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Detection of Faults on Nigeria 330kv Power Transmission Lines Using Artificial Intelligence (AI)

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Abstract- The occurrence of faults on Power Transmission Lines is inevitable. Various methods have been applied by researchers to detect these faults. Among the methods used for detecting faults on the transmission lines, Artificial Neural Network (ANN) been one of the recent artificial intelligence methods for fault detection has been employed in this research for the detection of fault on 330kV Power Transmission Line. Simulations were performed using MATLAB/Simulink R2018a on ANN fault detector with the pre-fault and fault signals as inputs of the ANN fault detector in order to identify the various faults that occurred on the line. The results showed that, the best training performance for the detection of faults was achieved at Mean Square Error (MSE) of 1.6856e^{-5}. and at Regression approximately equal to zero (9.8958e^{-1}). The simulation result is satisfactory since it satisfied the standard training performance of any ANN fault diagnosis system.

Indexed Terms- Power System, Transmission Line, Matlab/Simulink, Three Phase, Faults.

I. INTRODUCTION

In the past several decades, there has been rapid growth in the power grid all over the world which eventually led to the installation of a large number of new transmission and distribution lines. Moreover, the deregulation of electric power has increased the need for reliable and uninterrupted electric power supply to the end users who are very sensitive to power outage. One of the biggest problems in electrical power system is the interruption or the discontinuity of power supply which is caused by occurrence of faults [1][2].

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 for 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, 2019).

These faults are inevitable and normally are an abnormal flow of current in a power system's component. They cannot be completely avoided since some of them occur due to natural reasons which are beyond human control. Hence, when the power system has a well-coordinated protection system, it detects any kind of abnormal flow of current in the power system, identifies the fault type, accurately locates the position of the fault in the power system network and isolate it. The isolation of the fault must be very fast to avoid damage of power equipment and power outage. Also, the faults must be cleared very fast so as to restore power to the isolated areas. The clearing of the faults is done using protective devices which sense the fault, respond immediately and disconnect the faulty section from the good ones [3][4]. To protect the power system transmission lines, faults must be detected and isolated accurately. The control center of a power system contains large member of alarms which receives signals from different protection schemes for different types of faults.

In electric power system faults are disturbances that interfere with the normal flow of current. Their causes can range from natural phenomena such as lighting strikes to short circuited equipment within a substation caused by local wildlife. Fault durations can also vary from long-lasting, such as a failed cross arm on a transmission pole that requires a prolonged outage to fix, or transient, such as a tree making contact to an energized conductor before falling to the ground. The one thing in common for all faults is that they disrupt transmission service and can potentially be harmful to surrounding people and equipment.

In order to minimize the impact of faults on transmission lines and customer service, it becomes increasingly important to quickly and accurately pinpoint the location of a fault for isolation and repair. The past 20 years has witnessed the rapid development in various fields concerning the detection, classification and location of faults in power systems. The advances in signal processing techniques, artificial intelligence and machine learning, global positioning system (GPS) and communications have enabled more and more researchers to carry out studies with high breadth and depth in that the limits of traditional fault protection techniques can be stretched.

The computational ability of computers has also increased rapidly. High-performance computing solutions such as server clusters are able to complete distributed computing tasks within very short period of time, thus allowing methods with higher computation complexity to be implemented.

When the normal current flowing on the Power Transmission Line is diverted from the intended path to another path, the diversion is caused by the presence of fault on the transmission line. This fault developed on the electric transmission line can be caused by the reduction in the insulation strength between the phase conductors and earthed screen surrounding the conductors.

The faults on electrical power system transmission lines are supposed to be first detected, classified correctly and should be cleared in the least time as fast as possible. The protection system used for a transmission line can also be used to initiate the other relays to protect the power system from outages. A good fault detection system provides an effective, reliable, fast and secure way of a relaying operation.

II. METHODOLOGY

This chapter presents the methodological procedure for the implementation of the aim and objectives of this research. Figure1.0 is a flowchart diagram that represents the methodological procedure for this research.

At the decision box, if the relay set impedance Z_p is greater than or equal to the fault impedance on the line Z_f, no fault on line, there will be no further operation, but, if the impedance Z_p is less than the fault impedance Z_f, fault is detected.

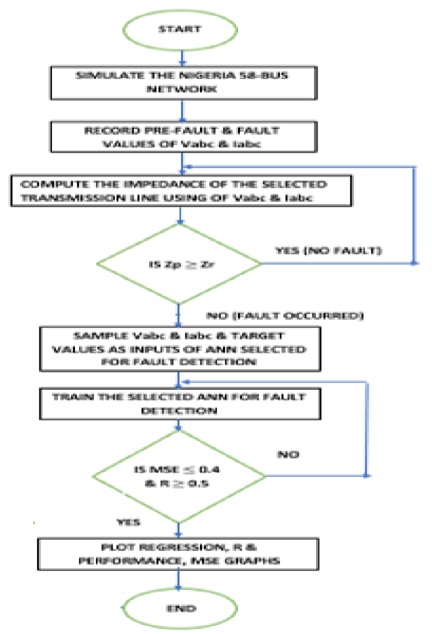

Figure1: Flowchart of the Research Methodology

A. Modeling of the Nigerian 58 – Bus Network

The Nigerian 58 – Bus Power System Network is built using the following parameters on table 1 and 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

