International Journal of Research and Review
Volume 11; Issue: 10; October 2024
Website: www.ijrrjournal.com
Research Paper
E-ISSN: 2349-9788; P-ISSN: 2454-2237

Artificial Neural Network-Based Fault Detection on Nigerian 330kv Power Transmission Line

Hammed Waheed Olalekan[1], Onyegbadue Ikenna Augustine[2], Guiawa Mathurine[3]

[1,2,3]Department of Electrical and Electronic Engineering, College of Engineering, Igbinedion University, Okada, Edo State, Nigeria

Corresponding Author: Hammed Waheed Olalekan

DOI: https://doi.org/10.52403/ijrr.20241047

ABSTRACT

In Nigeria, there will inevitably be ongoing difficulties with 330kv power transmission lines. This drop in insulation strength between the phase conductors and the earthed screen encircling the conductors may be the cause of the difficulties that have emerged on the electric transmission circuit. Many scholars have approached these problems in different ways. Fast Fourier Transform (FFT), Wavelet Transform, Fourier Transform, S-Transform, and Fourier Series are a few of the techniques utilized to address these transmission line problems. It has not been widely and thoroughly adopted to solve problems in Power System Engineering, according to numerous study studies on artificial neural networks (ANNs). Consequently, the 330kV Power Transmission Line problems have been addressed in this research by using artificial neural networks (ANNs). the training efficacy of any ANN challenges diagnosis system. The MATLAB/Simulink R2018a was utilized to conduct simulations on an ANN challenges detector. The ANN detector was trained with pre-fault and fault signals as inputs, allowing for the identification of different types of line difficulties. Results indicated that at Mean Square Error (MSE) of 1.6856e-5, the best training performance for the challenges was attained. At Regression, it approaches zero (9.8958e-1). Because it met the requirements, the simulation's outcome is acceptable.

***Keywords**: Power System, Transmission Line, Matlab/Simulink, Three Phase, Artificial neural networks, fault detection.*

INTRODUCTION

Nigeria's electrical power transmission system is an essential component of its energy infrastructure, designed to transport high voltage electricity from power generation stations to distribution networks and, ultimately, to consumers. The 330kV transmission network is particularly crucial due to its role in transferring large amounts of power across extensive distances, connecting major power plants to key load centers.

The reliability of the 330kV transmission system is vital for ensuring a stable and continuous power supply. Faults in the transmission network, such as line outages, short circuits, or equipment malfunctions, can lead to significant disruptions in power delivery. Effective fault detection and management are therefore critical to prevent widespread power outages, minimize damage, and ensure the safety and efficiency of the electrical grid.

According to (ogboh et al, 2023), In an electric power system, fault is an inevitable abnormality that occurs on the power system which courses the flow of current through unintended part, increases and decreases the current and voltage magnitudes respectively. An example is a short circuit which is a fault in which current bypasses the normal load. An open-circuit fault occurs if a circuit is interrupted by some failure. In three-phase systems, a fault may involve one or more phases and ground, or may occur only between phases. In a "ground fault" or "earth fault", current flows into the earth. The prospective short-circuit current of a predictable fault can be calculated or most situations. In power systems, protective devices can detect fault conditions and operate circuit breakers and other devices to limit the loss of service due to a failure (ogboh et al, 2023)

High voltage transmission systems have historically depended on conventional techniques for fault detection, such as: 1. Protective Relays: When abnormal conditions are detected, these devices, which monitor electrical characteristics such as voltage and current, activate circuit breakers. Their effectiveness may be constrained, particularly in big and complicated networks, by their inability to precisely identify and categorize defects. 2. Circuit Breakers: Circuit breakers separate problematic areas of the network when used in tandem with relays. Though they don't offer comprehensive diagnostic information regarding the kind or location of errors, they are crucial for system safety.

Although fundamentally, these conventional methods frequently suffer from imprecision and delay, especially in large-scale, dynamic systems like Nigeria's 330kV network. In Nigeria's transmission network, a number of elements make fault detection and management more difficult. A few of these factors are: 1. Aging Infrastructure: Due to its age, a large portion of the transmission infrastructure is more prone to failures and has lower fault detection efficiency. 2. Environmental Conditions: Nigeria's varied and occasionally severe weather can affect the dependability of transmission lines, which raises the likelihood of errors. 3. Maintenance Limitations: The diagnosis and correction of problems may be delayed due to a lack of infrastructure and resources for routine maintenance, which may impact the overall reliability of the system.

Because of its capacity to handle complex data and identify patterns, artificial neural networks, or ANNs, have become an effective tool in a variety of sectors, including power systems. Inspired by the neural networks seen in the human brain, artificial neural networks (ANNs) are able to learn from data, adjust to changes, and generate predictions.

ANNs in Fault Detection offer a number of benefits, such as: **1. Improved Pattern Recognition:** ANNs can find minute patterns in system data and electrical signals that conventional techniques would overlook, which improves fault detection accuracy. **2. Adaptability and Learning:** ANNs may adjust to changing fault circumstances and system modifications as they get more experience and learn from fresh data. **3. Real-Time Processing:** Faster defect identification and reaction are made possible by ANNs' capacity to evaluate data in real time. This is essential for reducing downtime and averting significant harm.

In order to meet the demand for more sophisticated, precise, and effective fault detection systems, this study attempts to assess how well artificial neural networks (ANNs) detect problems on Nigeria's 330kV transmission lines. The background of this study underlines the crucial need for enhanced fault detection techniques within Nigeria’s 330kV transmission network. This project aims to improve the nation's power transmission system's overall performance, efficiency, and dependability by utilizing artificial neural networks, hence promoting a more resilient and stable electrical infrastructure. To provide a steady and continuous supply of electricity, electrical power systems must be stable and reliable. The 330kV transmission network in Nigeria is essential for connecting generation sources to distribution networks and, eventually, to end users of high voltage power. Because of the vital nature of this infrastructure, it is crucial to identify and handle defects on these transmission lines in order to avoid power outages, save operating expenses, and preserve system integrity.

According to (Prasad et. al 2023), In this piece of work the detailed ANN based fault detection and location, simulation is done by using PSCAD/EMTDC in which modeling of DC micro grid including wind turbine, battery energy storage system, load and AC grid is done. In the model, DC currents signals are implemented as input data. The simulation results show that any type of DC fault can be accurately and fast detected. Samantaray SR has presented the new systematic fuzzy rule based approach for fault classification in transmission line. To identify the accurate phases involved in the fault process the classification of fault is important requirement of the distance relaying. For the initial classification the Decision Tree (DT) is used which is actually a knowledge representation method. (Prasad et. al 2023).

This work has presented the fault detection, fault classification and fault location of different faults such as LG, LLG, a nd LLLG which can possibly occur on double circuit overhead transmission lines. Mahanty et. al. has presented the use of radial basis function (RBF) neural network for the purpose of classification and location of faults in transmission lines. Instantaneous current/voltage samples are considered as an input to the artificial neural network. (Prasad et. al 2023).

AIM OF THE RESEARCH

To detect faults on Nigeria 330kv transmission line using Artificial Neural Network-Based Fault Detection

OBJECTIVES OF THE RESEARCH

- To promptly and precisely detect errors in order to reduce downtime and avoid harm.
- To precisely categorize the kind of fault (such as double line-to-ground, line-to-line, or line-to-ground).
- To determine the precise location of the fault along the transmission line
- To reduce the number of false negatives (missed defects) and false positives (false alarms).
- To make defect detection and reaction possible in real time.
- To make that the system performs well in a range of operational and environmental settings.
- To As an enhancement and supplement to conventional protection plans.
- To use fault analysis to optimize operating plans and maintenance schedules.
- To continually acquire fresh insights from data and gradually enhance the defect detection system.
- To lower the total cost of managing and detecting faults.

