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Fault Detection on Power System Transmission Line Using Artificial Neural Network (A Comparative Case Study of Onitsha – Awka – Enugu Transmission Line

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ABSTRACT:*This paper dwelt on the use of artificial neural network (ANN) method with Matlab Simulink 2016 to detect faults on the power system transmission line using Onitsha – Awka – Enugu as a cast study. The Onitsha - Awka – Enugu transmission line was modeled with Matlab Simulink 2016 using the transmission line pre-fault and daily fault data. Single line to ground (A – G), Double line to ground (AB – G), Line to line (A – B) and three phase (ABC) faults were simulated with the ANN method using Matlab Simulink 2016. However, the ANNshow detail detection and analysis of faults on the line. It was able to detect faults, classify them and locate thefault distance. The output results of the method where compared with the symmetrical component method (the conventional method). The comparison was done based on robustness/simplicity, less error, accuracy and efficiency. ANN was found the best in terms of the above comparative factors.*

KEYWORDS: *Fast Fourier Transform, Wavelet Transform, Artificial Neural Network, Symmetrical Components, Travelling Wave.*

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I. INTRODUCTION

In the past several decades, there has been a 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 the continuity of electrical power system supply is the occurrence of faults. These faults are inevitable and normally 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 it, identifies the fault type, accurately locates the position of the fault in the power system network and isolate it. The isolation of the faulty section must be very fast to avoid damage of the equipment and power outage. Also, the faults must be cleared very fast so as to restore the power to the isolated areas. The clearing of the faults are done using protective devices which senses the fault, respond immediately and disconnect the faulty section from the good ones.

II. METHODOLOGY

This chapter consists of the methodological procedure for the detection of faults on 330/132KV Onitsha – Awka – Enugu power system transmission line using Artificial Neural Network, ANN method. Figure 1 illustrates the typical single transmission line diagram used in this study.

The system parameters used for modeling, training and testing of ANN method are; Real Power 87.7MW, Reactive Power 21.40MVAR, Active Power of 90.27MVA with frequency of 50Hz. It consists of three buses and two transmission lines representing Onitsha – Awka and Awka – Enugu transmission lines which has 46Km and 50Km respectively. The zones of protection are also shown in the figure 1 as zone1 = 76.8km, zone2 = 144km and zone3 = 240km all from bus A.

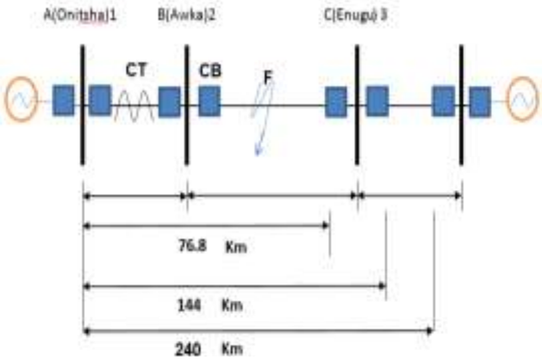

Figure 1: Onitsha – Enugu 330/132KV Single Transmission Line Diagram

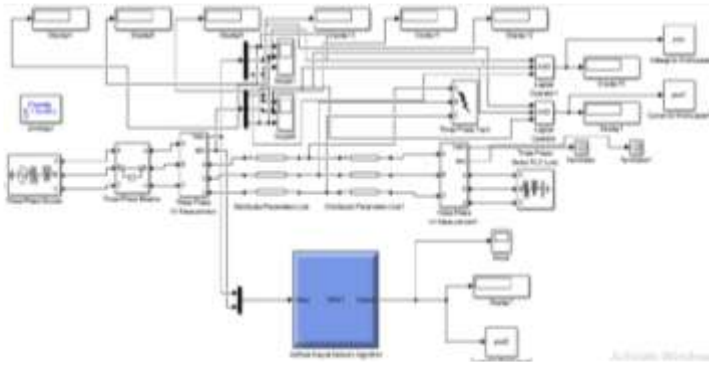

Figure 2: Artificial Neural Network (ANN) model of transmission line for fault diagnosis of 330/132kv Onitsha – Awka – Enugu transmission line.

III. MODELING THE POWER TRANSMISSION LINE SYSTEM

The electrical characteristics of a transmission line depend primarily on the construction of the line. The values of inductance and capacitance depend on the various physical factors. For example, the type of line, the tower geometry, and the length of the line must be considered. A 330/132KV transmission line system has been employed in this study to develop and implement the proposed strategy. Figure 1 shows a single line diagram of the system that is used throughout the research.

