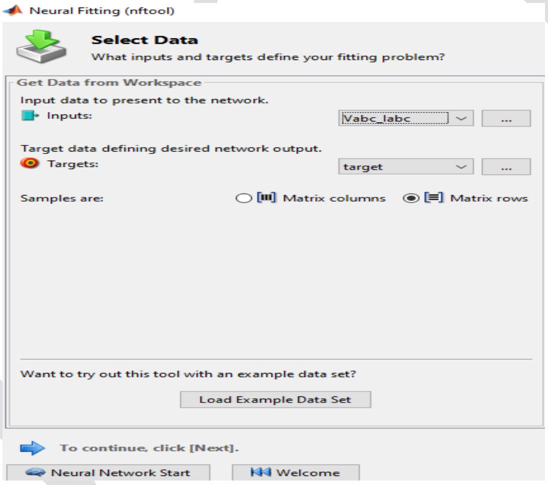


Figure 3: Data Sampling and Selection for ANN Input

In the process of choosing input data, the following procedure is used: The data from the transmission line, including three-phase Voltage (Vabc) and Current (Iabc) data, are obtained during the simulation of the MATLAB/SIMULINK modeled transmission line. A calculated desired data as well as an expected result data have both been sampled in the ANN fault detector. The Vabc Iabc and Target datasets were extracted from the Matlab workspace, each consisting of 2001 samples by 6 and 2001 samples by 1, respectively, in matrix rows. As illustrated in figure 3, these datasets were then sampled into an ANN fault detector machine and utilized for the selection of an ANN fault detection architecture as well as the data training process.

b) Instruction for Selected ANN Candidates

Because neural network training is one of the most important procedures in the development of ANN fault detectors and fault locators, the training data should be prepared in a methodical and meticulous way. In certain applications, training data is not always available as part of a real system; hence, a training simulator may be used to generate relevant data for the purpose of training an artificial neural network (ANN).

When creating training data, it should be representative of all possible scenarios in which the ANN will be asked to perform detection and classification tasks. This is due to the fact that the ANN will be required to perform detection and classification operations. As a consequence, training data sets may grow to be exceedingly enormous. The Back-Propagation Neural Network (BPNN) technique was employed during training. Figure 3.11 depicts the Training technique split down into its component sections.

The ANN is a network made up of interconnected neurons, with each layer acting as an input to the one below it. The weights of each layer are adjusted as needed to optimize the strength of signal transmission. The output generated by BPNN is known as a target output, while the result produced by the old technique is known as an actual output.

We are now aware of the discrepancy between the planned outputs and those generated by the process as a result of the inaccuracy. We used the error in our computations to get the Least Mean Square Error (LMSEE). If null errors are detected, the BPNN will work by delivering errors from the output layer in the other way.

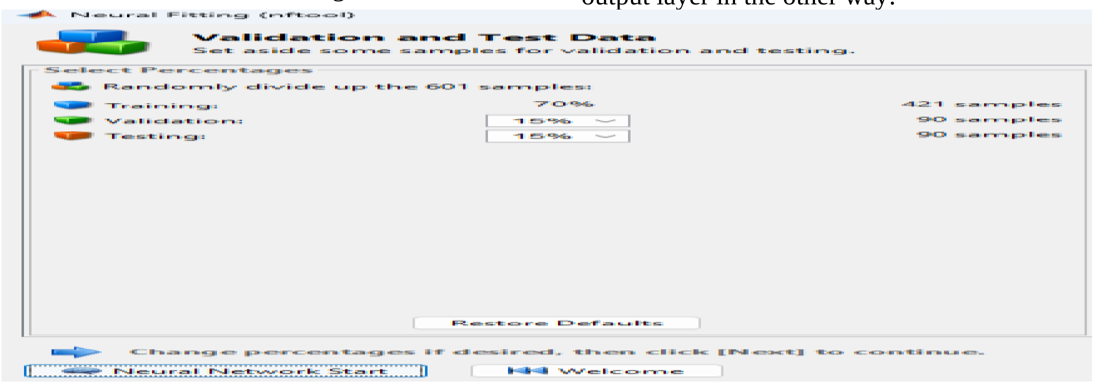


Figure 4: Selection and Sampling of Input Data into ANN

The Validation and Test Data training method indicates the number of input (Vabc Iabc) data samples that were obtained for the purpose of training, validating, and testing the selected ANN network in detail. It demonstrates that 421 samples (70 percent of 2001), 300 samples (15 percent of 2001), and so on were utilized for training, validation, and testing, accordingly.

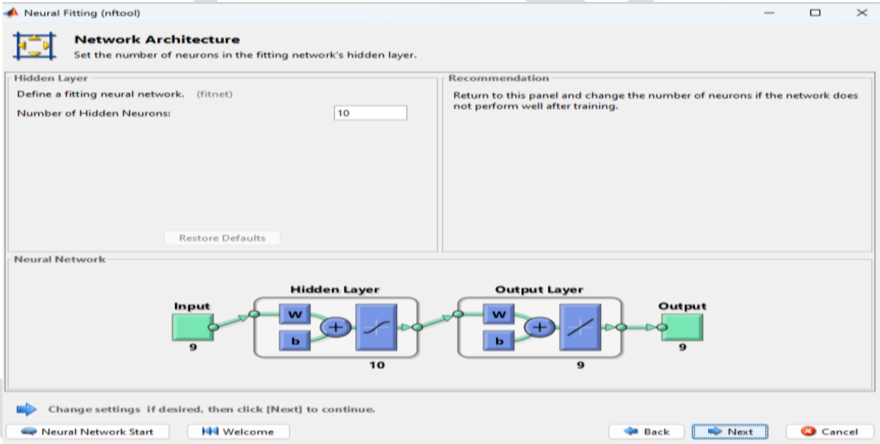


Figure 5: Selection and Sampling of Input Data into ANN

The chosen artificial neural network design that was utilised for training and fault detection is seen in Figure 5. Because of the structure of this ANN, we are able to make an informed decision on the number of neurons that should be included in the architecture's hidden layer.

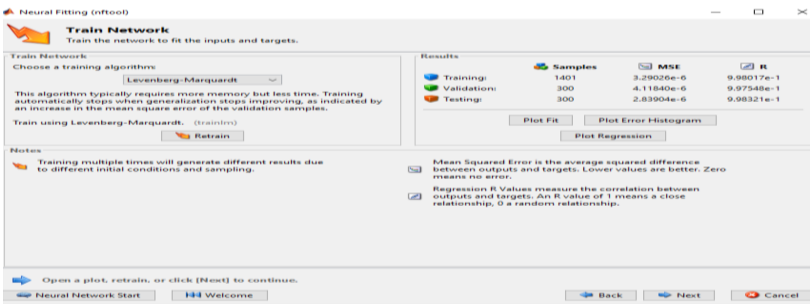


Figure 7: ANN Training Process

Figure 7 depicts the training network window. To train the specified network and samples, this window implements the Levenberg-Marquardt backpropagation training approach. When the regression and mean square error values are not attained, a method called retraining may be used. The retraining and neuron number modification will continue until convergence (regression R 1 0.5 and mean square 0.4) is reached. The ANN Fault Detector is trained by matching it to different sorts of data for a number of reasons, the most essential of which is that it learns how to recognize electrical faults (the research's assumption). Simulation is used to verify the trained ANN, which checks both the validity of the results and the performance of the trained ANN. As a result, checking and assessing the ANN output against the input data is critical. As seen in Figure 5, the suggested strategy is to train the ANN using simulated copies of the actual data. In addition, we apply a learning approach to find additional faults while the system is running in real time. The use of simulation would illustrate the study's applicability and relevance to the corporate world. To make an ANN, you must first describe the neural network's inputs and outputs for pattern recognition. Then, you must use correlations between these two sets of data to train the ANN. The network's inputs offer a picture of the status and transitory elements of the faults that must be recognized, and this must be carefully considered. The neural detector is designed to indicate the presence of a transmission line fault or the absence of a transmission line fault. The occurrence of such a breakdown may be established by directly assessing the condition of the power system, starting with the instantaneous voltages and currents and moving backwards. Because of this, a scaling method (also called signal normalization) must be used before the voltage and current signals enter the neural network in order to cut down on the time it takes to do the computing. To accomplish this, we used a scaling technique that may be characterized as the division of the magnitudes of the fundamental voltages and currents. The ANN may be regarded as a flexible system capable of learning connections via frequent data presentation and generalizing to new data that it has not previously seen. This is performed via training, which is based on the assumption that learning will occur.