MATERIALS AND METHODS

This chapter presents the methodology that will be used to carry out the goals and objectives of this research project. The methodological process for this study is depicted in a flowchart diagram in Figure 1. There won't be any more operations at the decision box if the relay set impedance Zp is larger than or equal to the fault impedance on the line Zf, indicating no fault online. If the impedance Zp is less than the fault impedance Zf, a defect is identified.

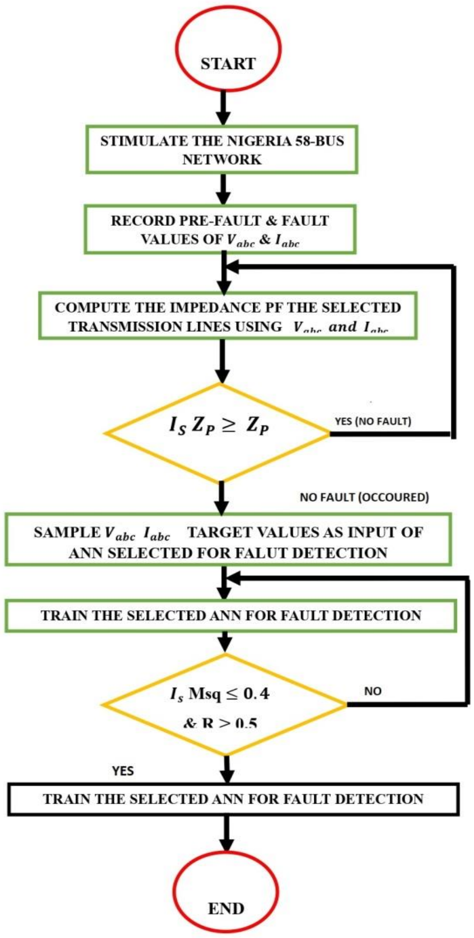

Figure 1: Flow chart of the Research Methodology

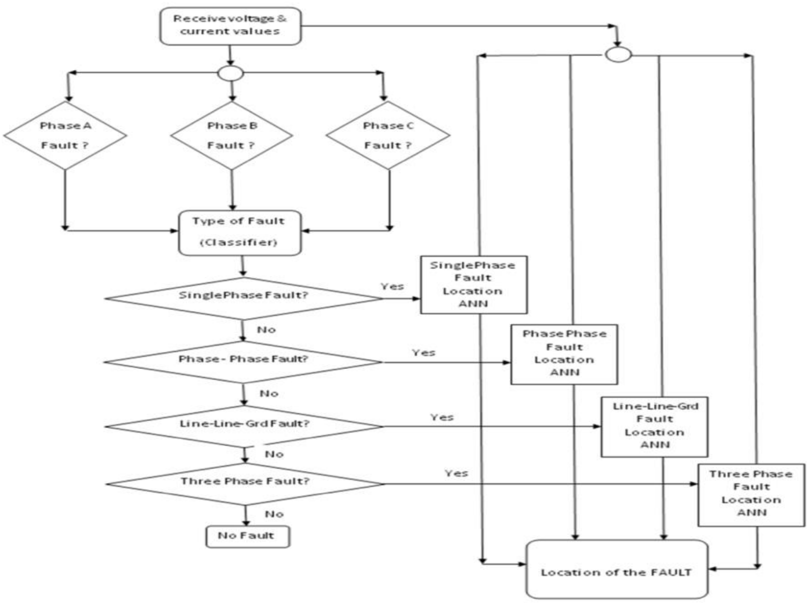

Figure 2 A flow chart showing the outline of the ANN

A. Introduction of Neural Network

An artificial neural network (ANN) is a kind of pattern for processing information that utilizes biological knowledge of the nervous system, such as how the entire nervous system of the body works (the central nervous system, which is made up of the brain and spinal cord, and the peripheral nervous system, which is made up of the nerves that connect and transmit information throughout the entire body).

The many densely interconnected processing units, or nerves, that make up a neural network cooperate to solve a given problem. Neural networks are specifically designed for specific use cases, such as data classification and learning-based pattern recognition. Supervised learning, a popular engineering topic, involves estimating a function using input-output data.

Neural network O-Mapping function of neural network X-Input Y-Out vector is represented in the following equation: Y=O(X)(1).

A massively parallel distributed processor, the neural network stores and makes use of knowledge. In the following three forms, it is similar to the human brain: Through learning, the network gathers the knowledge that is stored. Similar to how the brain picks up knowledge through learning.

Synaptic weights, often referred to as interneuritic correction strengths, are used to store learned information, much like synapses in actual neurons.

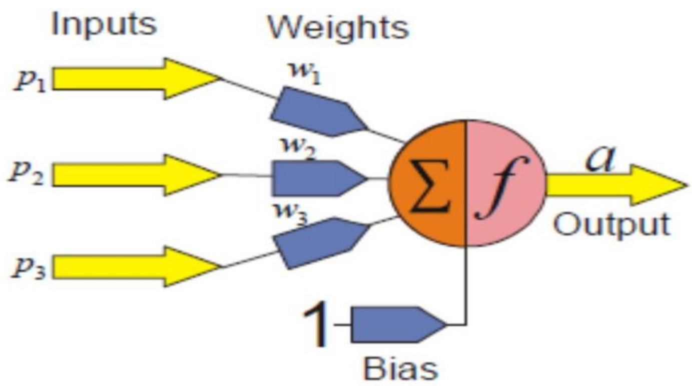

Figure 3 Overview of Artificial Neural Network

B. The Learning Process of Neural Network

A learning algorithm is responsible for this. This algorithm seeks to achieve a specified design goal by altering the synaptic weights of the network. A neural network can become generally capable after it has been trained. The neural network's ability to generate appropriate output for inputs not encountered during training is referred to as generalization. The basic characters of the neural network that is important in this work are as follows.

i. Input – Output mapping the network is presented with input samples and the weights are modified so as to minimize the difference between the network output and the desired output. Therefore, using supervised learning algorithm, one should known the target which is the output desire after that, the network is trained until the network reaches a state where there are no further significant changes in weights and is called the converging point.

ii. Non – linearity: A neuron represents a non-liner element. it means that the neural network made up of collection of neurons is also a non-liner system.

iii. Adaptively the neural network trained to perform particular function in a particular environment (input-output pairs) can be easily retrained to deal with minor changes in that environment.

The supervised learning has a most acceptable neural network called multi-layer perception (MLP).it has been in use 1986 and has the feed forward connection with free parameters (Adjustable weights).

Training the MLP network, means testing for the best weight so that the error obtained between network out and the desired output will be reduced. This process is iterated until the error can no longer be reduced (i.e. convergence point)

C. The Neuron

The figure 1 shows a biological neuron whose function is to represent a system or a communication channel unit. It transforms an input signal X into an output Ø (X). the function Ø (.). it can model a simple function like, the sigmold, radical basic, linear function e.t.c these function are showed in figure 6 and 7 to represent a system or a communication channel unit. it transforms an input signal X into an output Ø (X). the function Ø (.) it can model a simple function like, the sigmoid, radical basic, linear function etc.

The linear transfer function passes the neuron's input signal after multiplying it by some scaling constant (slope) and adding a neuron bias to its output port.

The log-sigmoid transfer function is used to produce an output that varies from 0 to +1 as the input varies from -∞ to +∞. The log–sigmoid is a differentiable function and that is why itb is suitable for networks that are trained with error back-propagation algorithm.

D. The Biological neuron to artificial neuron to artificial neuron model

The communication between neurons involves an electro-chemical process. The interface through which they interact with the surrounding neurons usually consists of several dendrites (input connection). These inputs connections are connected through the synapse to other neurons and one axon (output connection).

If the sum of the input signals surpasses the actual target size, the neurons will send an electrical signal through the axon to the brain.