The system consists of two power transformers of 330/132KV each located on either ends of the transmission line. The line has been modeled using distributed parameters.

The line is modeled with length of 96Km (Onitsha – New Haven transmission line), voltage level of 330/132KV, frequency of 50Hz, and the listed line parameters were built in the simulations.

Positive Sequence Impedance (Z^+) parameters

$X_1 = 0.0284\Omega/Km$ 1

$R_1 = 0.0038\Omega/Km$ 2

Zero Sequence impedance (Z^0) parameters

$X_0 = 0.0653\Omega/Km$ 3

$R_0 = 0.0296\Omega/Km$ 4

Shunt Admittance (B) parameters

$B_1 = 0.3771$ … ./Km 5

$B_0 = 0.2577$ …/Km 6

Surge Impedance = 300Ω

Conductor Type/Size

Bison / 4.7×10^{-12} Km^2

Thermal Rating = 1360A

$Z^1 = Z^+ + Z^0$ 7

$Z_P = (Z^+ + Z^0) \times L$ 8

$Z^+ = R_1 + jX_1$ 9

$Z^0 = R_0 + jX_0$ 10

Where Z_P is the primary impedance of the line, $Z^+$is the positive sequence impedance, $Z^0$is the zero sequence impedance, $R_1$and R_0 are the positive and zero sequence resistances, X_1 and X_0 are positive and zero sequence reactance of the line while L is the length of the transmission line which is equal to 96Km.

The primary impedance Z_P , of the line can be calculated using the listed line parameters

$$Z_P = (Z^+ + Z^0) \times L \qquad 11$$

Where

$$Z^+ = R_1 + jX_1 \qquad 12$$

and

$$Z^0 = R_0 + jX_0 \qquad 13$$

Substituting the values of R_1 , X_1, R_0 and X_0 in the equation above, we have

$$Z^+ = 0.003773 + j0.028377 \qquad 14$$

$$Z^0 = 0.029620 + j0.06527 \qquad 15$$

$$Z^+ + Z^0 = (0.003773 + j0.028377) + (0.029620 + j0.06527)$$

$$= 0.003773 + j0.028377 + 0.029620 + j0.06527 \qquad 16$$

$$Z^+ + Z^0 = 0.033393 + j0.093647 \qquad 17$$

$$Z_P = (Z^+ + Z^0) \times L \qquad 18$$

$$Z_P = (0.033393 + j0.093647) \times 96000 \qquad 19$$

$$Z_P = 3205.728 + j8990.112 \qquad 20$$

$$ZP = 9.5K\Omega < 70.4° \qquad 21$$

Diagnosis Of Fault Using Artificial Neural Network (Ann)

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 spiral cord and the peripheral nervous system, comprising the nerves that links and send information round the whole body).

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

Equation 22 describes the input – output ANN operational procedure which is a mapping process of a function Ø.

$$Y = \phi(X) \qquad 22$$

ϕ - 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 3.8. The network is capable of generalization [1].

The Learning Process Of Neural Network

This can be achieved by using a learning algorithm. The aim of this algorithm is to change the synaptic weights of the network to attain a desired design objective called ‘target’. Once the neural network is trained, it generalization the output through the mathematical processes stated in the equations 337 to 3.40. 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.

- Input – Output Mapping: The network is presented with input signals in the form of pre-fault and fault voltage and current phase values for both real and simulation conditions.

The weights are modified so as to minimize the difference between the network output and the desired output. However, applying supervised learning algorithm, the target values which is the desired output should be known.

After that, the network is trained continuously, until it reaches a state where there are no further significant changes in weights called the converging point.

- Non- Linearity: Here a neuron represents a non-liner element, which means that the neural network is made up of a collection of neurons called non-liner system.
- Adaptively: The artificial neural network selected and trained for a particular function in a particular environment (input-output pairs) can be easily retrained to deal with minor changes in that environment.

Moreover, the supervise learning has a most acceptable neural network called multi-layer perceptron (MLP) which has been in use since 1986. It has a feed-forward connection with free parameters called adjustable weights [2].

Training of the MLP network simply means testing for the best weight so that the error between network output and the target output will be reduced. This process is iterated until convergence point (a point where the error can no longer be reduced) is reached.