B. Detection of faults

We sampled the phase voltage and current on a per-unit level along with the goal values and fed them into the input neurons of the chosen ANN. The ANN was then trained and produced outputs for various transmission line faults. Both the quality of the data used to train the ANN fault detector and the accuracy of the measurements used as input determine its performance

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III. RESULTS

Fault Detection Using Artificial Neural Network

Pre-fault steady state Artificial Neural Network Training data

Inputs 'data' of 601x6 matrix, representing the prefault voltage and current data. These data comprised of 601 samples of 6 elements and Targets 'data_1' of 601x6 matrix, representing the prefault voltage and current data comprising also of 601 samples of 6 elements. The prefault input voltage and current data can be found in appendix 1.

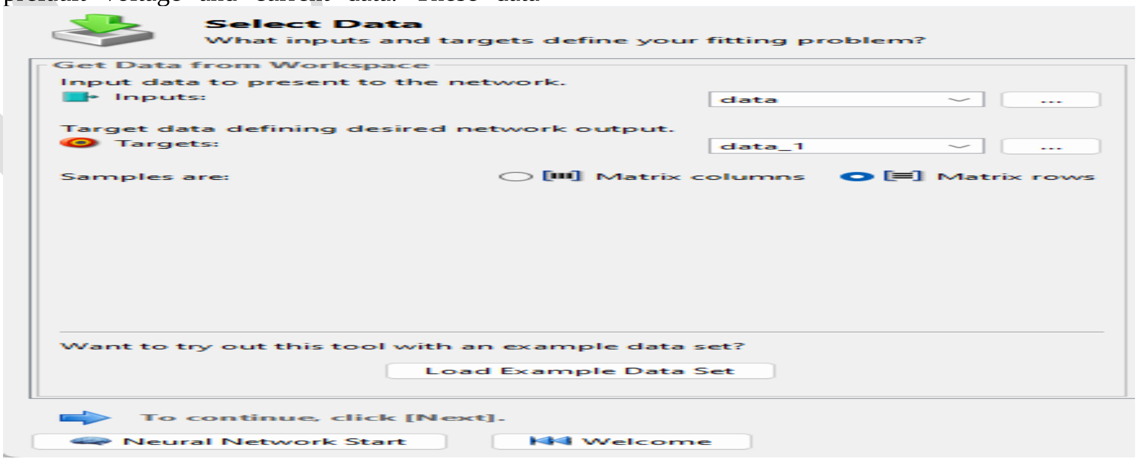

Figure 4.1: Selection of Training Data for The Pre-Fault Steady State Voltage and Current Conditions

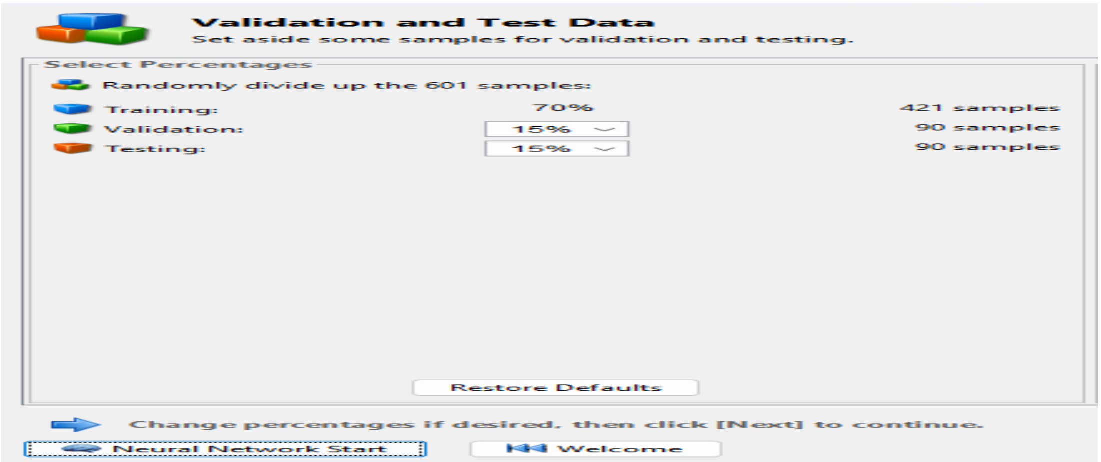

Figure 4.2: Validation and data testing for pre-fault voltage and current data

Three kinds of samples were used for the data validation and testing. 70% which is about 421 samples of the total 601 samples were used for training. These training sample are presented to the network during the training and the network is adjusted according to its error. 15% comprising of 90 samples out of 601 total sample were randomly selected and used for data validation. This validation is used to measure network generalization, and to halt training when generalization stops improving. The sample number of samples which is 15% comprising of 90 samples of the total 601 samples were also randomly selected and used for testing of the data. The data testing has no effect on the training and so it provides and independent measure of network performance during and after training.

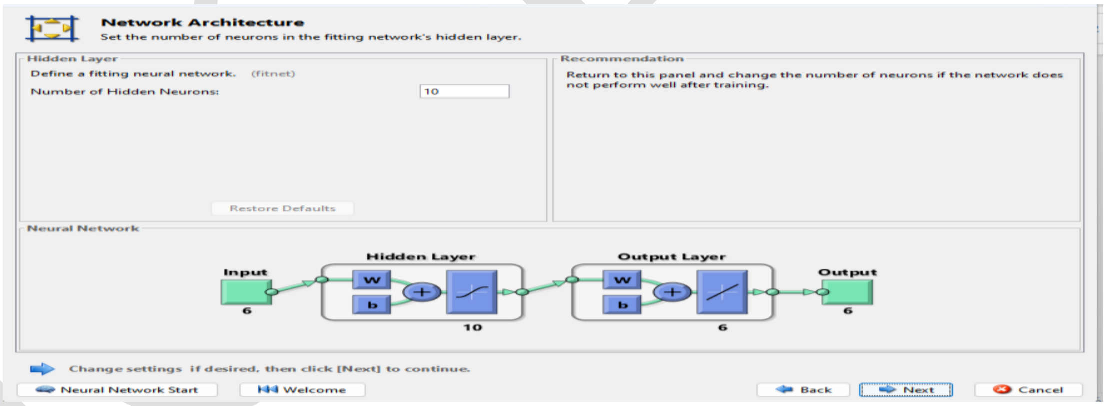

Figure 4.3: Network Architecture

The network architecture comprised of six inputs, ten hidden layer, six output layer and six output as depicted in Figure 4.3.