The neural network. describe the population of psychically inter-connected neurons whose input signals and output (target)signals defines a certain circuit.

The neuron maintains a summation principal operation. The dendrite of the biological neuron is equivalent to the input points of the artificial neurons.

The nucleus body or cells of the biological neuron is equivalent to the summation units of the artificial neurons. the output of the artificial neuron represents the axon which is connected to other inputs of the biological neuron. The whole body of an artificial neuron represents the axon which is connected to other inputs of the biological neuron. The whole body of an artificial neuron represents a complete single body of a biological neuron.

E. Neural Network Architectures

Neurons of a network are connected in an arranged manner that makes them too strongly influences their learning patterns which is used to train their network.

The various existing neural network architectures can be divided into four main categories:

a. single-layer feed-forward networks:
b. multilayer feed-forward networks
c. recurrent networks
d. lattice networks

in a single – layer feed – forward network, each element of the input vector is connected to each neuron input through the weight matrix, W. most widely used architecture in solving neural network problems. Among the existing multilayer feed forward networks trained by the error back-propagation algorithm(BP). Multilayer perception networks have been applied successfully of different problems since the advent of the error back-propagation learning algorithm. This network consists of an input layers of computation nodes and an output layer of computation nodes.

The inputs signal propagates through the network in a forward direction, layer by layer.

The error back-propagation learning algorithm has two phases. The first is usually referred to as the presentation phase or forward pass, while the second is the back – propagation phase or back pass.

In the presentation phase, an input vector X is presented to the network resulting to an output Y at the output layer during this phase the weight are all fixed then in the back-propagation phase, the weights are adjusted based on the error between the actual and desired output.

F. Methodology for the ANN

The ANN employed here has three stages, the detection, classification and Isolation stages. At each stage, an ANN is selected and trained for their task. The inputs of each network are the three phase currents
(I = {Ia Ib Ic}T) and voltages (V = {VaVbVc}T) of the line generated using Power system block set (simpower system).
A comprehensive scheme for fault diagnosis on transmission line system should accomplish the following three tasks.

1) Fault Detection: This is to establish and find out if a fault has occurred in the transmission line or not.
2) Fault classification: Here, the types of faults are determined.
3) Fault location: This is to determine in which zone the faulty line is located.

i. Selecting the proper network Multilayer perception network is the most acceptable and the best function approximates; while the supervised learning is the preferred algorithm for training a network for function approximation. Also, back-propagation learning algorithm is used for generalization, but requires long training period and may possibly coverage to a minimal value.
ii. Training of the Selected ANN The training of Neural Networks forms one of the most important steps in the development of ANN fault detectors and fault locators, and therefore training data should be methodically and thoughtfully prepared. In some applications training data is not always available as part of a real system, and therefore the use of a training simulator can be used for generating relevant data for training ANN.
When developing training data, the data should be representative of all possible scenarios under which the ANN will be called upon to perform its detection and classification functions. Thus, training data can become huge sets of data. The Back-Propagation Algorithm (BPNN) has been used for training. Figure 11 gives an overview of the Training process.
The ANN is an interconnection of neurons, where each layer of neurons form inputs to successive layers. Each layer is adjusted by weights and enhance signal transmission strength. The output that was produced by BPNN is a target output and the output produced by the conventional method is an actual output.
The error makes us to understand the difference between the desired outputs and the actual process outputs. For us to calculate the Least Mean Square Error we used the error. When null error is obtained the BPNN will operates by propagating errors backwards from the output layer.

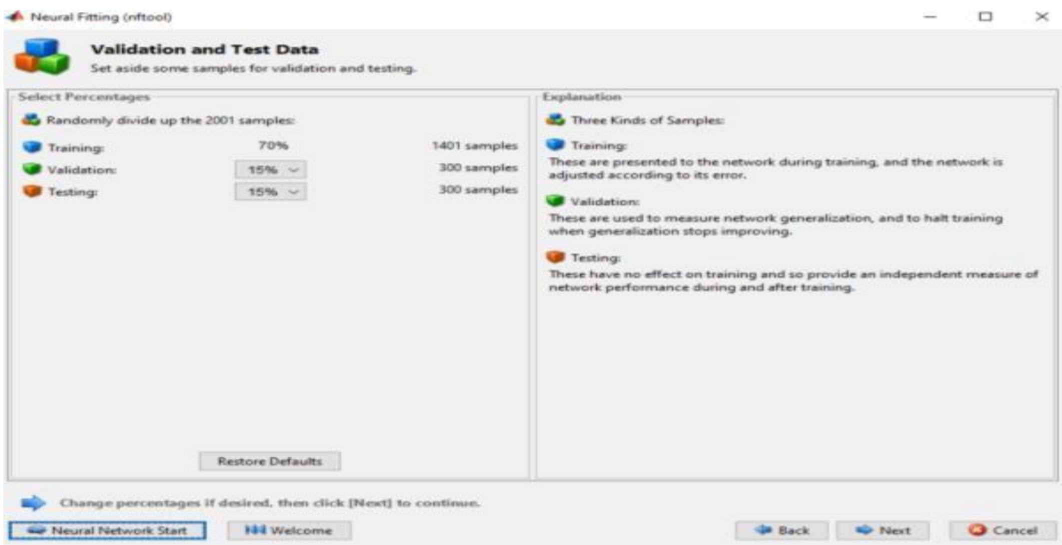

Figure 4 Selection and Samplingof Input Data into ANN

The Validation and Test Data is a training process that show the detail number of samples of input (Vabc_Iabc) data extracted for training, validation and testing of the selected ANN network. It shows that a total number of 1401 (70% of 2001), 300 (15% of 2001) samples each were used for training, validation and testing respectively.

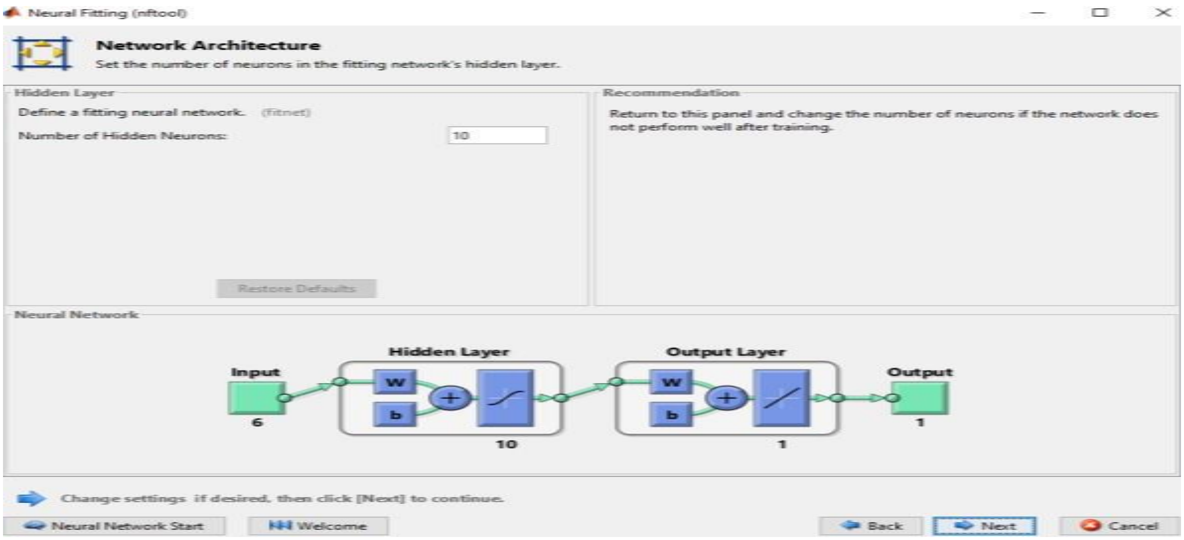

Figure 5 ANN Training Process

Figure 5 is the training network window which uses Levenberg-Marquardt back propagation training algorithm for training of the selected network and samples. A retraining process is possible when Regression and Mean Square Error values are not achieved. The retraining and change in number of neurons will continue until a convergence (Regression R $\leq$ 1 $\geq$ 0.5 and Mean Square $\leq$ 0.4) is reached.