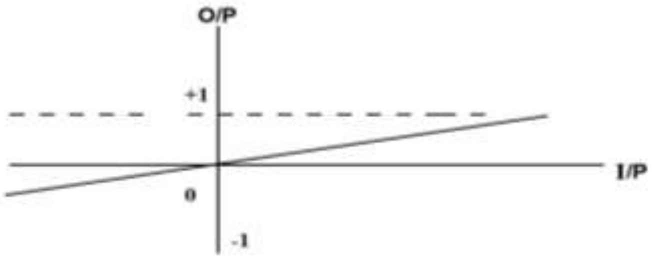

Figure 3: Linear transfer function

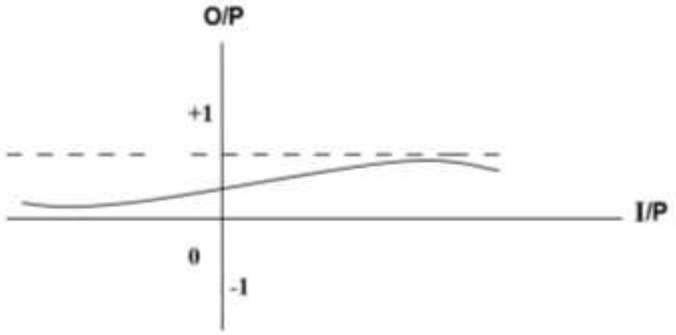

Figure 4: Log - sigmoid transfer function

The linear transfer function carries the input signal of the input neuron through the hidden neuron after multiplying it by some scaling constant (slope) and adding a neuron bias to its output port.

The log-sigmoid function is defined as

$$Y = \frac{1}{(1+e-x)} \qquad -\infty < x < \infty \qquad 23$$

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

The Biological Neuron To Artificial Neuron Model

The similarities between the biological and artificial neuron can be explained using sensory parts of the biological neuron. Communication between the biological neurons involves an electro-chemical process. The interface through which they interact with the other neurons is by using their dendrites (input connections). These dendrites are connected through the synapse to another 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 (hidden neurons). The sending of the electrical signal or data to the brain or hidden neuron is through the process called backpropagation algorithm method.

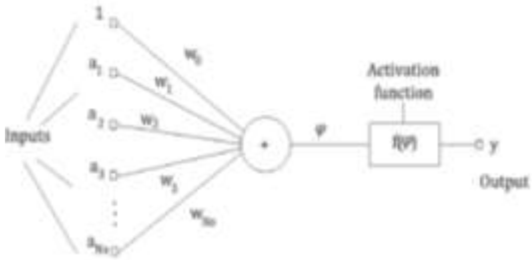

Figure 5: Simple neuron model

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 principle 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.

Neural Network Architectures

The neural network architecture is an arrangement of input signals or data connected to the input neurons and linked to the output neurons through the hidden neurons. Each input neurons, hidden neurons and output neurons are all located on the input, hidden and output layers respectively. The neurons of a particular network are connected in an arranged manner that makes them to strongly influence their learning patterns which is training their network. The various existing neural network architectures can be divided into four main categories:

- Single – layer feed – forward networks
- Multilayer feed – forward networks
- Recurrent networks
- 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, while multilayer- feed – forward networks is the most widely used architecture used 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) [2] [3].

Multilayer Perception Networks

The Multilayer perceptron network have 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 backpropagation phase, the weights are adjusted based on the error between the actual and desired output [2] [3] [4].

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

Presentation Phase

Considering the above multilayer perceptron network analysis, the following symbols where used in this work [2] [3].

- 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
- W_{ji}: 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.
- ϕ (.): 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:

$$h_j^H = b_j + \sum_{T=1}^{NI} w_{ji} X_1 \qquad 24$$

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

$$y_j^H = \emptyset(h_j^H) \qquad 25$$

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

$$h_k^o = b_k + \sum_{j=1}^{J=1} w_{kj} y_j^H \qquad 26$$

Consequently, the network output is then given by

$$y_k = \emptyset(h_k^o) \qquad 27$$

IV. THE ERROR BACK-PROPAGATION LEARNING ALOGRITHM

An output error is defined as the difference between the network output and the desired output value that is for the K^{th} output neuron [2] [3] [4].