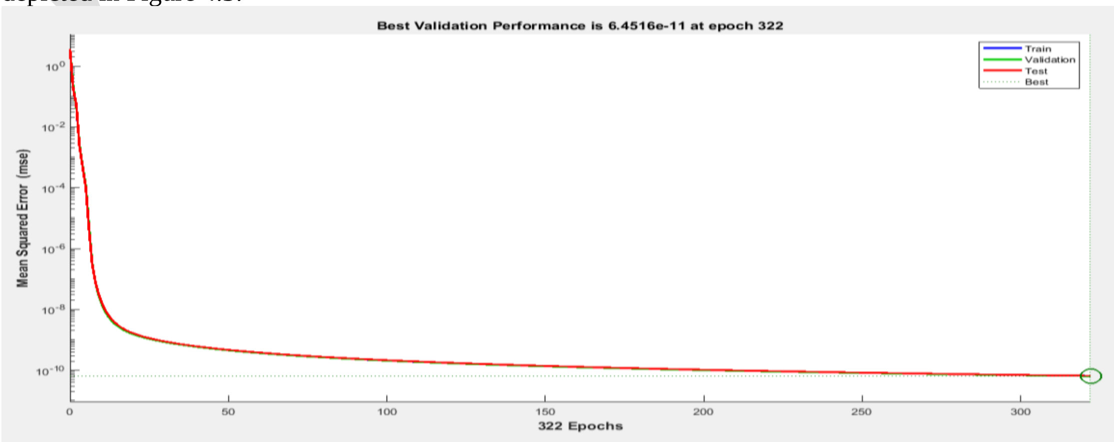

Figure4.4: Performance plot.

The performance plot shows how well the neural network can learn from the data you give it. The data given to it is divided into three parts: training, validation and test. The training part is used to adjust the network's weights, which are like knobs that control how the network processes the inputs. The validation part is used to check if the network is learning well or not. The test part is used to evaluate how the network performs on new data that it has not seen before. The plot has two axes: the horizontal axis shows the number of epochs, and the vertical axis shows the error. An epoch is one complete cycle of presenting all the training data to the network. The error is a measure of how different the network's outputs are from the targets, which are the correct answers you want the network to produce. The lower the error, the better the network is at learning. The plot has three curves: one for the training error, one for the validation error, and one for the test error. The training error shows how the network's performance improves on the training data as it learns. The validation error shows how the network's performance changes on the validation data as it learns. The test error shows how the network's performance is on the test data, which is the most important measure of how good the network is. The plot also shows the best validation performance and the best epoch of 322. The best validation performance is the lowest validation error that the network achieved during the training. The best epoch is the epoch at which the network achieved the best validation performance.

It can bee seen from the graph that the network achieved the best validation performance at epoch 322, which means that at that point, the network had the lowest error on the validation data set. You can also see that the error lines were decreasing steadily until epoch 322, which means that the network was learning well. You can also see that the value lines were changing smoothly until epoch 322, which means that the network was learning fast.

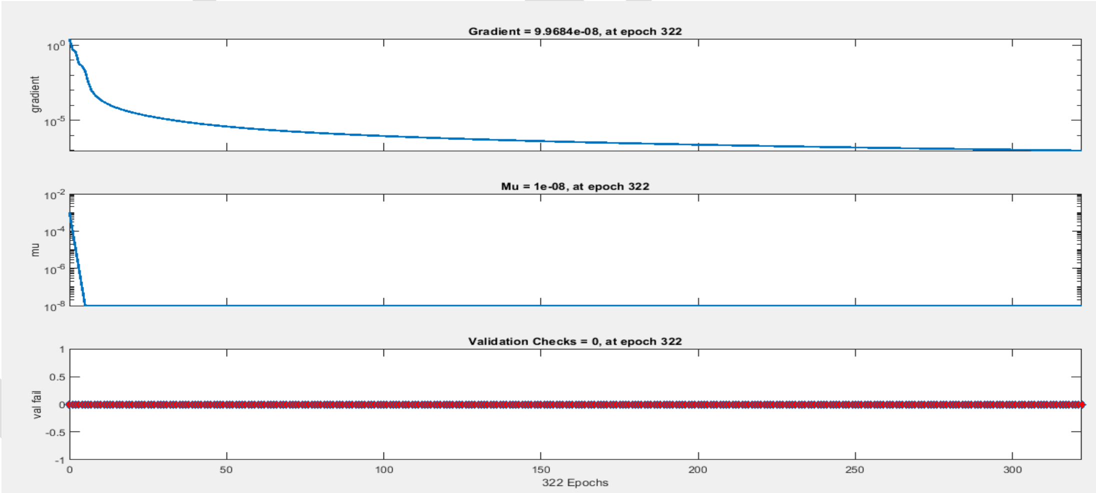

Figure 4.5: Training state plot

The training state result is a graph that shows how the neural network is learning from the data given to it in MATLAB simulation. The gradient is a number that tells the network which direction to change the weights and biases to reduce the error. The validation checks are a number that tells the network how many times it can do worse on the validation data set before it stops learning. The mu is a number that helps the network avoid getting stuck in a bad place.

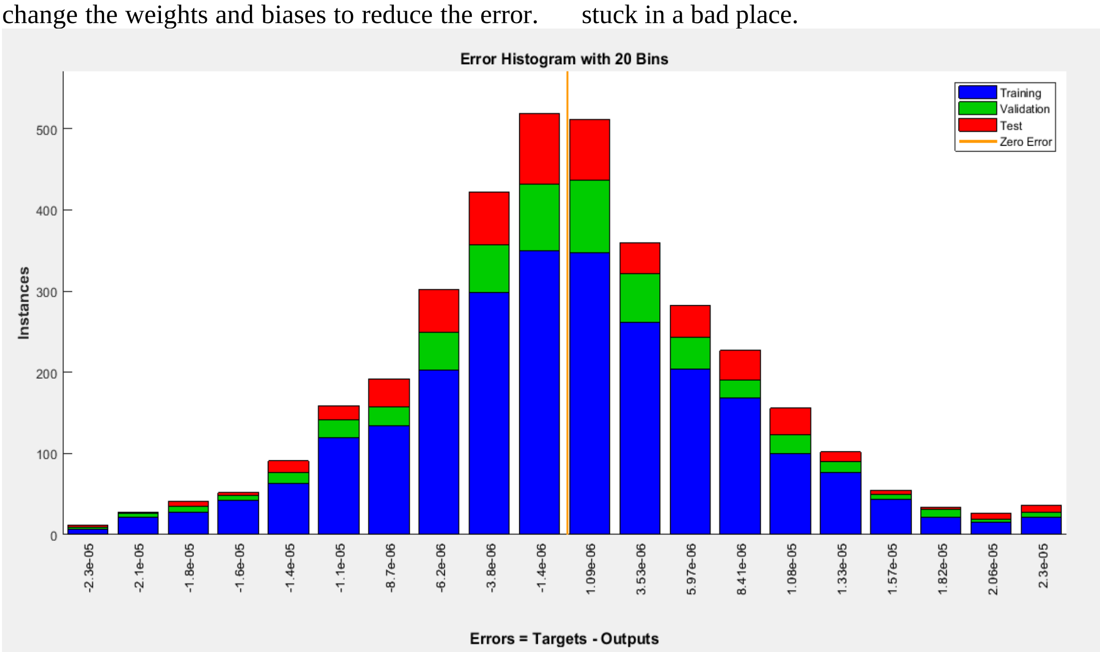

Figure 4.6: Error histogram

The error histogram in MATLAB neural network training result shows how the errors between the target values and the predicted values are distributed. The errors are calculated as the difference between the target values and the predicted values, which are the outputs of the neural network. The error histogram helps us to see how well the neural network fits the data and how much variation there is in the errors. The error histogram of 20 bins means that the range of error values is divided into 20 equal intervals, and each interval is represented by a vertical bar. The height of the bar shows how many instances or samples have an error value within that interval. The error histogram of 500 instances means that the total number of samples used to calculate the errors is 500. These samples can be from the training, validation, or test data sets, depending on which one you want to evaluate. The error histogram helps to assess the performance of the neural network and identify potential problems.The error histogram tells you how good your neural network is. If the bars are near the zero error line, it means your neural network is very accurate, and it made small errors. If the bars are far from the zero error line, it means your neural network is not very accurate, and it made big errors. The closer the bars are to the zero error line, the better your neural network is. From the above error histogram plot, we can see that the error histogram has the highest bin bars centered around Zero error line, meaning that the neural network from the training has a low error