The ANN Fault Detector experiences training which has many reasons of matching to different kinds of data, of which electrical faults forms the basis of this study. The validation of the trained ANN is performed via simulation, where the accuracy of the results and its performance is verified. Therefore, validation and testing of ANN output to input data is most important.

As can be seen from Figure 3.9, our proposed solution is to use actual data (simulated) for training of the ANN. In addition, we apply a learning methodology to learn new faults as the system performs in real time. Simulation would show the feasibility of this research and its application to industry.

To create an ANN, the inputs and outputs of the neural network the pattern recognition must be explained, and correlated to train the ANN. The inputs to the network give a picture of the condition and transient characteristics of the faults to be detected, and this should carefully take into a consideration.

The neural detector is designed to indicate the presence of a transmission line fault presence, or the fault absence. The appearance of such a fault is given by identifying directly the power system state starting from the instantaneous voltages and currents. Consequently, before that the voltages and the current signals enter to the neural network, a scaling technique (or signal normalization is performed) has a great importance in order to reduce the execution computing time. For this purpose, we adopted a scaling technique expressed by the division of the magnitudes of the fundamental voltages and currents. ANN can be considered as an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new previously unseen data. This is via training, and it assumes that learning takes place.

G. Modeling of the Nigerian 58– Bus Network

The Nigerian 58 – Bus Power System Network is built using the following parameters on table 3.1 and 3.2 Also, the 58–Bus Network is modeled using Matlab/Simulink tool for the implementation of the ANN selected structure for detection of faults on the Power System Network.

Table 1 Classification and representation of transmission lines

S/NO	TYPE OF LINE	LINE LENGTH (Km)	MODEL OF REPRESENTATION	REMARKS
1	Short Line	Up to 80 (50miles)	Series Impedance ($R + jX_L$)	Neglects Shunt X_C
2	Medium Line	80 to 240 (50 to 150 miles)	Normal π or T network	Lumped Parameters
3	Long Line	Above 240 (Above 150 miles)	Equivalent π or T network	Distributed Parameters

Table 2 Conductor materials and conductivity value

S/NO	MATERIALS	PARAMETER	VALUE
1	Aluminum hard drawn 61% conductivity	β_{Ro}	228
2	Copper annealed 100% conductivity	β_{Ro}	234.5
3	Copper hard drawn 97.3% conductivity	β_{Ro}	241.5

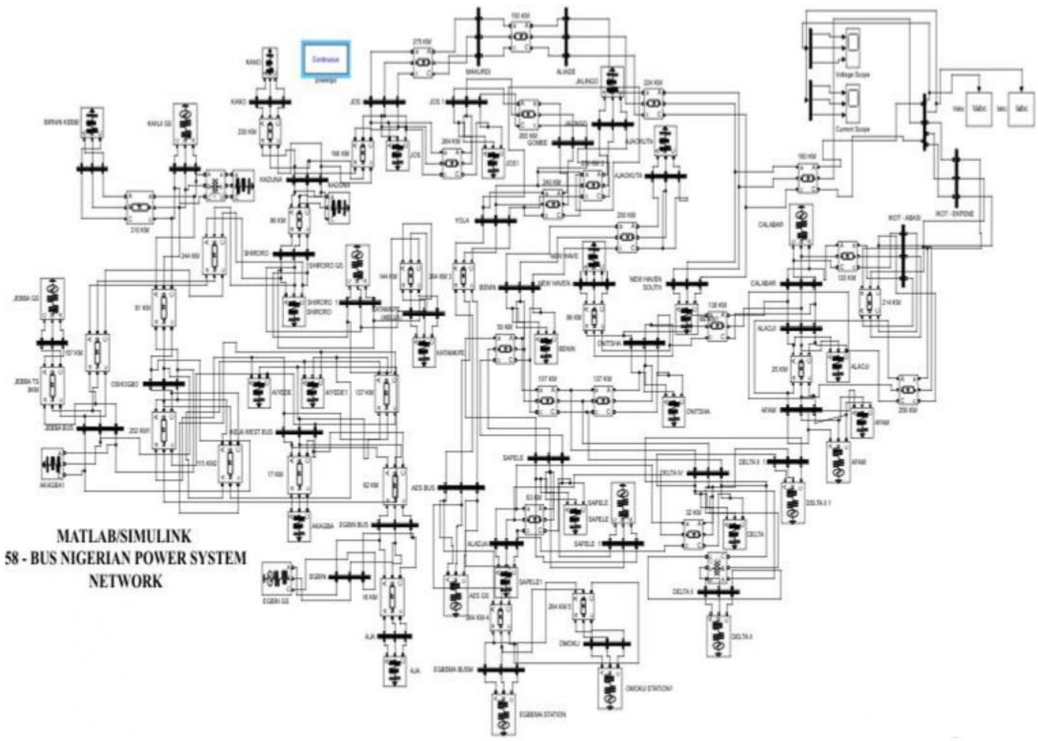

Figure 6 Nigeria58-BusPowerSystemNetwork

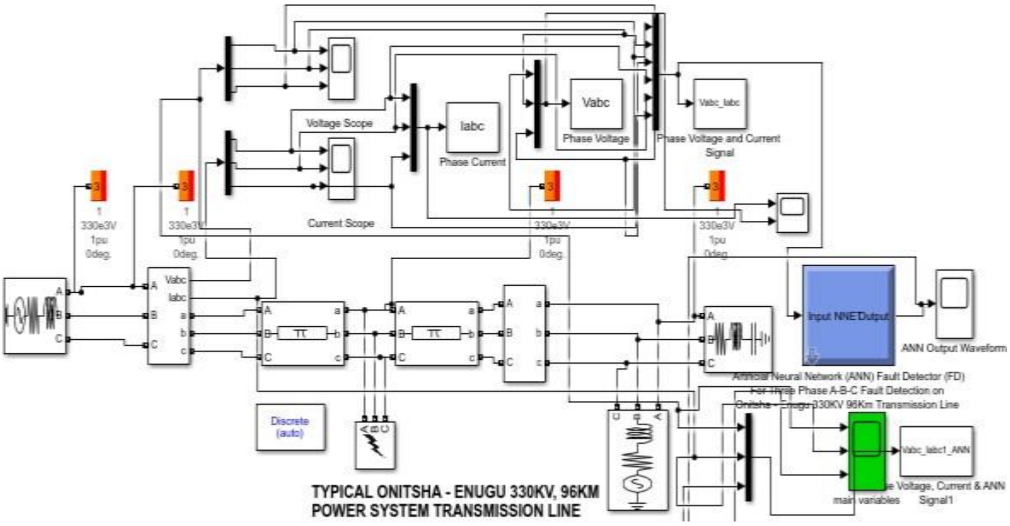

Figure 7 A Matlab/Simulink Modeled of Onitsha –Enugu of Nigeria 58–Bus Power System Network

The network comprises of –Generating Stations, ---Transmission Lines, ---Buses and---Loads

H. Transmission Line Modelling

Considering our case study area, Onitsha–Enugu330KV transmission line which is 96 Km distance. It corresponds to the line length less than 100km and belongs to short line category. The shunt admittance or shunt reactance (jωcl) of the transmission line is very small enough to be negligible resulting to the simple equivalent circuit of figure 4.