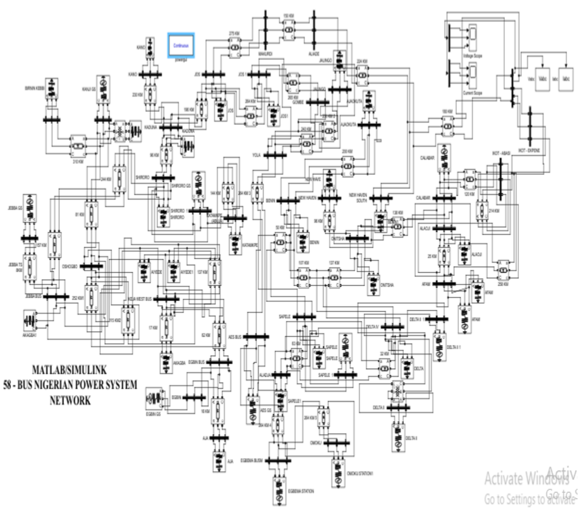

Figure 2: Nigeria 58-Bus Power System Network

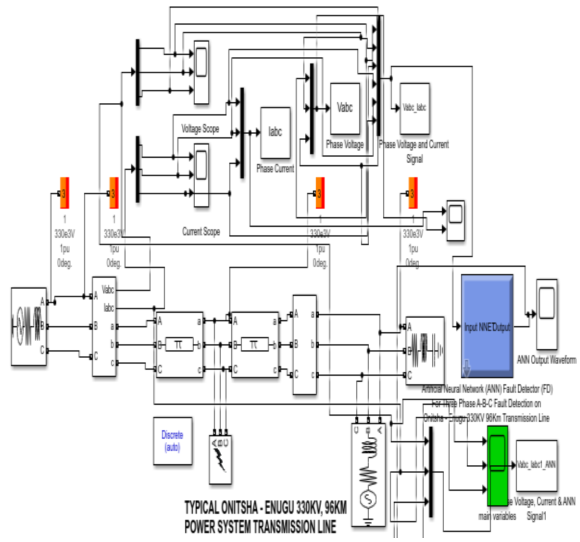

Figure 3: A Matlab/Simulink Modeled of Onitsha – Enugu of Nigeria 58 – Bus Power System Network

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

B. Transmission Line Modeling

Considering our case study area, Onitsha – Enugu 330KV transmission line which is 96Km 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 figure4.

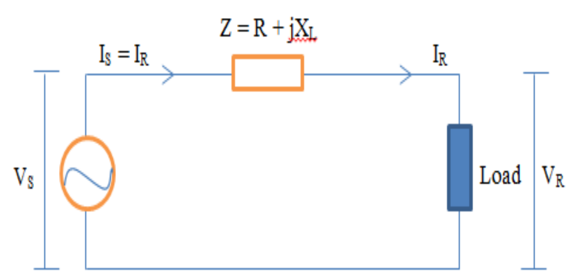

Figure 4. Equivalent circuit of short transmission line

The relationship between the sending and receiving – ends voltage and currents can be written as;

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

Thus,

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

$$|V_S| = [\,(|V_R|^2 + |I|^2(R + X_L)^2 + 2(|V_R||I|(R\cos\emptyset_R + X_L\sin\emptyset_R)]^{\frac{1}{2}} \quad (3)$$

$$|V_S| = |V_R|[1 + \frac{2|I|R\cos\emptyset_R}{|V_R|} + \frac{2|I|X_L\sin\emptyset_R}{|V_R|} + \frac{2|I|^2 X_L(R^2 + X_L{}^2)}{|V_R|^2}\quad]^{\frac{1}{2}} \quad (4)$$

$$\frac{2|I|^2 X_L(R^2 + X_L{}^2)}{|V_R|^2} \cong 0 \quad (5)$$

Then,

$$|V_S| = |V_R|[1 + \frac{2|I|R\cos\emptyset_R}{|V_R|} + \frac{2|I|X_L\sin\emptyset_R}{|V_R|}\quad]^{\frac{1}{2}} \quad (6)$$

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

$$|V_S| = |V_R|[1 + \frac{2|I|R\cos\emptyset_R}{|V_R|} + \frac{2|I|X_L\sin\emptyset_R}{|V_R|}\quad]^{\frac{1}{2}} \quad (7)$$

$$|V_S| = |V_R| + \quad |I|(R\cos\emptyset_R + X_L\sin\emptyset_R) \quad (8)$$

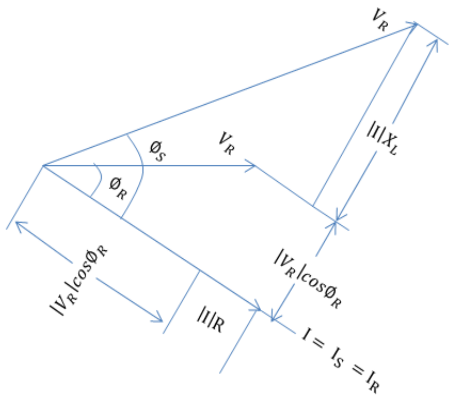

Figure 5: Phasor diagram of distance 96Km Onitsha –Enugu transmission line

C. Introduction of Neural Network

Artificial Neural Network (ANN) is an information processing Pattern which uses the biological nervous systems knowledge, such as the operations of complete nervous system in the body (the central nervous system, comprising the brain and the spinal cord and the peripheral nervous system, comprising the nerves that links and send information round the whole body) [2][5][6].

The neural network composed of a large number of highly inter connected processing elements (nerves) working in union to solve a specific problem.

The neural network is designed for a specific application such as pattern recognition or data classification through the learning process.

A common engineering problem is that of estimating of function using the input- output values and this is known as supervised learning.

In the equation (1) below, the neural network plays the role of mapping function Ø.