The output error of the K^{th} output neuron is given as

$$e_k = d_k - y_k \qquad 28$$

d_k = desired output value

y_k = Network output value

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

$$e = \frac{1}{2}\sum_{k=1}^{NO} e_k^2 \qquad 29$$

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;

$$\frac{\partial \epsilon}{\partial w_{ki}} = \frac{\partial \epsilon}{\partial e_k} \text{ X } \frac{\partial e_k}{\partial y_k} \text{ X } \frac{\partial y_k}{\partial h_k^o} \text{ X } \frac{\partial h_k^o}{\partial w_{ki}} \qquad 30$$

If we compute each term, we will obtain as follows

$$\frac{\partial \epsilon}{\partial w_{kj}} = e_k \qquad 31$$

$$\frac{\partial e_k}{\partial y_k} = 1 \qquad 32$$

$$\frac{\partial y_k}{\partial h_k^o} = \emptyset_k h_k^o \qquad 33$$

$$\frac{\partial h_k^o}{\partial w_{kj}} = y_j^H \qquad 34$$

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

$$\frac{\partial \epsilon}{\partial w_{ki}} = -e_k \emptyset_k h_k^o y_j^H \qquad 35$$

The change $\blacktriangle w_{kj}$ which is applied to the weight matrix that is connected to the hidden layer to the output layer is also given as

$$\Delta w_{kj} = -\eta\left(\frac{\partial e}{\partial w_{kj}}\right) = \eta\epsilon_k \emptyset_k h_k^o y_j^H \quad 36$$

Where ŋ is a constant known as the step-size or learning rate. We can also rewrite the equation 36 as;

$\Delta w_{kj} = \eta\delta_k y_k^H$ 37

Where $\delta_k = \epsilon_k \emptyset_k h^o{}_k$ 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.

$$\frac{\partial \epsilon}{\partial w_{kj}} = \frac{\partial \epsilon}{\partial e_k} \times \frac{\partial e_k}{\partial y_k} \times \frac{\partial y_k}{\partial h_k^o} \times \frac{\partial h_k^o}{\partial w_{kj}} \times \frac{\partial y_j^H}{\partial h_j^H} \times \frac{\partial h_j^H}{\partial w_{ji}} \quad 38$$

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

$\Delta w_{kj} = -\eta\delta_k X_i$ 39

$\delta_i = \emptyset_j h_j^H \sum_{k=1}^{NO} \delta_k w_{kj}$ 40

Therefore in general, the connection term is calculated using:

$\Delta w_{kj} = \eta\delta_m X_i$ = Learning rate x local gradient x Input to the layer 41

- 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. Figure 3.9 and 3.10 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 backpropagation 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.

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;

$$Y = \frac{1}{1+e^{-x}} \qquad -\infty < x < \infty \quad 42$$

Since the log-sigmoid function is differentiable,

Therefore

$$\frac{\partial_y}{\partial_x} = \frac{e^{-x}}{(1+e^{-x})^2} = Y(1-Y) \quad 43$$

V. 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 [5].

Neural Network-Based Approaches For Power System Problems

The power system is gradually coming closer to its limits. This is due to the increase in energy demand and various problems that arise preventing the expansion of the transmission lines system. This condition requires a significantly less consequence power system operations by monitoring the system state in a more detailed form than it were before. Fortunately, there are large quantities of available data which can be used to design a system that will monitor the state of the power system and which will also be implemented in the system for the expansion of transmission lines in the country.

One of the problems that is affecting the progress in the expansion of transmission line systems is the lack of evaluation techniques for fast operation of protection systems in the power systems; owing to the fact that the power system and the area to be covered to ensure increase in development in the country requires high dimensionality and non-liner system. This makes it difficult to model the power system transmission line.

In view of this, a new fast data processing technique such as Neural Network can be used for a high dimension and non-liner system for increasing the power system transmission line.

The Neural network has the ability of modeling functional relationships between input and output data without the explicit knowledge of an analytic model. It adapt to several data sets within a short time interval.

Other area where neural network has been applied successfully was in load forecasting, security assessment, control, system identification etc.

Neural Network For Transmission Line Relaying

Distance relaying is the most popular and correct protection scheme used in high voltage applications. In the type of relaying or protection, the relay can be either over reaches or under reaches, depending on the operating conditions of the power system and the location of the fault. Since the power detection and classification is performed traditionally on-line, new pattern recognition techniques (neural network) that are quick in detecting developed faults are implemented to detect the changing power system condition quickly and accurately [4].

Networkarchitecture Used For Transmission Line Protection

To employ neural network techniques successfully, some fundamental issues should be considered. Among these issues is the selection of the network architecture and the learning algorithm, such as the net size, learning step, number of training patterns and number of iteration.