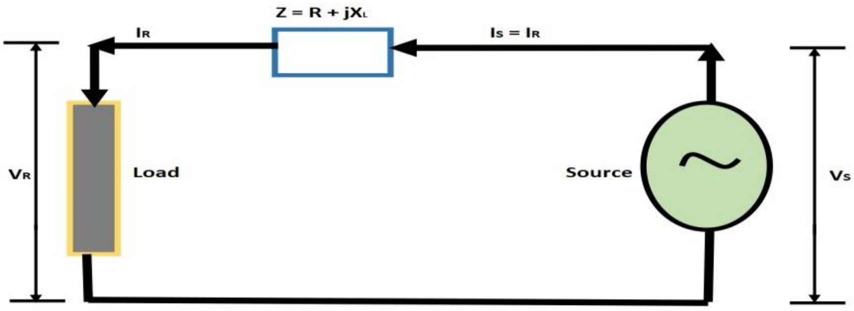

Figure 8 Equivalent circuit of short transmission line

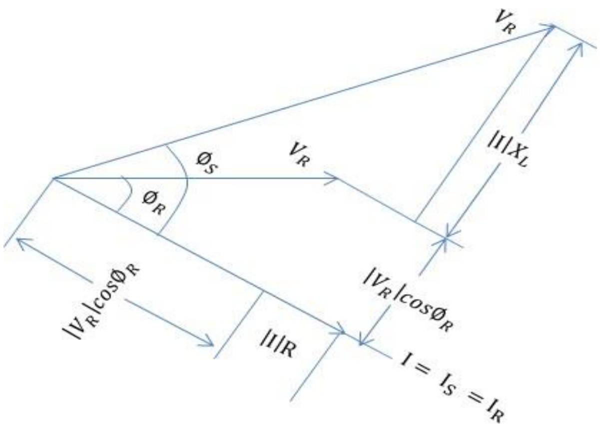

Figure 9 Phasor diagram of distance 96 Km Onitsha-Enugu transmission line

RESULT AND DISCUSSION

A. ANN Application of for Fault Detection on the Nigeria 330KV Transmission Line

Regardless of the length of the transmission line (short, medium, or long), the significance of fault detection lies in its ability to identify, track, and safeguard the lines in the event of a failure. The ANN approach is centred on pinpointing the defect's location on the transmission line, kind of fault, and time of occurrence. Numerous fault kinds, locations, fault resistances, and inception angles are tested for the ANN detector and classifier. Artificial Neural Networks (ANN) for real-time transmission line fault detection and classification that can be applied to digital protection in production systems.

In order to maintain system stability in today's highly interconnected power systems, early fault detection and fast isolation are necessary. Faults on transmission lines must be detected, classified, and located quickly. This approach is based on the action of each phase current and voltage. The outputs of the ANN indicate the fault presence and it type. All test results show that the fault suggested detector and classifier can be used to support a new system generation of the protection relay:

Neural Networks (ANNs) employ currents as its inputs for a variety of reasons. Due to the constant presence of Current Transformers (CTs) at each line for protection and monitoring, current signals measured at one end of the line have only been utilized as the inputs to ANN algorithms. Sometimes, for financial reasons, voltage transformers (VTs) may not be employed.

The only current signals that can be utilized for fault detection and classification are those that are measured at one end of the transmission lines. Since the neural network uses voltages and currents as inputs, its output will be quick and produce high-quality results. To determine the reactive power of the load, the ANN technique makes use of these voltages and currents.

This Chapter presents an overview of the use of ANN to fault detection for transmission line issues. As previously said in the chapters, it is critical to be able to recognize and find transmission line faults since they can result in equipment damage, blackouts, and the closure of power system networks. In the event that transmission line defects go unnoticed, the power system's whole network of networks will experience a significant collapse. Transmission line modelling is necessary to guarantee that faults can be promptly identified and that ANNs can provide reliable readings. Three phase transmission lines are simulated using Simulink.

i. Simulink Model for Nigerian 330KV Transmission Line Fault Detection Using the Nigerian 330kV Enugu-Onista, 50 HZ, 96 km transmission line as a case study, the three-phase power system network model is simulated in MATLAB/Simulink software. Figure 3 illustrates its components, which include voltage and current measurements, circuit breakers, transmission lines, and loads. Power provision to the load is the transmission lines' primary function. The generator produces the power, which is then sent to the load via the transmission line network.

A circuit breaker is a device that makes or breaks the electrical connection of a system and it interrupts the flow of current in an electrical circuit. The load is the feeder of the consumers, whereby the consumers fed from it and ANN can be able to detect some faults like overload current. The Load may be designed as radial or ring feeders on the power system; the ring feeder has a back-up supply while the radial feeder is a straight-line supply to the consumers.

Earlier systems use a conventional method on the transmission lines to detect the fault which takes timeto detect the fault and gives inaccurate results. Conventional algorithms are based on upon Kirchhoff Voltage and Current Laws on a well- defined model for transmission line protection.

Conventional distance relays consider power swing of voltage and current as a fault and tripping mechanism. Such faulty components would lead to severe consequences and contributed to power system instability. The application of Artificial Neural Networks to transmission line faults gives accurate results. Transmission Line parameters are shown in Table 1

As shown in Figure 3, the three-phase transmission line consists of two three phase sources simulating a synchronized power system. The transmission line includes PI transmission line component, with points for the measurement of voltage and current. In addition, three phase loads are distributed along the length of the transmission line. A three-phase fault simulates transmission line phase to ground, phase to phase and three phase faults.

Table 3 Transmission Line Parameters

S/N	LINE PARAMETERS	VALUES
1	Length (Km)	96
2	Voltage (kV)	330
3	Positive Sequence Resistance (Ohm/Km)	0.0114
4	Zero Sequence Resistance (Ohm/Km)	0.2467
5	Positive Sequence Inductance (Ohm/Km)	5.684e-4
6	Zero Sequence Inductance (Ohm/Km)	3.0890e-3
7	Positive Sequence Capacitance (Ohm/Km)	1.3426e-8
8	Zero Sequence Capacitance (Ohm/Km)	8.5885e-9

B. ANN PRE-PROCESSING

The accuracy of the ANN performance can be affected by noise and spurious harmonics that are commonly superimposed on measurements of voltage and current. Analogue signal filtering is used in actual systems to minimize undesired signals and eliminate these harmonics. Utilizing per unit values streamlines the processing of the simulation data and handles all phase calculations.