Y = Ø (X) (1)
Ø - Mapping function of neural network
X - Input
Y - Out vectors.

The neural network is a massively parallel distributed processor that store knowledge and make it available for use. It resembles the human brain in the following three forms:

The knowledge stored is acquired by the network through a learning process. Just as brain learns and acquire the knowledge through learning.

Inter nervous correction strengths, known as synaptic weights are used to store the knowledge acquired, just like synapse in the biological neuron in figure 3.17. The network is capable of generalization [2][5][6].

D. The Learning Process of Neural Network

This is done by a learning algorithm. The aim of this algorithm is to change the synaptic weights of the network to attain a desired design objective. Once the neural network is trained, it is capable of generalization. Generalization refers to the capability of the neural network to produce reasonable output for inputs not encountered during the training process.

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 know 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 a 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 supervise learning has a most acceptable neural network called multi-layer perceptron (MLP).
It has been in use since 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 output and the desired output will be reduced. This process is iterated until the error can no longer be reduced (i.e convergence point) [2][5][6].

E. 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 sigmoid, radial basic, linear function etc. These functions are shown in figure 6 and 7to 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, radial 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 function is defined as

$$Y = \frac{(1)}{(1+e-x)} \quad -\infty < x < \infty \qquad (9)$$

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 it is suitable for networks that are trained with error back-propagation algorithm.

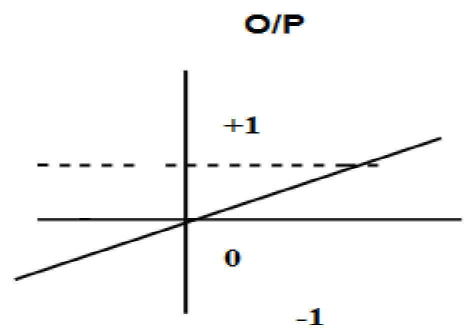

Figure 6: Liner Transfer Function

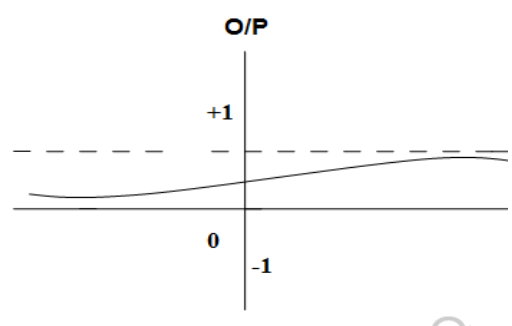

Figure 7: Log-Sigmoid Transfer Function

F. The Biological 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 connections). 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.

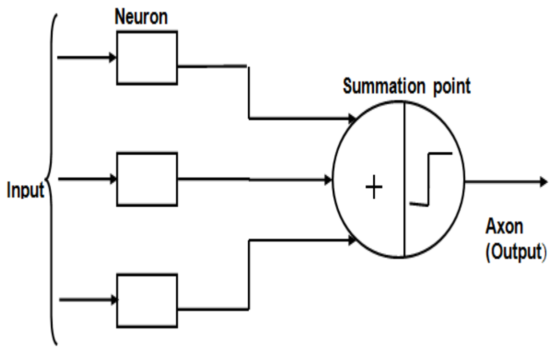

Figure 8: Simple Neuron Model

The neural network describes the population of psychically inter-connected neurons whose input signals and output (targets) 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 cell 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 a complete single body of a biological neuron.

G. Neural Network Architectures

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

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

1 Single – layer feed – forward networks
2 Multilayer feed – forward networks
3 Recurrent networks
4 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 is the multilayer perceptron network trained by the error back-propagation algorithm (BP).

H. Multilayer Perception Networks

Multilayer perceptron network has been applied successfully to different problems since the advent of the error back-propagation learning algorithm. This network consists of an input layer, one or more hidden 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 synaptic weights are all fixed. Then in the back-propagation phase, the weights are adjusted based on the error between the actual and desired output.

The details of this multilayer perceptron error back-propagation process are presented below:

I. Presentation Phase

Considering the above multilayer perceptron network analysis, the following symbols were used in this work.

NI: Number of neurons in the input layer

NH: Number of neurons in the hidden layer

NO: Number of neurons in the output layer

X: Input vector

h^H: Input for the hidden layer

h^O: Input for the output layer

y^H: Output of the hidden layer

y: Output of the network

Wji: matrix (NH X NI) of synaptic weight connecting the input and hidden layers.

W_{kj}: Matrix (NO X NH) of synaptic weight connecting the hidden layer and the output layer.

b: bias, or threshold vector.

O (.): The non-liner function performed by the neuron

I = {I: NI}: a neuron in the input layer

J = {I: NH}: a neuron in the hidden layer

K = {I: NO}: a neuron in the output layer.

Once an input vector is presented to the input layer, one can calculate the input to the hidden layer as follows:

$$h_j^H = b_j + \sum_{T=1}^{NI} W_{ji} X_1 \quad (9)$$

Each neuron of the hidden layer takes its input h_j^H and uses it as the argument function and produces an output given by

$$y_j^H = \emptyset\, h_j^H \quad (10)$$

Then, the inputs to the neurons of the outputs layer are calculated as

$$h_k^o = b_k + \sum_{j=1}^{NH} W_{kj} y_j^H \quad (11)$$

However, the network output is then given by;

$$y_k = \emptyset\,(h)_k^o \quad (12)$$

J. The Error Back-Propagation Learning Algorithm

An output error is defined as the difference between the network output and the desired output value that is for the Kth output neuron.