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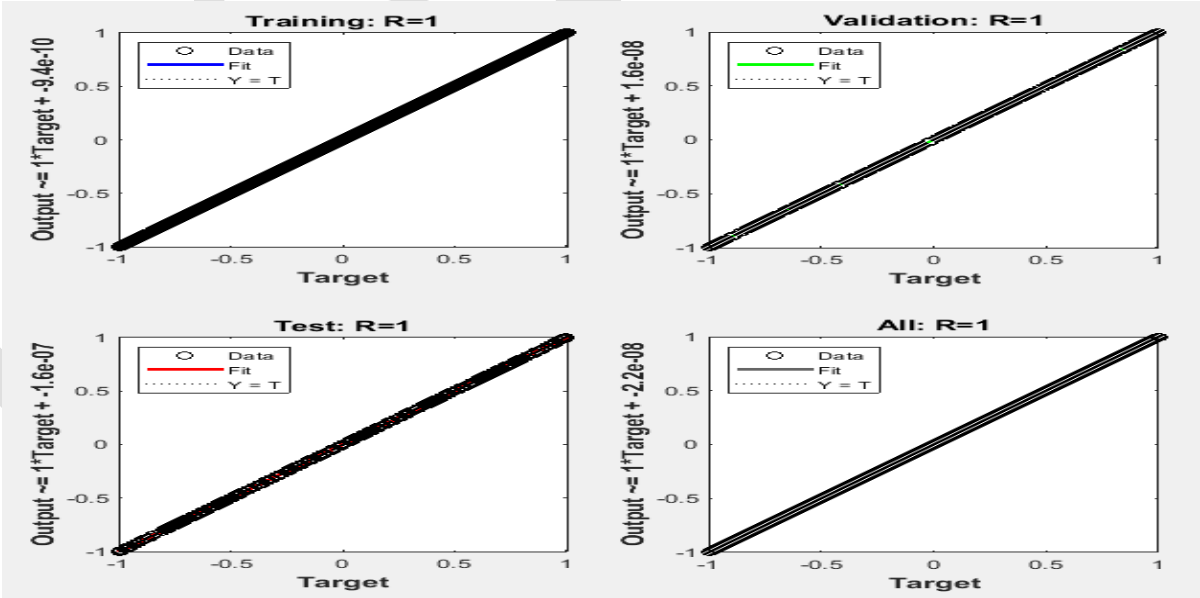

Figure 4.7: Regression Plot

The MATLAB neural network regression plot shows how well a neural network can predict the values of something based on some data. Here we used a neural network to predict if there is a fault in a power system based on the voltage and current signals. The data we used to train the neural network are the current signals and their fault status. The graph has two axes: the horizontal axis and the vertical axis. The horizontal axis shows the target values, which are the correct or expected values of the network we want to predict. The graph also has a line that goes from the bottom left corner to the top right corner. This line is called the best fit line, and it shows the ideal relationship between the target values and the output values. If the target values and the output values are exactly the same, then all the points will be on this line. The graph also has many dots that are scattered around the line. Each dot represents one signal and its fault status. The position of the dot shows the target value and the output value for that signal. For example, a dot that is close to the line means that the neural network predicted the fault status of the signal very accurately. A dot that is far from the line means that the neural network predicted the fault status of the signal very poorly. The graph can help you to see how good the neural network is at predicting. The dots on the above plot are well aligned on the horizontal line signifying no fault condition.Line to Ground Fault Detection results from the Artificial Neural Network Training data.

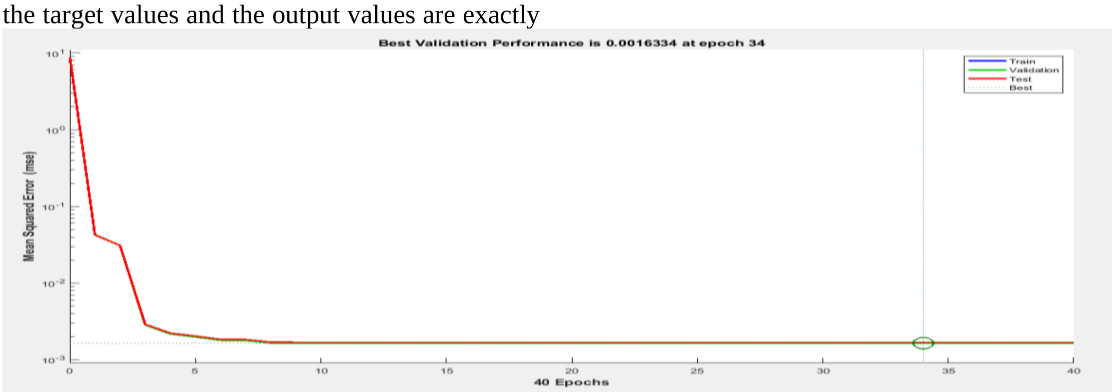

Figure 4.8: L-G Validation Performance Plot

The validation plot has three curves: the training curve, the validation curve, and the test curve. The training curve shows the performance on the training data, which are the data that the neural network learns from. The validation curve shows the performance on the validation data, which are some data that the neural network does not learn from, but uses to check its progress. The test curve shows the performance on the test data, which are some data that the neural network does not see at all, until the end of the training. The validation plot can tell us some important things about the neural network:

i. If the training curve goes down, it means the neural network is learning from the data, and reducing its error.
ii. If the validation curve goes down, it means the neural network is generalizing well, and can handle new data that it has not seen before.

iii. If the test curve goes down, it means the neural network is reliable, and can perform well on the final data that we care about.

iv. If the training curve goes down, but the validation curve goes up, it means the neural network is overfitting, and memorizing the data, instead of learning the patterns. This can make the neural network perform poorly on new data.

v. If the validation curve goes down, but the test curve goes up, it means the neural network is not robust, and sensitive to small changes in the data. This can make the neural network perform inconsistently on different data.