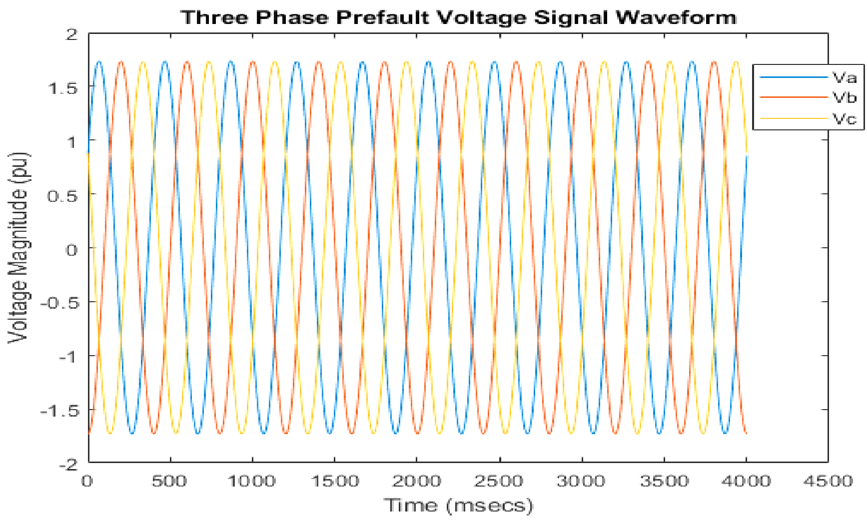

Figure 10 Three Phase Pre-fault Voltage signal Waveform

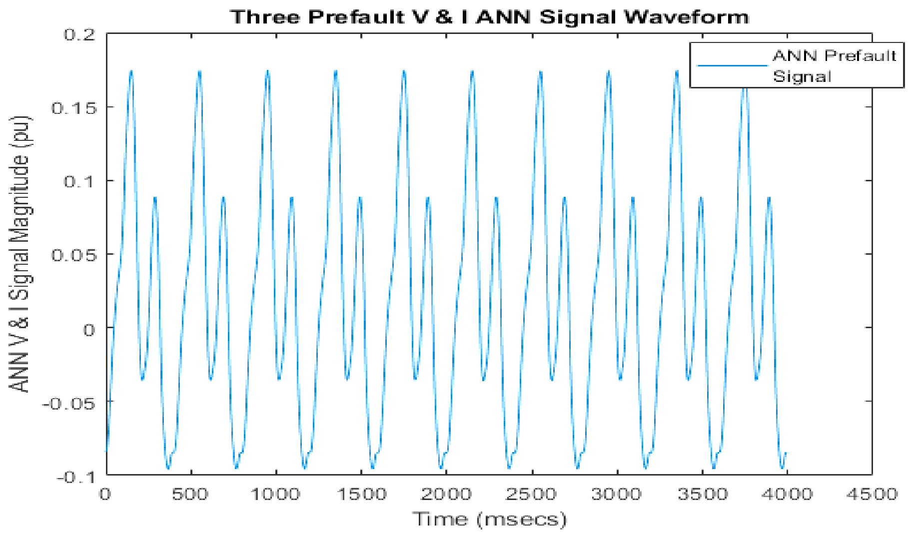

Figure 11 Three Phase Pre-Fault Current Signal Waveform

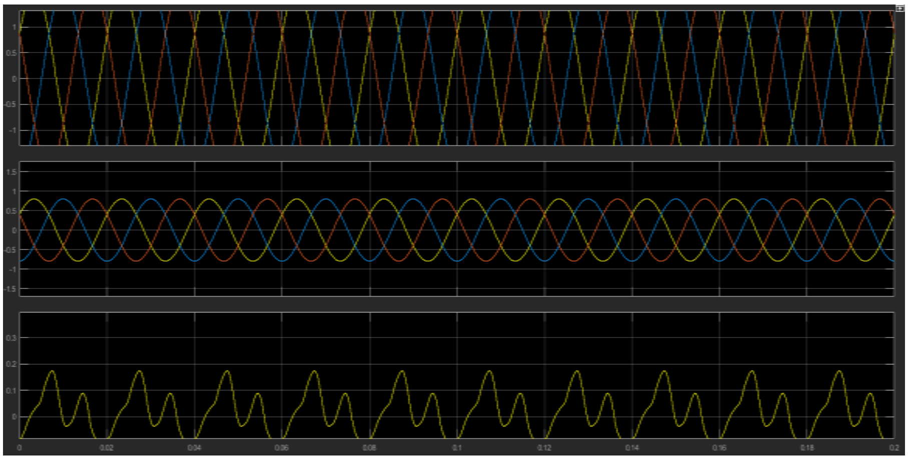

Figure 12 ANN Response to Pre-Fault Voltage & Current Signals

The Onitsha – Enugu 330kV Power transmission line's ANN response plot of pre-fault voltage, current, and their ANN equivalent signals against simulation time before to fault incidence is shown in Figure 13. It demonstrates that the signals' relative magnitudes for the A–B fault voltage, current, and ANN waveforms are 0.2, 1.5, and 0.4 pu.