The output error of the Kth output neuron is given as

$$e_k = d_k - y_k \quad (13)$$

d_k = desired output value

y_k = Network output value

Using the output error, we can obtain the summed square errors as follows:

$$\epsilon = \frac{1}{2}\sum_{k=1}^{NO} e_k^2 \quad (14)$$

This error is to be minimized during the learning process. It is a function of all the variables of the network and using the chain rule, we can calculate the gradient of the error with respect to the weight matrix connecting the hidden layers to the output layer as given below;

$$\frac{\partial\epsilon}{\partial_{wkj}} = \left(\frac{\partial\epsilon}{\partial_{ek}}\right)\left(\frac{\partial_{ek}}{\partial_{yk}}\right)\left(\frac{\partial_{yk}}{\partial_{hko}}\right)\left(\frac{\partial_{hko}}{\partial_{wkj}}\right) \quad (15)$$

If we compute each term, we will obtain as follows:

$$\frac{\partial\epsilon}{\partial_{wkj}} = e_k \quad (16)$$

$$\frac{\partial_{ek}}{\partial_{yk}} - 1 \quad (17)$$

$$\frac{\partial_{yk}}{\partial_{hko}} = \emptyset_k\ hko \quad (18)$$

$$\frac{\partial_{hko}}{\partial_{wkj}} = y_j^H \quad (19)$$

But, if we combine these expressions above, we will obtain that;

$$\frac{\partial\epsilon}{\partial_{wkj}} = e_k \emptyset_k (hko) y_j^H \quad (20)$$

The change ▲wkj which is applied to the weight matrix that is connected to the hidden layer to the output layer is also given as

$$\Delta W_{kj} = -\eta \frac{\partial\epsilon}{\partial_{wkj}} = -\eta e_k \emptyset_k h_k^0 y_j^H \quad (21)$$

Where ŋ is a constant known as the step-size or learning rate. We can also rewrite the equation (21) as:

$$\Delta W_{kj} = -\eta \delta_k y_k^H \quad (22)$$

Where $\delta_k = e_k \emptyset_k(hko)$ is called the local gradient term. But to update the weights connecting the input layer to the hidden layer, we need to repeat the procedure above according to the following equation.

$$\frac{\partial\epsilon}{\partial_{wkj}} = \left(\frac{\partial\epsilon}{\partial_{ek}}\right)\left(\frac{\partial_{ek}}{\partial_{yk}}\right)\left(\frac{\partial_{yk}}{\partial_{hko}}\right)\left(\frac{\partial_{hko}}{\partial_{wkj}}\right)\left(\frac{\partial_{yj}^H}{\partial_{hj}^H}\right)\left(\frac{\partial_{hj}^H}{\partial_{wji}}\right) \quad (23)$$

After calculating each of the term above, the connection to the weight matrix is written as:

$$\Delta W_{ij} = -\eta \delta_j X_i \quad (24)$$

$$\delta_j = \emptyset_j\left(h_j^H\right) \sum_{k=1}^{NO} \delta_k W_{kj} \quad (25)$$

Therefore, in general, the connection term is calculated using:

$\Delta W_{im} = \eta \delta_m X_i$= Learning rate x local gradient Input to the layer (26)

Neuron Transfer functions Ø (.) of the hidden layer are different from the one in the output layer. These activation or transfer functions are of many kinds which are used for selecting the right weighted input sum and to produce an output.

The selection of the transfer function depends on the task of the neuron. Equations (27) and (28) shows difference kind of transfer functions that are commonly used in neural network.

The Hard limit Transfer function: This kind of transfer function sets the neuron output to 0, if the net input value n is less than 0 or, set the output to 1, if the net input n is greater than or equal to 0.

The linear transfer function: This function passes the neurons signal after multiplying it by some gradient constant (slope) and then adds a neuron bias to its output.

The log-sigmoid transfer function: This transfer function is commonly used in back-propagation networks. It is used to produce an output that varies from 0 to + I as the input varies from- ∞to ∞. It is a differentiable function [2][4].

The linear transfer function is normally used in the output layer while the sigmoid function is used in the hidden layer.

The log – sigmoid transfer function is defined as;

$$Y = \frac{(1)}{(1+e-x)} \quad -\infty < x < \infty \quad (27)$$

Since the log-sigmoid function is differentiable, Therefore,

$$\frac{\partial_y}{\partial_x} = \frac{e-x}{(1+e-x)^2} = Y\,(1 - Y) \quad (28)$$

K. 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 = {Va Vb

Vc}T) of the line generated using Power system blockset (simpowersystem).

A comprehensive scheme for fault diagnosis on transmission line system should accomplish the following three tasks [2][4].

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 [2][4].

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.

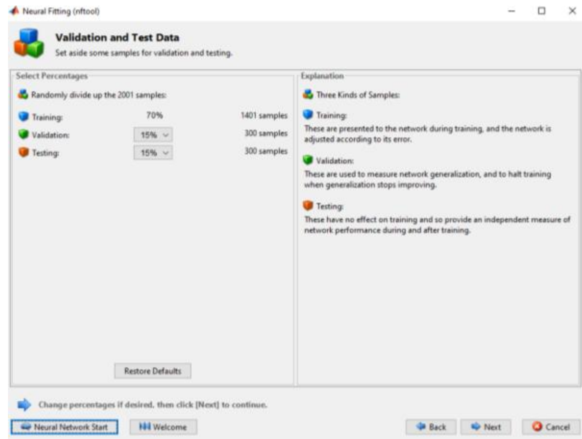

Figure 9: Selection and Sampling of Input Data into ANN

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.