We talked on back-propagation algorithm with supervised learning. However, it has its disadvantages such as slow learning process and requires large training sets.

Another alternative is the use of unsupervised learning.

A typical unsupervised learning commonly used is the self-organizing maps (SOM) developed by Kohonen.

The SOM network possesses the advantage of fast learning and small training sets. However, due to the absence of a desired output information, it not suitable in the work. Rather, it is used as a front-end to an output layer with desired target information through a supervised training process, which means the combination of both supervised and unsupervised learning integrated together. This has the capability of sorting out a very complex, dimensional, highly non-liner problems like transmission line fault diagnosis [6].

Table 1: Per Unit Real Pre-fault Voltage and Current values from Onitsha transmission station.

Case No	Input Vector (Per Unit Phase Voltage and Current)							Fault Type/Zone
	Date/Time/ Location	V_{af} (pu)	V_{bf} (pu)	V_{cf} (pu)	I_{af} (pu)	I_{bf} (pu)	I_{cf} (pu)	
1	17/2/2018 16:38:22 32Km	1.4652	1.3250	1.3492	0.6586	0.2596	0.0000	A TO G Zone 2
2	04/01/2018 14:31:47 51.77Km	1.4841	1.3598	1.3311	0.3032	0.4212	0.3318	B to G Zone 1
3	02/01/2018 16:07:51 20Km	1.4818	1.3576	1.3258	0.2977	0.3432	0.3262	C To G Zone2
4	20/03/2018 19:08:30 33Km	1.0542	1.2581	1.3215	0.0000	0.0000	0.0000	A To B Zone1
5	01/02/2018 17:35:42 103Km	1.8932	1.0879	1.1250	0.0000	0.0000	0.6628	B To C Zone2
6	20/02/2018 18:40:45 69Km	1.0231	1.3215	1.3520	0.0000	0.0000	0.0000	A To C Zone3
7	27/05/2018 22:18:30 93Km	0.4700	0.4600	0.4700	0.2200	0.1050	0.1250	AB To G Zone2
8	13/03/2018 17: 28:18 89Km	0.4200	0.5000	0.4600	0.1480	0.1450	0.1650	BC To G Zone 1
9	16/6/2018 17:35:17 64Km	0.4800	0.4300	0.4000	0.2000	0.1480	0.1450	AC To G Zone 1
10	23/4/2018 17:35:17 88Km	0.4000	0.4500	0.4900	0.2200	0.1400	0.1490	A To B To C Zone 1

Table 2: Per Unit Real Fault Voltage and Current values from Onitsha transmission station.

Case No	Input Vector (Per Unit Phase Voltage and Current)							Fault Type/Zone
	Date/Time/ Location	V_a (pu)	V_b (pu)	V_c (pu)	I_a (pu)	I_b (pu)	I_c (pu)	
1	17/2/2018 16:38:22 232.4Km	1.4561	1.3311	1.3273	0.7279	0.4355	0.4982	A TO G Zone 3
2	04/01/2018 14:31:47 51.77Km	1.4333	0.9098	1.2795	0.6292	5.1247	0.1716	B to G Zone 1
3	02/01/2018 16:07:51 11.49Km	1.4636	0.8371	1.2803	0.3761	0.2804	9.5717	C To G Zone1
4	20/05/2018 19:08:30 133Km	2.5433	1.3501	1.7540	0.0000	0.8234	0.0000	A To B Zone2

5	01/02/2018 17:35:42 105Km	1.9265	1.1129	1.1523	0.0000	0.0000	0.0000	B To C Zone2
6	20/02/2018 18:40:45 96Km	2.2540	1.0251	1.6345	0.0000	0.0000	0.7315	A To C Zone1
7	27/03/2018 22:18:30 93Km	1.5600	1.1200	1.4720	2.5600	3.1050	0.1250	AB To G Zone1
8	13/03/2018 17: 26:18 89Km	1.4300	1.5600	1.5610	0.4480	4.0450	3.1450	BC To G Zone 1
9	16/6/2018 17:35:17 64Km	1.4402	1.3320	1.4020	5.4200	0.1480	4.2650	AC To G Zone 1
10	23/4/2018 17:35:17 88Km	0.5000	0.5500	0.6900	0.1900	0.2400	0.2590	A To B To C Zone 1

VI. RESULT ANALYSIS

The ANN employed here has three stages, the detection, classification and location stages. At each stage, an ANN is selected and trained for the given task. The inputs of each network are the three phase currents ($I = \{Ia \quad Ib \quad Ic\}^T$) and voltages ($V = \{Va \quad Vb \quad Vc\}^T$) of the line obtained from the Onitsha transmission line station and the generated ones using Power system blockset (simpowersystem) termed real and simulated parameters.