To make a good neural network, the validation plot needs to have low and stable curves, especially the validation and test curves. From 4.8, we can deduce that the neural network validation plot is low and stable meaning it has low error and can learn from new data

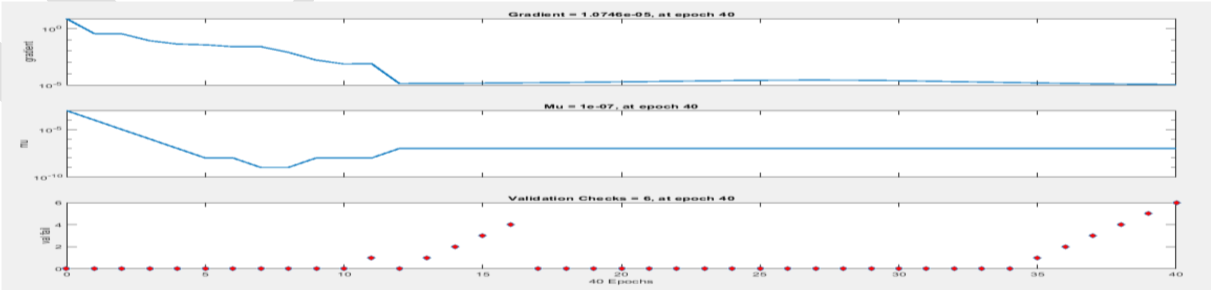

Figure 4.9: L-G Training State plot

The neural network training state plot can help us see if the neural network is learning well, or if it needs some changes. The gradient, which is how much the neural network changes its neurons after seeing the data.The validation check, shows how often the neural network checks its progress on some data that it does not learn from. The learning rate, which is how fast the neural network changes its neurons during the training. The learning rate tells us how the neural network adapts to the data, and how sensitive it is to the changes.

From Figure 4.9, the gradient is seen to be decreasing, which means the neural network is getting closer to the best solution. The validation check is happening at the right time, which means the neural network is checking its progress regularly. The learning rate is changing, which means the neural network is adapting to the data.

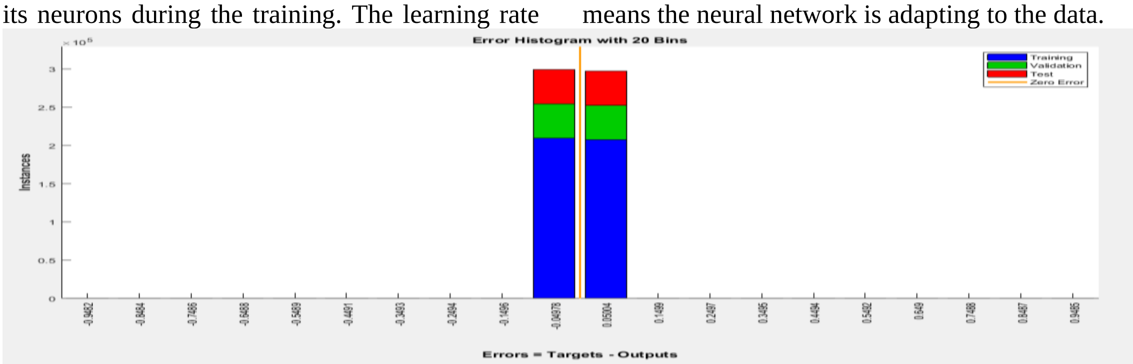

Figure 4.10: L-G Error Histogram

From Figure 4.10 we can see that the error histogram bars are near the zero erro line, this means that the neural network is very accurate.

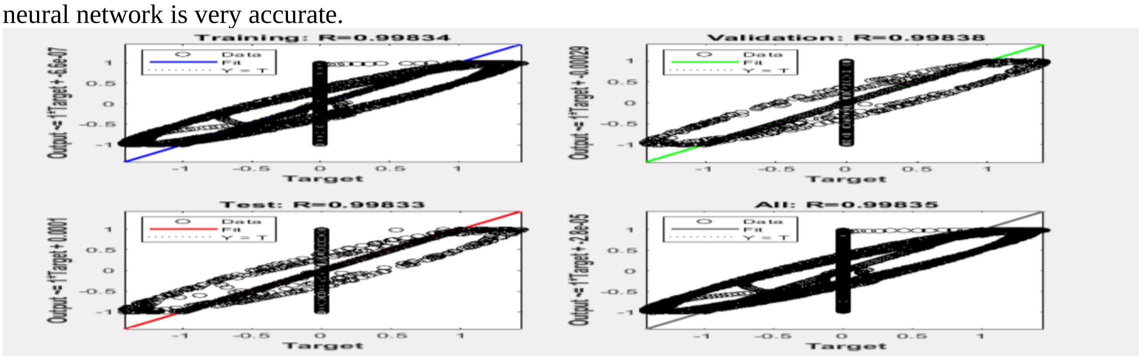

Figure 4.11: L-G Regression plot

Line to Line Fault Detection results from the Artificial Neural Network Training data