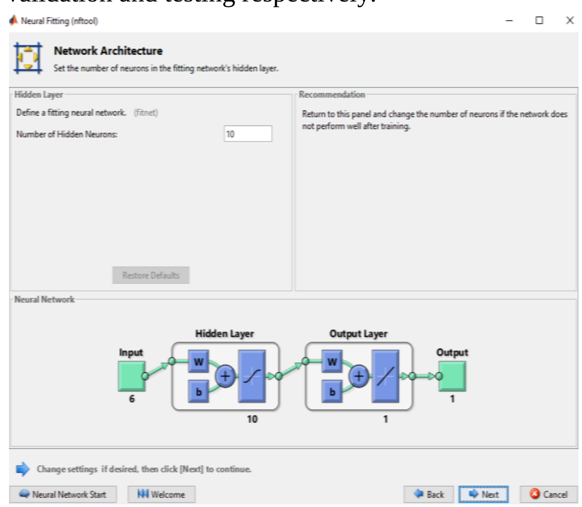

Figure 10: Selection and Sampling of Input Data into ANN

Figure 10 show the selected ANN network architecture used for training and detection of fault. This ANN structure enables us to select intelligently, the number of neurons in the hidden layer of architecture.

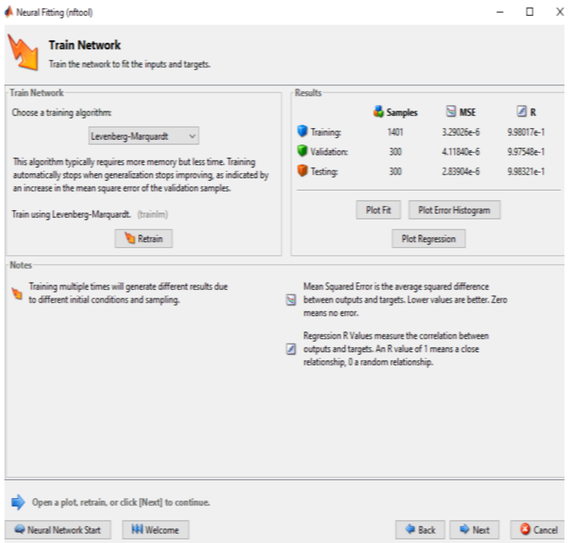

Figure 11: ANN Training Process

Figure 11 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 ≤ 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 11, 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.

III. RESULTS ANALYSIS

A. The Application of ANN for Fault Detection on the Onitsha -Enugu 330KV Transmission Line

The importance of Fault Detection is to detect, monitor and protect the transmission lines if there is a fault, irrespective of the transmission lines size (short or long). The method focuses on identifying when the fault occurred, classifying the type of fault and its location on the transmission line. The ANN detector and classifier are tested on many fault types, various locations, and different fault resistances and various inception angle. The Artificial Neural Networks (ANN) for the fault detection and classification on real time transmission line which can be used in the production system digital protection.

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 the test results show that the fault suggested detector and classifier can be used to support a new system generation of the protection relay at high speed and accurately. Recent power systems are highly interconnected requires early fault detection and fast isolation to maintain system stability. Faults on transmission lines need to be detected, classified and located quickly.

There are many reasons why ANN is used for currents as the inputs to the Neural Networks. Current signals measured at one end of the line only have been used as the inputs to the ANN algorithms because Current Transformers (CT's) are always present at each of the line for measurement and protection purposes. VTs may sometimes not been used due to revenue reasons.

Current signals measured at one end of the transmission lines only can be used for fault classification and location. Voltages and currents are utilized as an input to the neural network therefore ANN output will give good results and very fast. ANN method uses these voltages and the currents to obtain the load reactive power.

This Chapter gives an overview of the application of ANN to fault detection for transmission line faults. It is important as described in previous chapters to be able to identify and locate transmission line faults, because faults can cause damage to equipment, outages and shutdown of power system networks. If the faults occur on the transmission lines without noticing them therefore, there will be some major breakdown in the entire networks of the power system.

We need to model transmission lines to ensure that if there is a fault it can be detected on time and ANN can give accurate readings. Simulink have been used to simulate three phase transmission lines.

i. Simulink Model for Fault Detection on Onitsha – Enugu 330KV Transmission Line

The three-phase power system network model is simulated in MATLAB/Simulink software using Onitsha – Enugu 330kV, 50 HZ, 96km transmission line as a case study. It consists of voltage and current measurements, circuit breakers, transmission line and load which are shown in Figure 3. The main purpose of the transmission lines is to supply power to the load. The power supply is generated by the generator and supplies to the load through 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 time to 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 3.

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

A. ANN Pre-Processing

Measurements of Voltage and Current are typically superimposed with noise and spurious harmonics, which can disturb the accuracy of the ANN performance. In real-systems, analogue filtering of signals is used to remove these harmonics, to minimize unwanted signals.

The use of per unit values simplifies the processing of the simulation data, and performs the calculation for each and every phase [3][4][5].