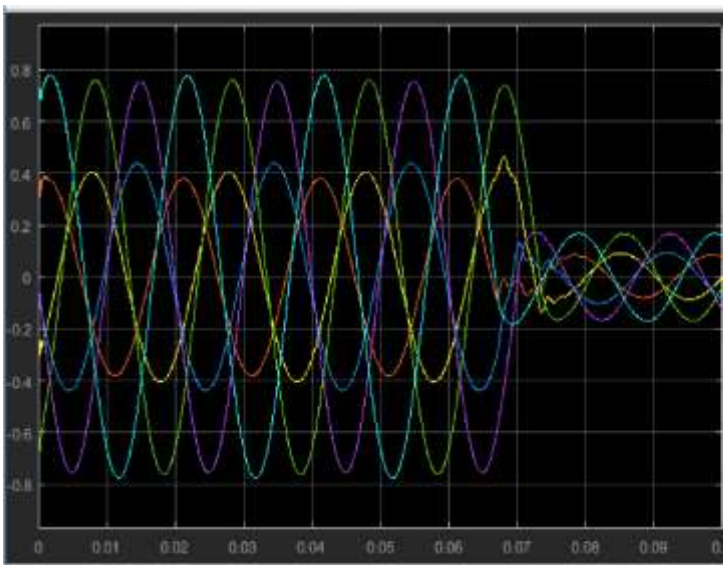

Figure 6: Three phase Voltage and Current signal Waveform illustrating the no fault condition of the transmission line.

Figure 6 show a sinusoidal waveform of the three phases of the transmission line at no fault condition. It is also a representation of no fault voltage and current waveform. The voltage waveform has it voltage amplitude of the three phases as phase A = 0.79, phase B = 0.78 and phase C = 0.77 all in per unit. That of the current waveform is phase A = 0.39, phase B = 0.40 and phase C = 0.41 all in per unit.

This waveform shows that, there is no fault detected from the transmission line and that, the little variations in the amplitude phase values of both voltage and currents in per unit is confirmation that in transmission line there is little but no harmonics.

Training Of Data

In the training process, the input data which are the per-unit values of the voltage and currents of each phase at the reference fault point of bus B and converted to binary values are sampled into the proposed network. The output of this training process is the fault condition of the power system transmission line network shown on table 1.

Design Of The Neural Networks For The Detection Of Fault

In other to design the neural network for addressing the fault detection problem, several different topologies of network or architectures of MLP (Multi-Layer perceptron) neural network where studied. The criteria used in implementing and selecting the appropriate MLP neural networks for the above task are the network size, suitable learning rule/algorithm and the size of the training data.
Here, the back propagation algorithm, using the Levenberg-Marguradt optimization learning rule was used [2] [3].

Selecting The Right Network Size

When selecting the right size of the network, the training time must be reduced, the number of hidden layers and neurons in those layers should be smaller to obtain the right network size. Therefore, the smaller number of the neurons on the hidden layer, the smaller the network. And so, when the network is trained, it converges.

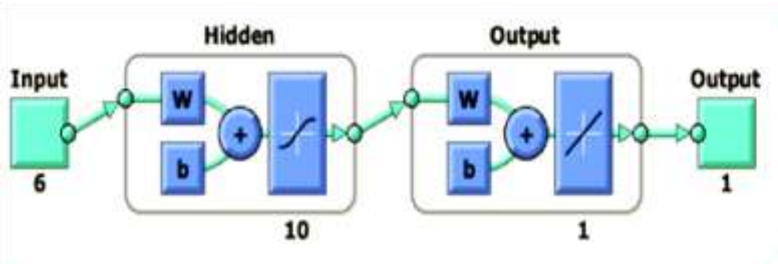

Figure 7 – BP Ann selected for fault detection

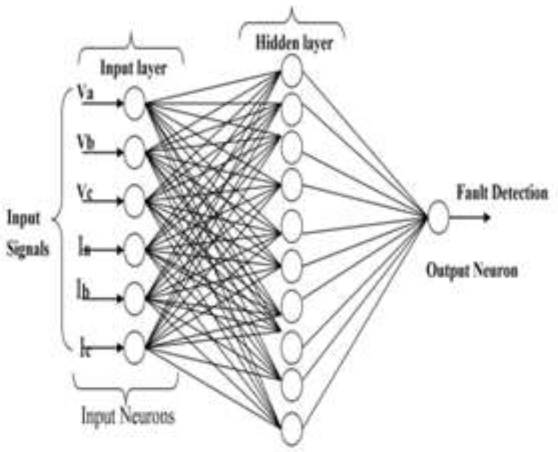

Figure 8: BP Ann selected for fault detection

The convergence of the network parameter values describes the point at which the training stops. However, a minimum number of neuron is general needed to a given problem like this work. The networks used here for the detection represent the best network for the task after extensive trial and error calculation.