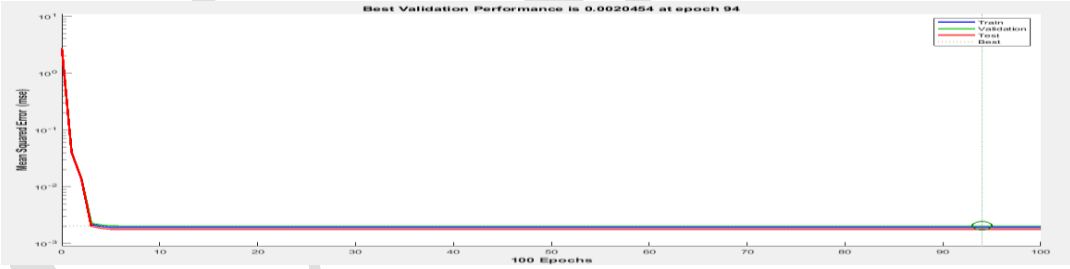

Figure 4.12: L-L Performance Plot

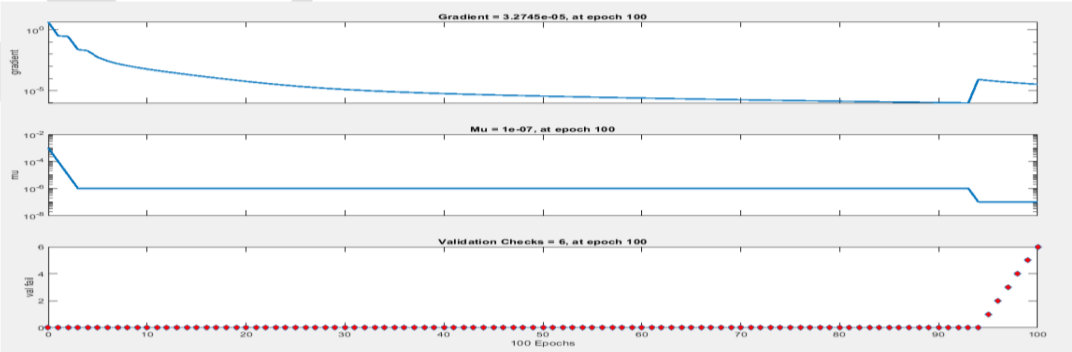

Figure 4.13: L-L Training state plot

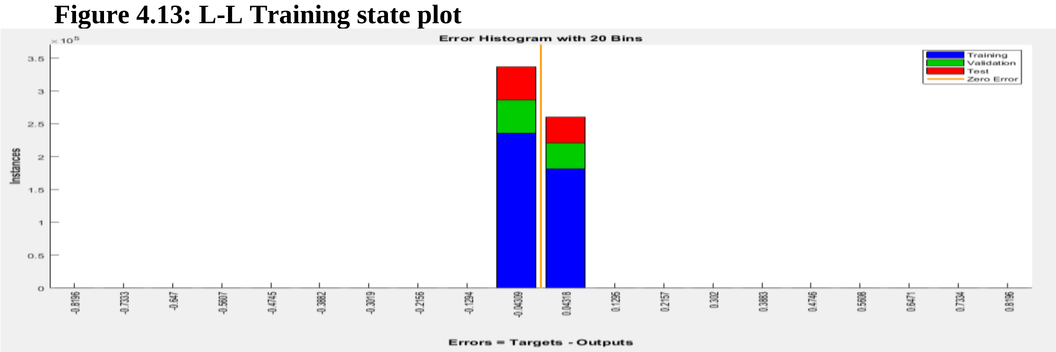

Figure 4.14: L-L Error Histogram

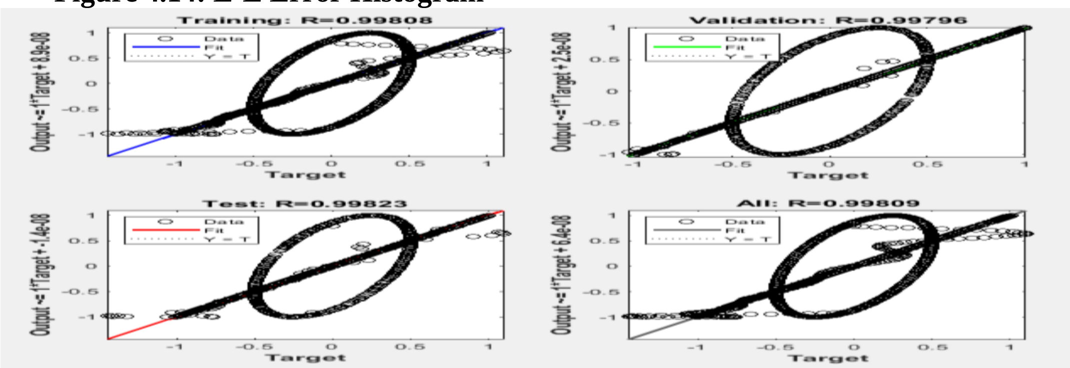

Figure 4.15: L-L Regression Plot

Line to Line to Ground Fault Detection results from the Artificial Neural Network Training data