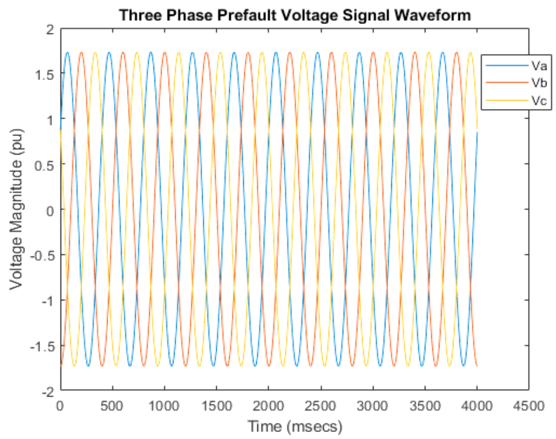

Figure 12: Three Phase Pre-fault Voltage Waveform

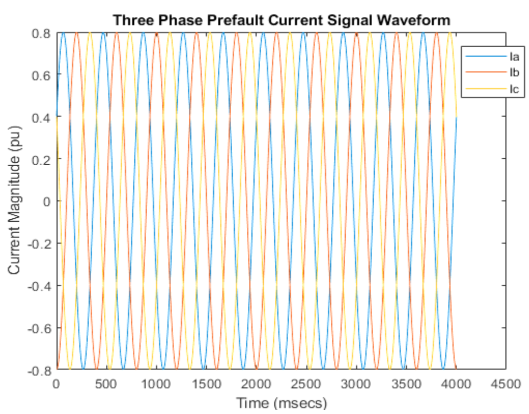

Figure 13: Three Phase Pre-fault Current Waveform

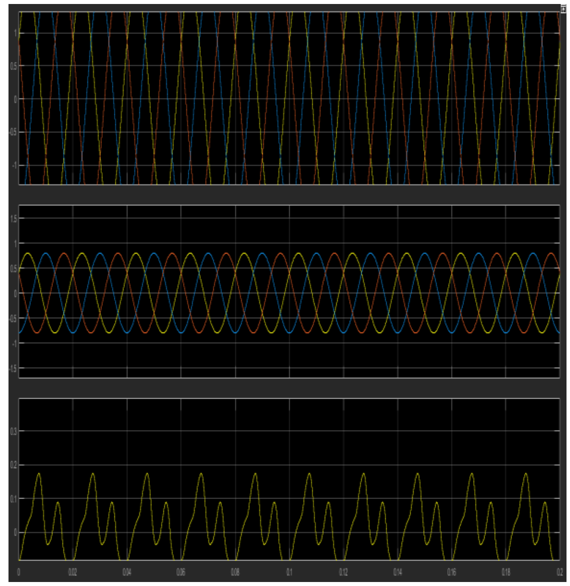

Figure 14: ANN response to Pre-fault V&I Signals

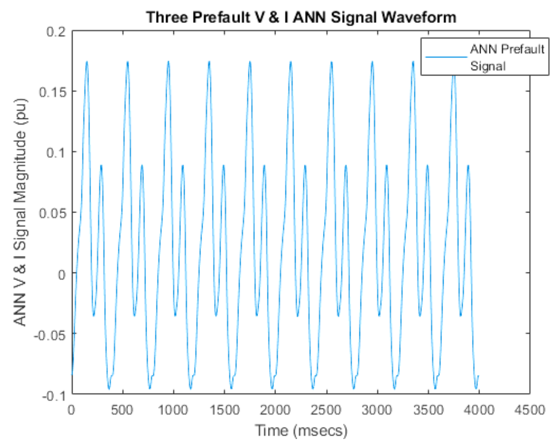

Figure 15: ANN response to Pre-fault V&I Signals

Figure 14 is the ANN response plot of pre-fault voltage, current signals and their ANN equivalent signals against simulation time before fault occurrence on the Onitsha – Enugu 330kV Power transmission line. It shows that the magnitudes of the signals are 0.2. 1.5 and 0.4pu for A – B fault voltage, current and ANN waveforms respectively.