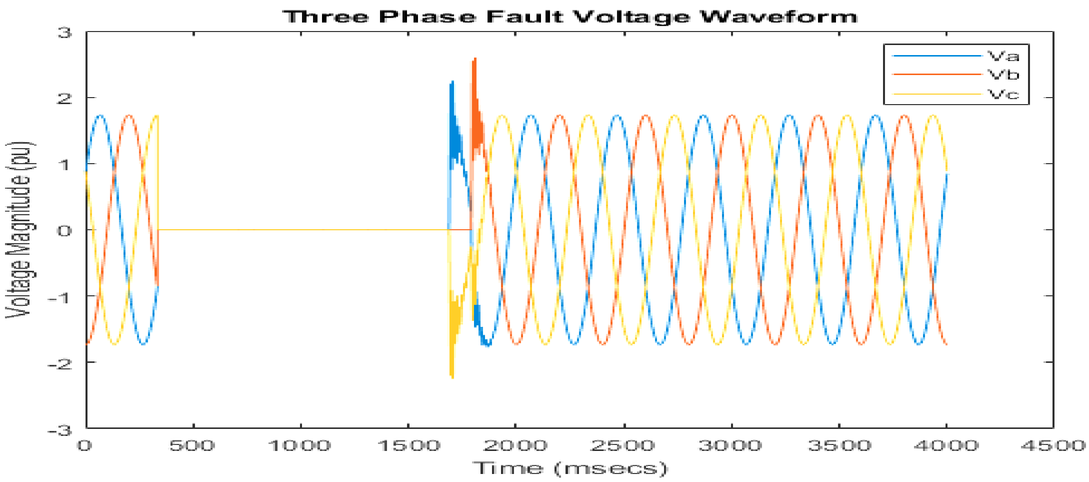

Figure 14 Three Phase Fault Current Waveform

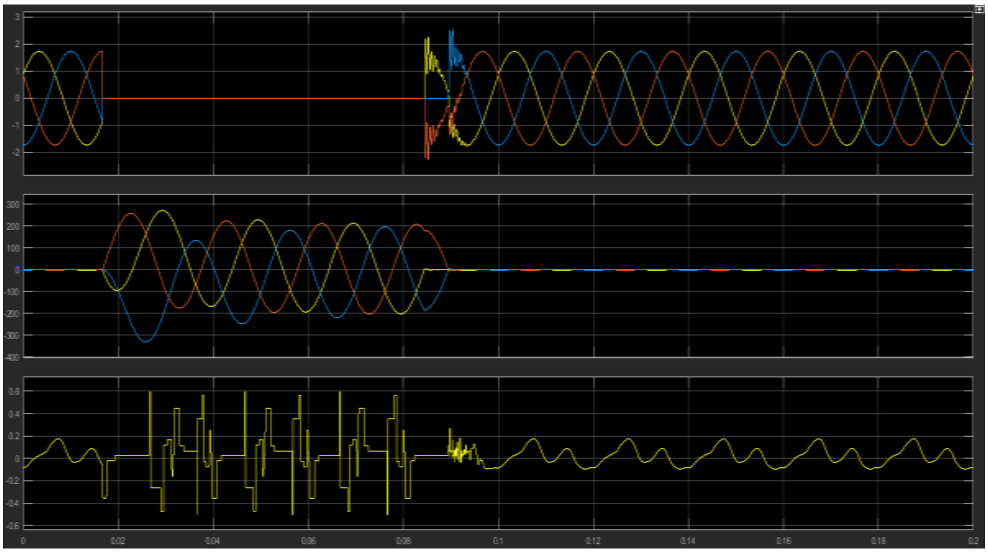

Figure 15 ANN response to Pre-fault V&I Signals

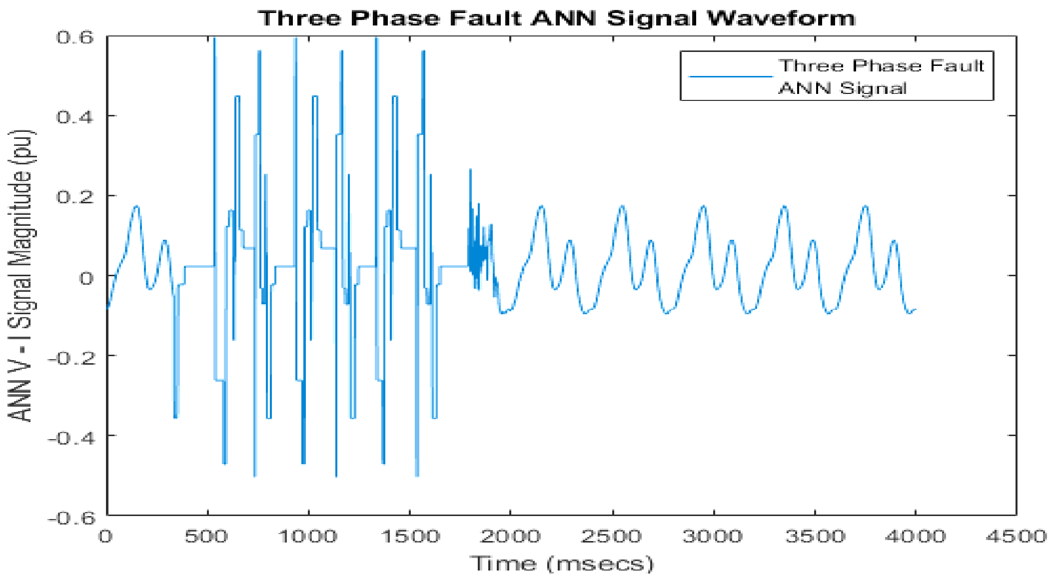

Figure 16 ANN response to ABC fault

Figure 16 is the ANN response plot of A – B - C fault voltage, current signals and their ANN equivalent signals measured versus simulation time on the 330kV power transmission line between Onitsha and Enugu during a fault. It demonstrates that, for the A, B, and C fault voltage, current, and ANN waveforms, respectively, the signal magnitudes are 0.35, 2.0, and 0.2pu. This indicates that a failure on the transmission line is the cause of the increase in the ANN signal magnitude for the A-B-C fault and the drop in voltage magnitude relative to the current. From Figures 16 to 18, it is evident that the ANN accurately detects the problem, as evidenced by increases in the ANN fault detector's signal magnitude when different faults are simulated. A change in the training set could also boost the output. A Three Phase System Results with a Fault.

On the transmission lines, modelling studies were conducted for various fault resistances. Three phase fault type line-line-line (A-B-C) and pre-fault are taken into consideration. The pre-fault voltage and current waveform of the 330kV Onitsha – Enugu transmission line is depicted in Figures 12 and 13. In contrast, the ANN's response to the voltage and current pre-failure signals is seen in figures 14 and 15. The three-phase fault voltage and current waveform of the 330kV Onitsha-Enugu transmission line during the fault is depicted in Figures 16 and 17. However, the ANN's reaction to the voltage and current three-phase fault signals is seen in figures 18 and 19.

Table 4 Three Phase Pre-fault and Fault Data

S/N	V_a(pu)	V_b(pu)	V_c(pu)	I_a(pu)	I_b(pu)	I_c(pu)	ANN Response (pu)	Fault Type
1	1.75	1.75	1.75	0.80	0.80	0.80	0.17	Pre-fault
2	0.00	0.00	0.00	280	270	200	0.60	A-B-C

Figures 16, 17, 18, 19, and Table 4 show that during the fault, there is a voltage drop from 1.75(pu) to 0.00 and an increase in currents from 0.8 to above 200(pu) in each phase. The ANN answers also show when a failure occurs on the line. This is OK since it complies with electrical standard circuit analysis results, which state that when a power system malfunction arises, the voltage magnitude will drop and the current would rise.

C. VALIDATION OF FAULT DETECTION USING MATLAB/SIMULINK TOOL

Since the purpose of the pre-fault condition section is to examine the pre-fault condition of the line, the entire 96 km of line length is taken into account. The results demonstrate that the three-phase voltage magnitudes per unit are greater than the magnitude of the corresponding current. Electrical circuit theory states that when the line is in the pre-fault condition, it is usual for the line voltage magnitude to be greater than the current magnitude. However, the line is 96 kilometres when there is a three-phase fault. In order to locate the fault distance on each of the ten zones and determine the three-phase fault voltage and current per unit magnitudes, simulation was run on the ten zonal lines. The three-phase voltage and current parameters of each simulated lines were used as inputs of the selected ANN for fault detection on the line. The results show the selected ANN network architecture for fault detection, simulation window process, training performance of the data and the regression analysis for acceptable fault detection

Table 4 displays the 2001 data samples for the six (6) inputs of the ANN design depicted in Figure 20, which are the three phase fault Voltages (Va, Vb, Vc) and Currents (Ia, Ib, Ic). In addition, there are one output layer and ten concealed layers. Its training has given it the goal of identifying three phase faults on Phases A, B, and C. The output serves as a common fault alarm since it is programmed to respond to any of the fault situations that are shown (or Trip)

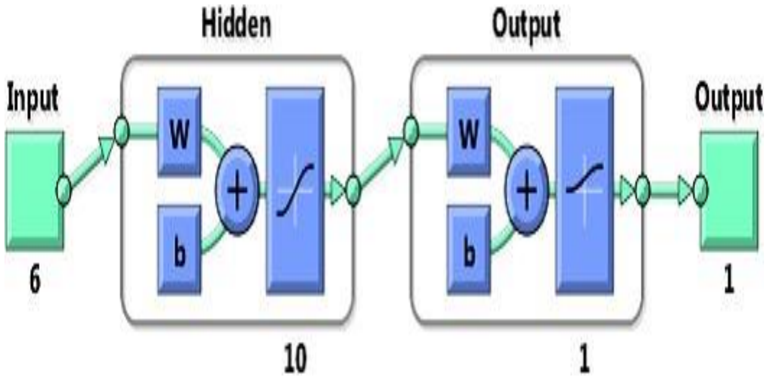

Figure 17 The ANN Selected Architecture orStructure for fault detection

In general, all ten zones with varying line lengths were chosen to use the aforementioned figure 20, Figure 17 shows a more detailed representation of the planned ANN, its input, hidden and output layers. In order to detect problems in the transmission line, the ANN Matlab/Simulink Fault Simulator automatically selects it during fault simulation. Depending on how difficult the problem is that needs to be solved, the number of hidden layers and neurones in each layer of the artificial neural network (ANN) should be present in the inputs and outputs of the network. The neural network with three layers, six neurones in the input layer, and one neurone in the output layer is utilised for fault detection, as shown in figure 20.

Based on the Bias Weights, the log-sigmoid function assesses the output and suggests the optimal outcomes for the output layer and hidden layer. The ANN must be trained in order to obtain the proper magnitude and correlations for all of the inputs and outputs of the neural network. The size and complexity of the challenge determine which inputs the neural network will use. An artificial neural network (ANN) becomes more sophisticated the more inputs and outputs it has. There are a lot of hidden layers as a result. Effective decision making is made possible by the size of the hidden layers. Three phase voltages and currents at 50 Hz serve as the basis for the inputs. The transmission line's two ends were used to measure the three phase voltages and currents. The ANN output would validate a defect for any of the three phases, and the fault type was categorized along the transmission line. With a 96-kilometer line, the following outcomes were attained.