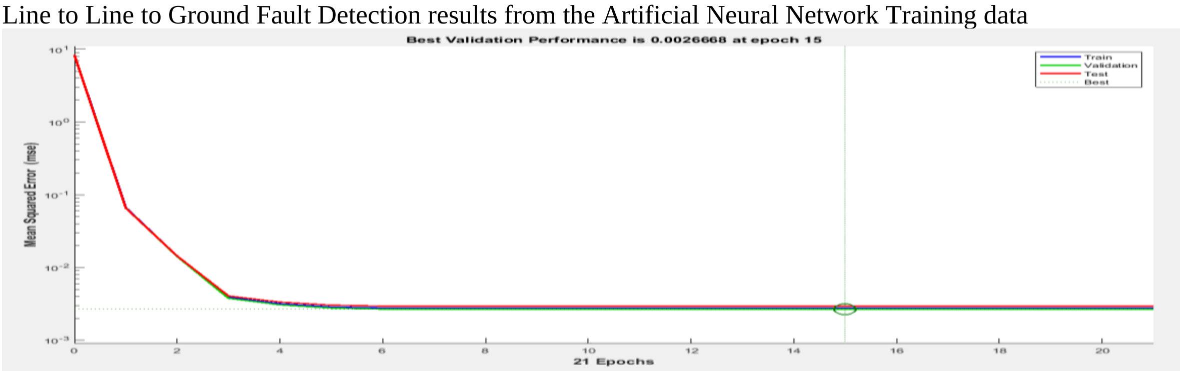

Figure 4.16: L-L-G Performance Plot

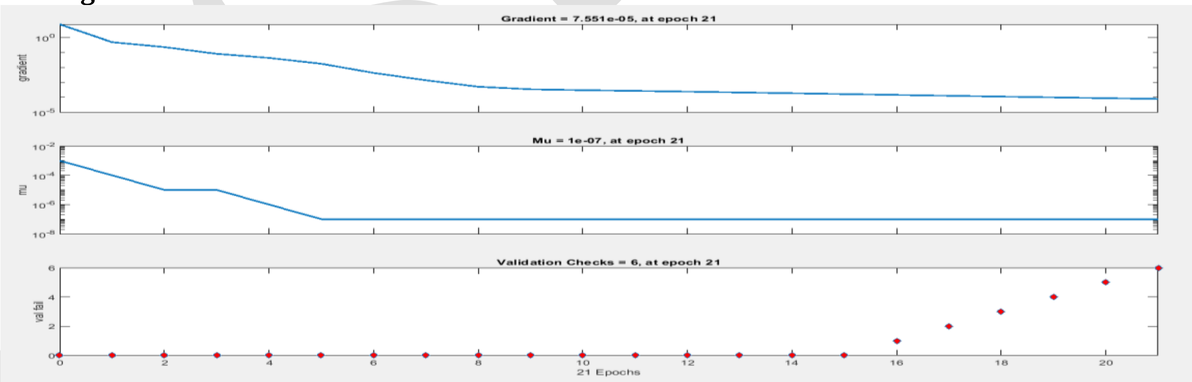

Figure 4.17: L-L-G Training state plot

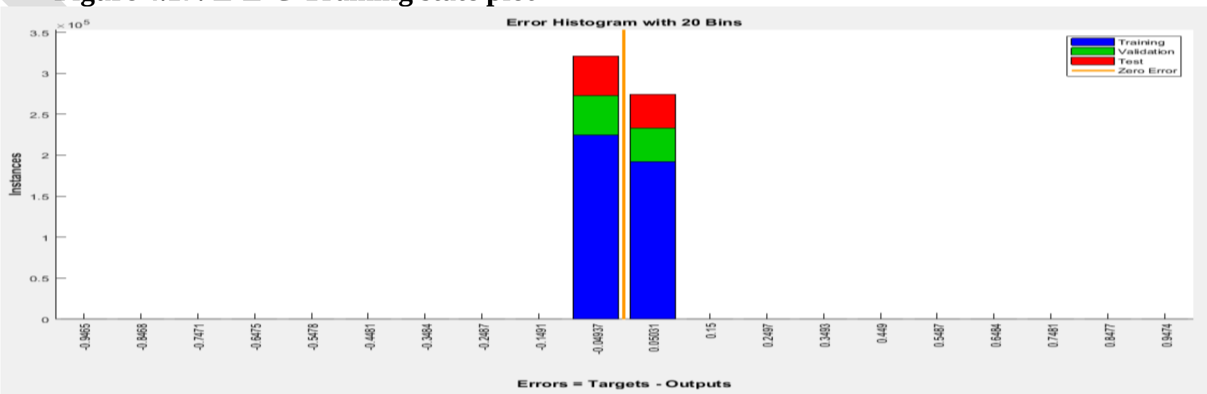

Figure 4.18: L-L-G Error Histogram plot

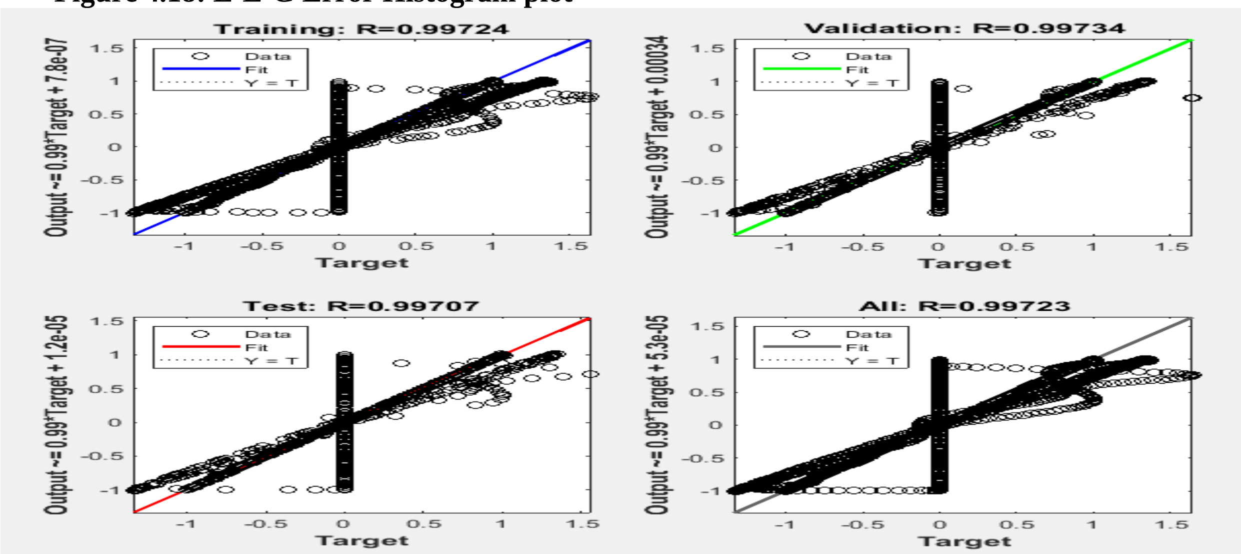

Figure 4.19: L-L-G Regression Plot

Line to Line to Line Fault Detection results from the Artificial Neural Network Training data

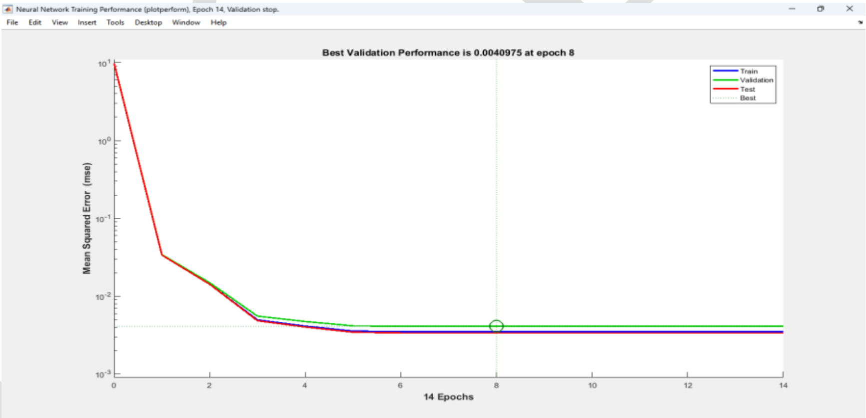

Figure 4.20: L-L-L Performance Plot

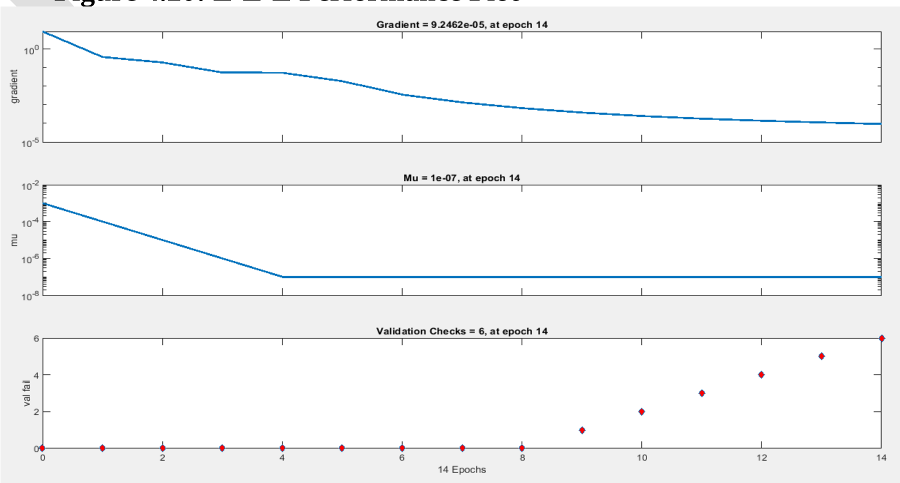

Figure 4.21: L-L-L Training state plot

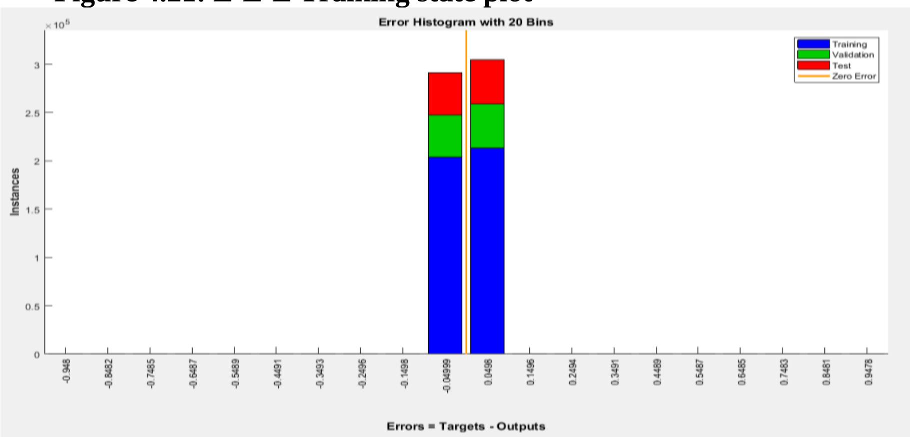

Figure 4.22: L-L-L Error Histogram Plot

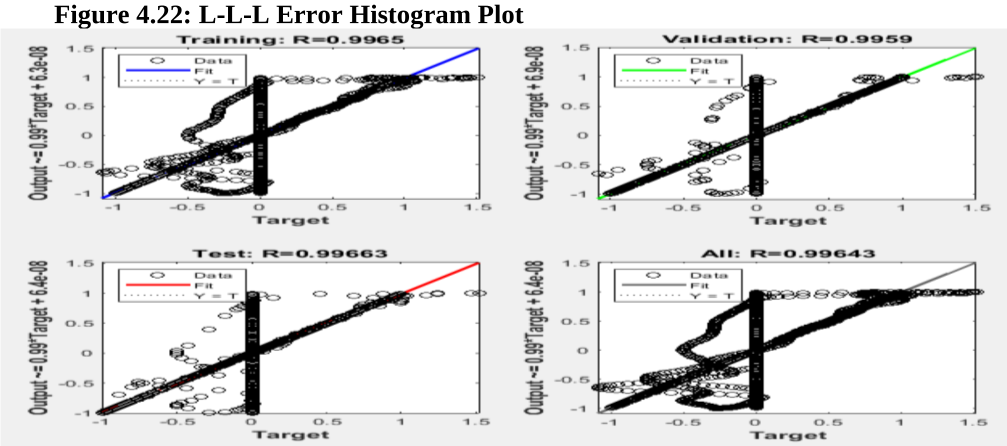

Figure 4.22: L-L-L Regression Plot

Line to Line to Line to Ground Fault Detection results from the Artificial Neural Network **Training data**