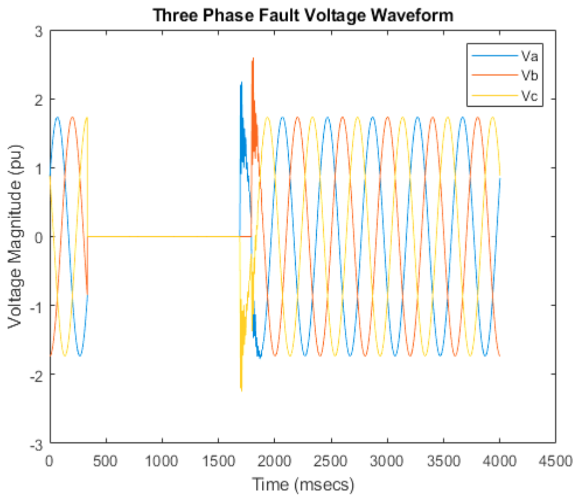

Figure 16: Three Phase Fault Voltage Waveform

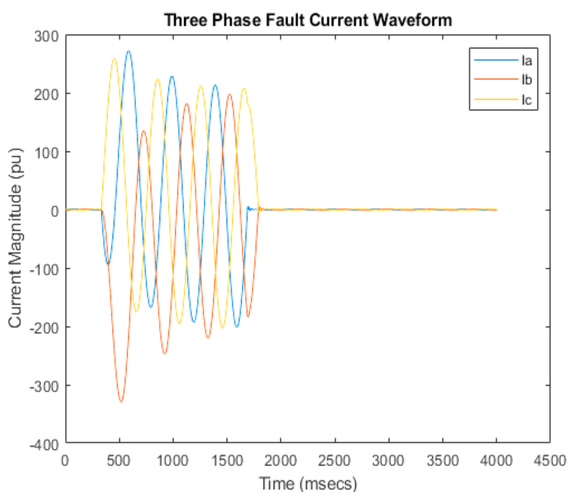

Figure 17: Three Phase Fault Current Waveform

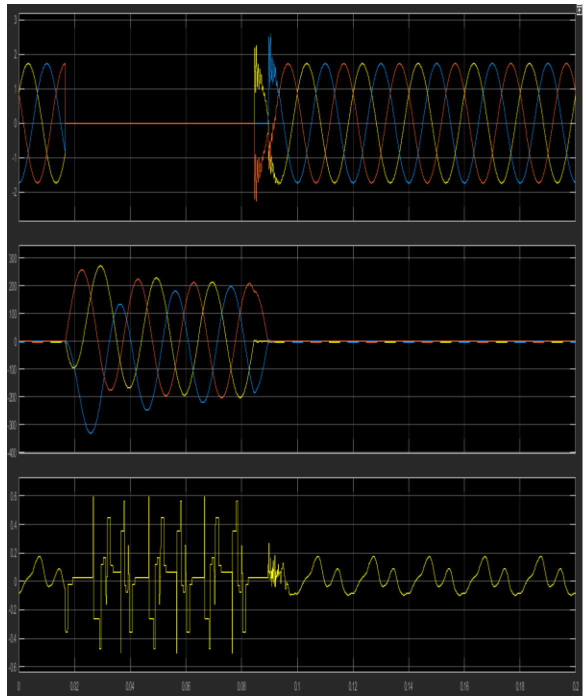
Figure 18: ANN response to Pre-fault V&I Signals

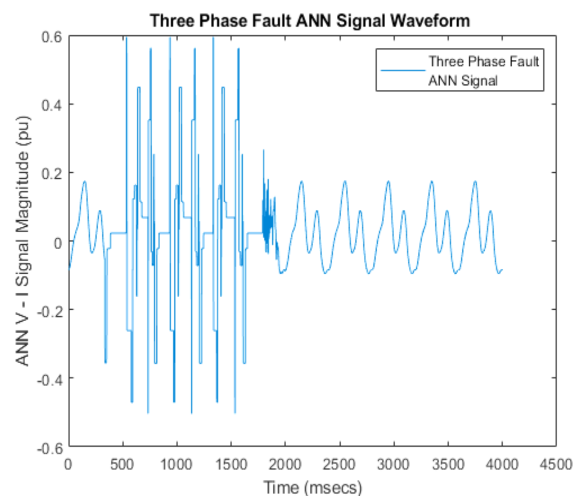

Figure 19: ANN response to ABC fault

Figure 18 is the ANN response plot of A – B - C fault voltage, current signals and their ANN equivalent signals against simulation time during fault occurrence on the Onitsha – Enugu 330kV Power transmission line. It shows that the magnitudes of the signals are 0.3. 2.0 and 0.2pu for A – B - C fault voltage, current and ANN waveforms respectively. This means that, the decrease in voltage magnitude against that of the current and increase in ANN signal magnitude for A – B - C fault is as a result of fault occurrence on the transmission line. It can see clearly from Figures 16 to 18 that the ANN correctly identifies the fault, since there are increases in signal magnitude of ANN fault detector when various faults were simulated. Change in training data could also improve the performance.

A. Three Phase System Results with a Fault

The simulation studies were done for different fault resistances on the Transmission Lines. Pre-fault and three phase fault typeline-line-line (A-B-C) are considered. Figures 12 and 13 show the pre-fault voltage and current waveform of the Onitsha – Enugu 330kV transmission line before the fault. While figures 14 and 15 are the ANN response to the pre-fault signals of voltage and current. Figures 16 and 17 show the three-phase fault voltage and current waveform of the Onitsha – Enugu 330kV transmission line during the fault. But figures 18 and 19 are the ANN response to the three phase fault signals of voltage and current.

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

As can be seen from the figures 16, 17, 18, 19 and table 4, there is voltage drop from 1.75(pu) to 0.00 and increase in currents from 0.8 to above 200(pu) respectively in all the phases during the occurrence of fault. The ANN responses also reflect the occurrence of fault on the line. This is satisfactory as it conforms to the electrical standard circuit analysis results that, whenever fault occurs on the power system the voltage magnitude will decreases and current increases.

D. Validation of Fault Detection using MATLAB/Simulink Tool

Under pre-fault condition in section, the whole 96Km line length is taken into consideration, since it's to check pre-fault condition of the line. The result show that the per unit three-phase voltage magnitudes are larger than the magnitude of their current counterpart. According to electrical circuit theory, it is normal for the line voltage magnitude to be greater than the current magnitude when the line is at pre-fault condition.

However, under three-phase fault condition, the line is 96Km.Simulation was performed on the of the ten zoned lines with a view of determining the three-phase fault voltage and current per unit magnitudes and locating the fault distance on each of the ten zones.

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 an acceptable fault detection

The ANN architecture shown in Figure 20 has 2001 data samples of six (6) inputs, namely, three phase fault Voltages (Va, Vb, Vc) and Currents (Ia, Ib, Ic)shown on table 4. It also consists of 10 hidden layers and 1 output layer. Its objective (based upon its training) is to detect three phase faults on Phases A, B and C. The output is trained to give a response to any of the fault conditions presented, and thus represents a common fault alarm (or Trip).

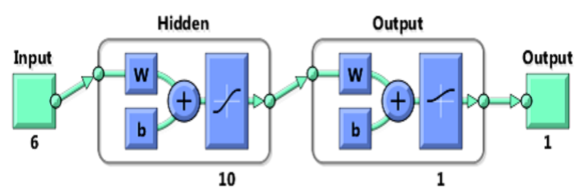

Figure 20: The ANN Selected Architecture or Structure for fault detection

Generally, the above figure 20 was selected for all the ten zones of different line length.