After extensive simulation, we decided that the selected network would have one hidden layer, with 10 hidden neurons. The selected neural networks for the fault detection using real and simulated data isgiven in figure 8.

Training Procedure And Learning Rule

The back-propagation learning algorithm based on Levenberg-marquardt optimization method was used for the training of the proposed network.

This is because the standard back propagation training algorithm is slow and generally requires small learning rate for stable learning process. But the Levenberg-marquardt optimization back-propagation method requires small learning rate but faster in training.

Through the application of various improvement techniques to different network architectures, we obtained that the most suitable training method for the above task was the back-propagation method based on the Levenberg-marquardt optimization method.

During the training process, different learning rate were tried in the hidden and output layers. The training process stops when the difference (error) between the output values expected and the target value input in the network is negligible and thus, tend to converge to zero difference.

Regression Analysis Of The Network Training

The regression analysis was also used in analyzing the training and the output of the network. The regression is a measure of the correlation between the un-normalized output and the targets. Thus, if Regression R is 1, it means that, there is a close relationship between the output and the target (i.e. their values tend to converge to the same value or that their differences are zero or approximately zero). At this point one can now stop the training. But if R is zero, it means not yet converged and their difference is still very large, therefore, the network needs to be trained more. The regression graphs for the fault detections is shown in figure 14 to 50 using real and simulated data.

The regression graph is used to analyze the output—target relationship of the network. During the training process, the target is used to check for the error, as the Neural Network will produce the output.

The regression graph is a plot of output against target which is the main parameters for analyzing the best network within the best period. However, if the regression graph is not a straight line, it means that, there is so much error or that the error is high and the scattered points of the plot are not closely related, instead, scattered far from each other. But if they are closely related, that means, we will obtain a straight line regression graph.

Therefore, regression graph analyses is used to get the best straight line that illustrates the output – target relationship and that the best training process was used. This best line fitting of the network also tells us that the error which is the difference between the output and target is not high.

Means Square Error (Mse)

This is the average square difference (error) between normalized output and the target. When the MSE is zero, it means that there is no error in the training process, but if MSE is greater than 0.5 it means that the error is higher. Therefore, for a good training result, MSE should be within the range of 0.0000 – 0.4000. Figure 11 to 47 show the MSE (Performance graph) of the ANN trained for fault detection.

Testing (Generalization) Of The Network

The neural network performance for the above task was analyzed using the mean square error (MSE) called performance graph and are shown on figures 11 to 47 using real and simulated data.

Since the network output and target values converged and produced error which is almost zero and was able to classify correctly both the normal and faulty condition, we conclude that the detection of the fault on the power system transmission line was successful.

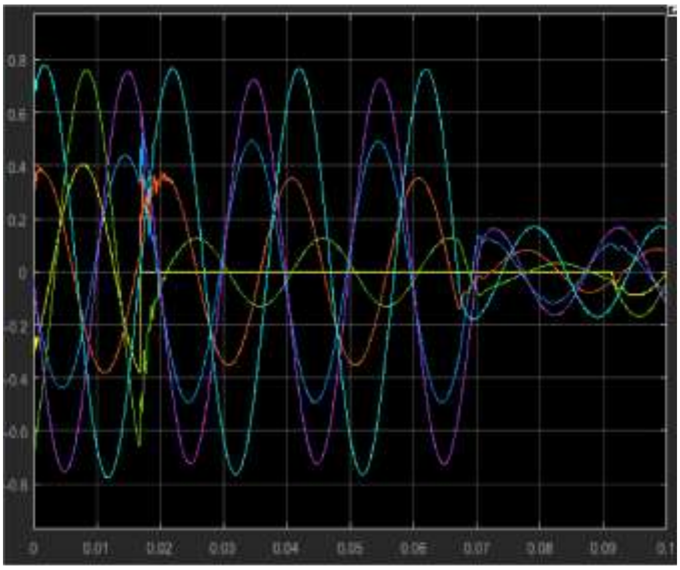

Figure 9: Phase A – Ground three phase fault voltage and current signal waveform.