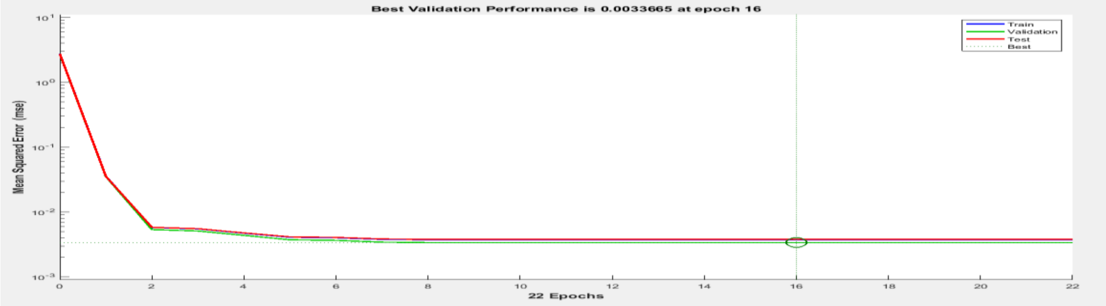

Figure 4.23: L-L-L-G Performance plot

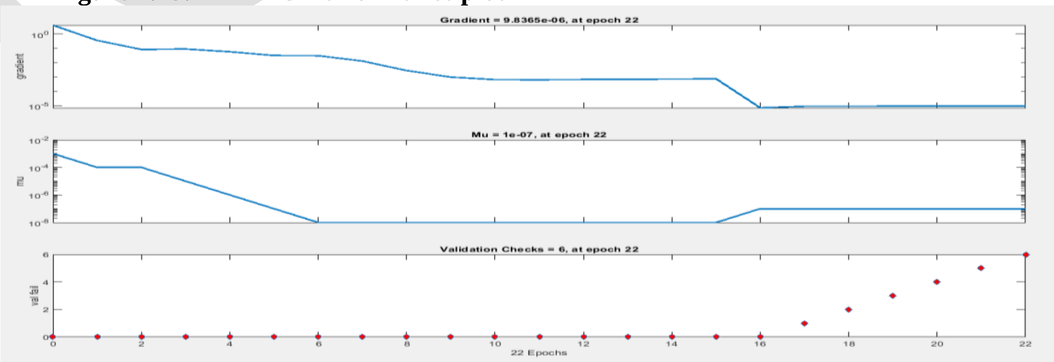

Figure 4.24: L-L-L-G Training state plot

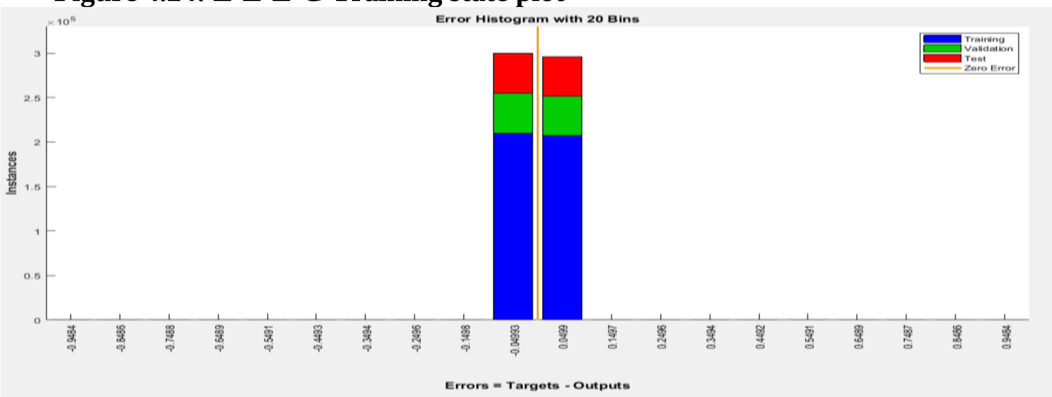

Figure 4.25: L-L-L-G Error Histogram plot

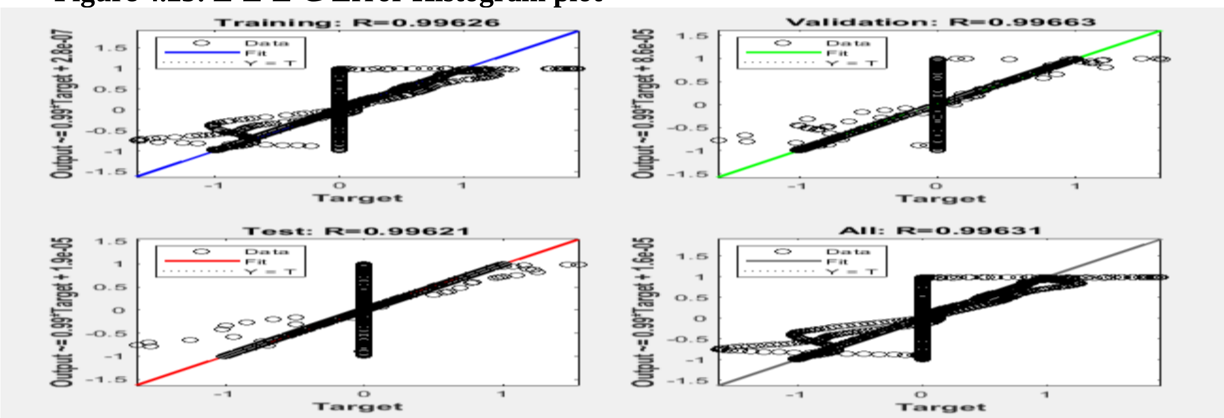

Figure 4.26: L-L-L-G Regression Plot

The figures from 4.11 to 4.26 illustrate the different patterns of the results for various fault scenarios, compared to the no fault condition. The regression plot patterns deviate from the best fit lines, indicating the presence of fault conditions on the transmission line. The other plots, such as the error histogram, training state, and performance validation plot, confirm and verify the accuracy of the neural network in detecting faults on the transmission line.

CONCLUSION

In this research, we have successfully demonstrated the application of Artificial Neural Networks (ANNs) for fault detection in high-voltage transmission lines. The study focused on the Onitsha to Enugu transmission power system in Nigeria, utilizing both simulation and field data to validate the effectiveness of the proposed ANN-based fault detection scheme. The results from the ANN training and validation processes indicate that the neural network can accurately detect various types of faults, including line-to-ground (L-G), line-to-line (L-L), double line-to-ground (L-L-G), and three-phase faults (L-L-L and L-L-L-G). The performance plots, error histograms, regression plots, and training state plots consistently show that the ANN achieves high accuracy and reliability in fault detection.

The ANN's ability to learn from pre-fault and fault data, adapt to new fault scenarios, and generalize well to unseen data highlights its potential as a robust tool for enhancing power system protection. The use of MATLAB/Simulink for modeling and simulation provided a comprehensive platform for testing and validating the ANN's performance under various fault conditions. Furthermore, the research highlights the importance of selecting appropriate training data and network architecture to optimize the ANN's performance. The Levenberg-Marquardt backpropagation training method proved effective in minimizing errors and achieving convergence.

In conclusion, the ANN-based fault detection technique offers a promising alternative to conventional protection schemes, addressing the limitations of distance protection and improving the accuracy and efficiency of fault detection in high-voltage transmission lines. This research contributes to the ongoing efforts to enhance power system stability, reliability, and sustainability, particularly in the context of the Nigerian power grid. Future work may involve exploring the integration of other machine learning techniques, such as support vector machines and decision trees, to further improve fault detection and classification. Additionally, real-time implementation and testing of the ANN-based scheme in a live power system environment would provide valuable insights into its practical applicability and performance.

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