Figure 20 gives a more detailed view of the designed ANN, its input, hidden and output layers. It is automatically selected during fault simulation by the ANN Matlab/Simulink Fault Simulator for the detection of faults on the transmission line.

The inputs and outputs of the neural network should have a number of hidden layers according to the complexity of the problem being solved and a number of neurons of each layer of the ANN. As can been seen in the figure 20, the neural network of three layers, six neurons in the input layer and one neuron in the output layer is used for detection of faults. The log-sigmoid function evaluates the output and recommends the best results on the hidden layer and output layer according to the Bias Weights (b).

To achieve the right magnitude and correlations for the total number of the inputs and outputs of the neural network, training of the ANN is required. The selection of the inputs of the neural network is based on the size and complexity of the problem. The higher the number of inputs and the number of outputs is, the more detailed the complexity of the ANN is. This results in a large number of hidden layers. The size of the hidden layers allows for effective decision making. The inputs are based upon 50Hz and three phase voltages and currents.

The three phase voltages and currents were measured on both ends of the transmission line. The type of fault was classified along the length of the transmission line, whereby the ANN output would confirm a fault for any of the three phases.

The following results were obtained when the length of the line is 96Km [6][7].

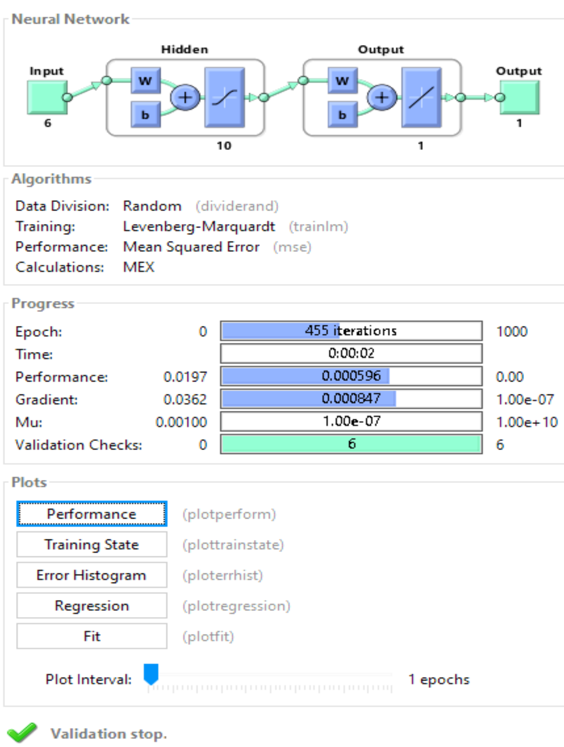

Figure 21: ANN Simulation Window Processes

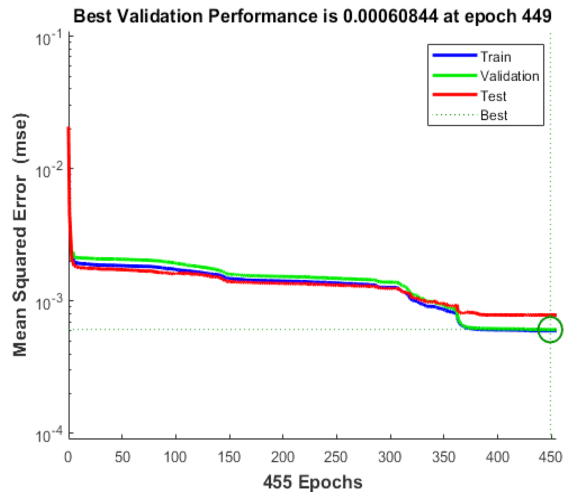

Figure 22: Performance for the Training Process of Fault Detection for 96Km

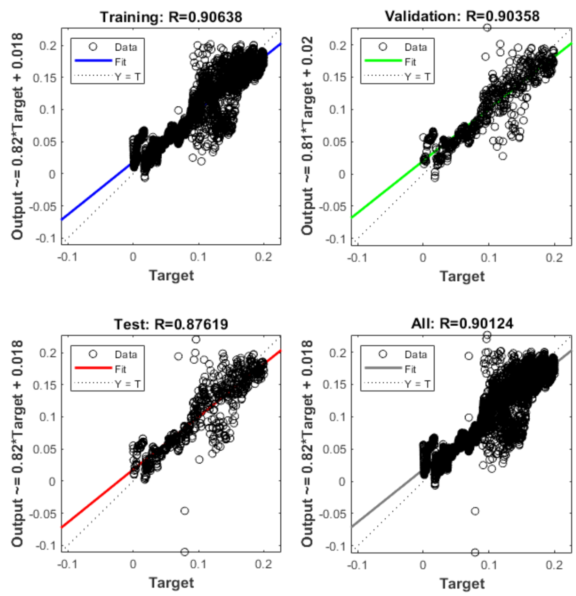

Figure 23: Regression analysis of the ANN for the Fault Detection for 10Km

Figure 22 is the performance graph that shows the performance result of the training process. It shows that, at MSE = $6.0844e^{-5}$, the training gives the best training, validation and test results for fault detection.

Figure 23 shows the regression plot of 0.90124 of the output verses targets for the detection and simulation of the three phases fault using ANN. According to the ANN performance standard, if the Regression R is 1s.0 or less than 0.45, it shows that the training process and results can be accepted. But anything different from that is not accepted as good result, and the data should be retrained. As can be seen, the correlation is good and showing R is approximately 1 at 449 epochs.

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