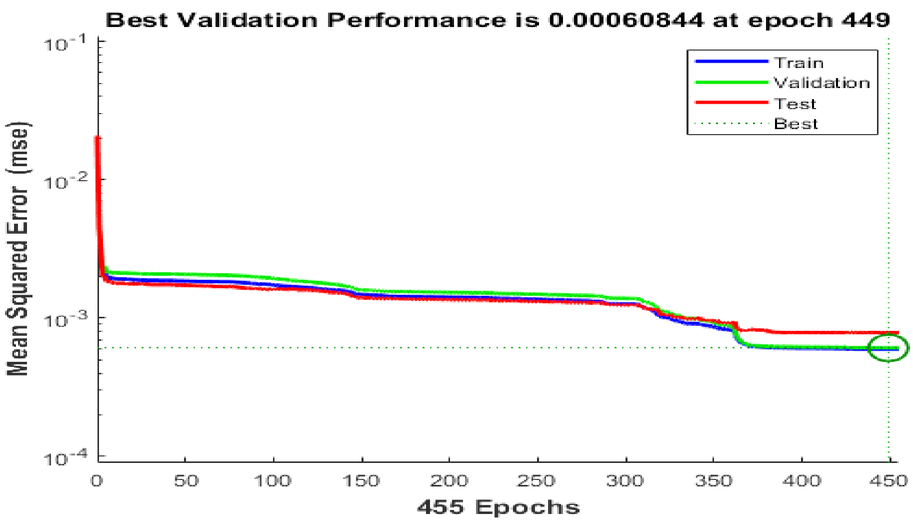

Figure 18 ANN Simulation Window Processes

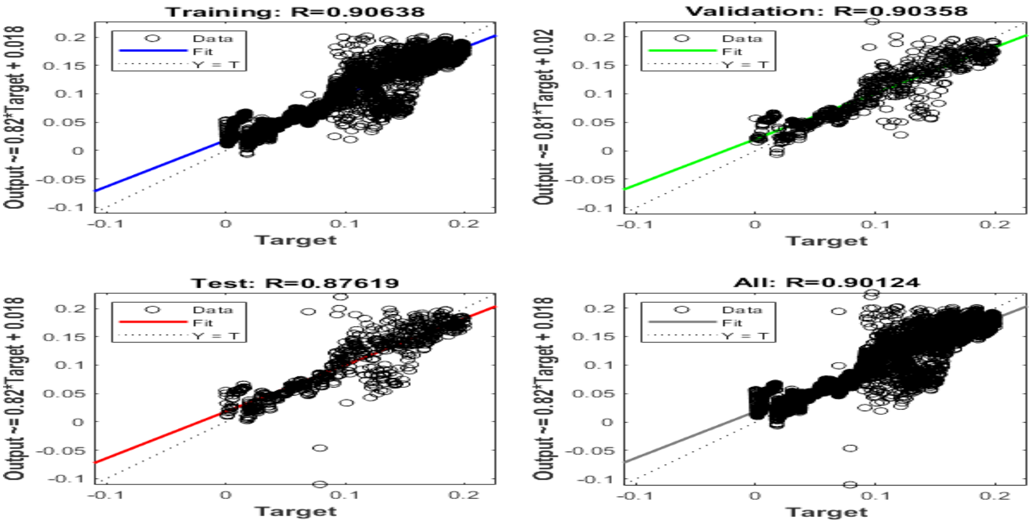

Figure 19 Regression analysis of the ANN for theFault Detection for 10Km

Figure 20: Regression analysis of the ANN for theFault Detection for 10Km

Figure 20 is the performance graph that shows the performance result of the training process. It demonstrates that the training provides the best training, validation, and test outcomes for defect detection at MSE = 6.0844e-5. The regression curve of 0.90124 between the output and the targets for the three-phase fault simulation and detection using ANN is displayed in Figure 23. The training procedure and outcomes can be acceptable if the Regression R is 1s.0 or less than 0.45, in accordance with the ANN performance criterion. Anything less than that, however, is not considered a satisfactory outcome, and the data needs to be retrained. The correlation is strong and shows that R is close to 1 at 449 epochs, as can be observed.

CONCLUSION AND RECOMMENDATION

CONCLUSION

ANNs have shown to be a very useful instrument for 330kV transmission line fault detection. Their capacity to represent intricate, non-linear connections makes them ideal for accurately diagnosing and categorizing various fault kinds. When it came to fault identification, the ANN-based fault detection system showed excellent accuracy and dependability. In terms of fault classification accuracy as well as detection speed, this system performed better than conventional fault detection techniques, which is crucial for maintaining the stability and dependability of the electrical power grid.

The results could be tested because regression and mean square were used to compute the hypothesis' results. The hypothesis results were acknowledged. According to the findings, retraining and changing the number of neurons will continue until a convergence of (mean square 0.4 and regression R10.5) is attained. This would have a long-term positive impact on the fault detection ratio on Nigeria's 330kv transmission lines.

RECOMMENDATION

Promote further research and development to enhance the capabilities of fault detection and ANN algorithms. Working together with academic institutions and business leaders can spur innovation and guarantee that defect detection systems continue to be at the forefront of technology. To sustain and enhance an ANN's accuracy over time, train and validate it continuously using updated data. The system will be better able to adjust to modifications in the fault detecting characteristics and transmission network through routine upgrades and retraining.

Provide engineers' and technicians' familiarization with ANN-based fault detection systems through training sessions. Developing internal knowledge will improve these cutting-edge systems' efficient use and upkeep. Work with legislators and regulatory agencies to establish an atmosphere that encourages the use of cutting-edge defect detection systems. In the power industry, ANN-based solutions can be implemented and accepted more widely if standards and norms are established. The Nigerian power industry may improve the efficiency and dependability of its transmission network by implementing these suggestions, which would ultimately lead to a more resilient and stable electricity infrastructure.

Declaration by Authors

Acknowledgement: None
Source of Funding: None
Conflict of Interest: The authors declare no conflict of interest.

REFERENCES

1. Shafiullah MD. Fault diagnosis in two-terminal power transmission lines. Elsevier. 2022: 159-194.
2. Diamenu G. Statistical analysis of electric power distribution grid outages. European Journal of Engineering and Technology Research. 2021: 27-33.
3. Gupta S. K. (2019) Power System Engineering January 2020''. 4232/1, Ansari Road, Dariyaganj, Delhi-110002 ISBN: 978-81- 88114-91-7
4. Ogboh V. C, Ezechukwu O. A, Madueme T. C. (2019) Analysis of Fault Detection Algorithm for Power System Transmission Lines Using DFT And FFT''. Ire Journals Volume 3 Issue | ISSN: 2456-8880 Ire 1701668 Iconic Research and Engineering Journals 142.
5. Saritha M., Viji C., Aravind K., Joel O. B., Linu B., Juhina A., Priya S. (2021). Fault Detection and Location in Transmission Line using Pole Climbing Robort''. International Journal of Engineering Science & Research Technology. ISSN: 2277-9655. March, 2019.
6. Okwudili O. E., Ezechukwu O. A., Onuegbu J. (2019). Artificial Neural Network Method for Fault detection on Transmission Line''. International Journal of Engineering Inventions E-ISSN: 2278-7461, P-ISSN: 2319-6491 Volume 8, Issue 1 [January 2019] PP: 47-56 www.Ijeijournal.Com
7. 7. Ogboh, V. C., Nwangugu, E. C., &Anyalebechi, A. E. (2019). Fault Detection on Power System Transmission Line Using Artificial Neural Network (A Comparative Case Study of Onitsha–Awka–Enugu Transmission Line. American Journal of Engineering Research (AJER) 2019, 8(4), 32-57.
8. A.J. Mazon, I. Zamora, J. Gracia, K. Sagastabeitia, P. Eguia, F. Juradoand J. R. Saenz, "Fault Location Systemon Double Circuit Two-Terminal Transmission Lines Based on ANN'S", IEEE Power Tech Proceedings, Porto, Vol.3,10-13 Sep2021.

How to cite this article: Hammed Waheed Olalekan, Onyegbadue Ikenna Augustine, Guiawa Mathurine. Artificial neural network-based fault detection on Nigerian 330kv power transmission line. *International Journal of Research and Review*. 2024; 11(10): 518-535. DOI: *https://doi.org/10.52403/ijrr.20241047*

******