This waveform illustrates the amplitudes of the voltage and current when phase A – Ground fault occurred on the transmission line.

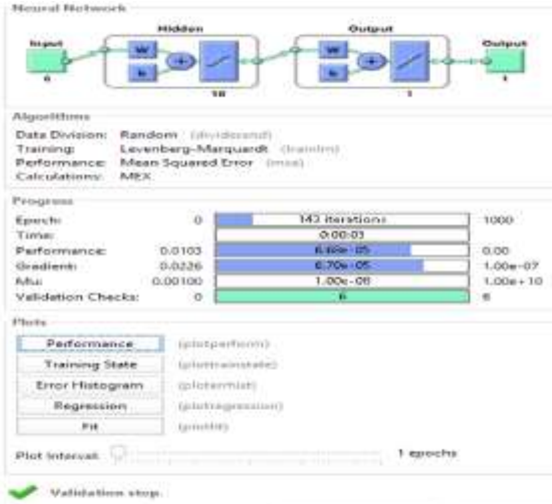

Figure 10 – BP Ann training procedure selected for A – G fault detection

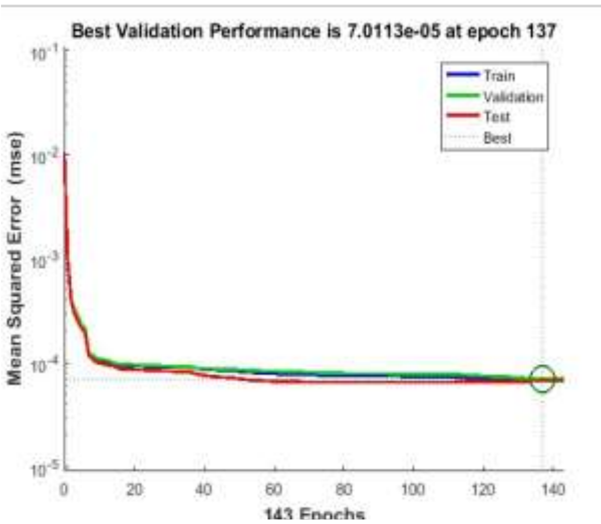

Figure 11 – Mean Square Error (MSE) graph for A – G fault detection

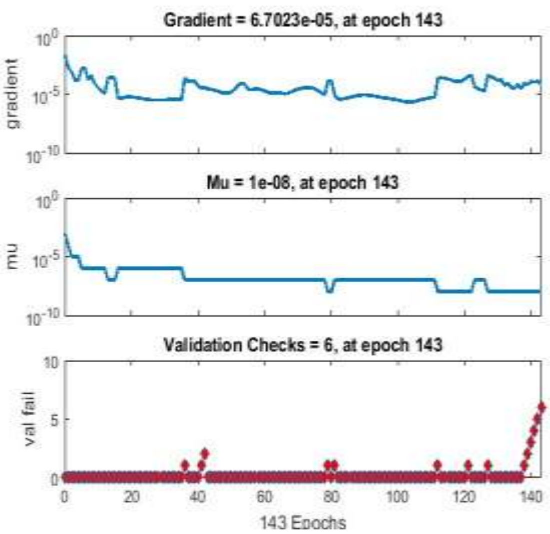

Figure 12 – Gradient and performance graph for A – G fault detection

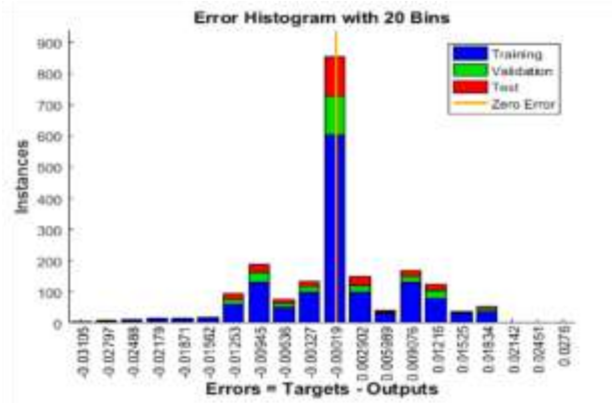

Figure 13 – Error histogram for A – G fault detection

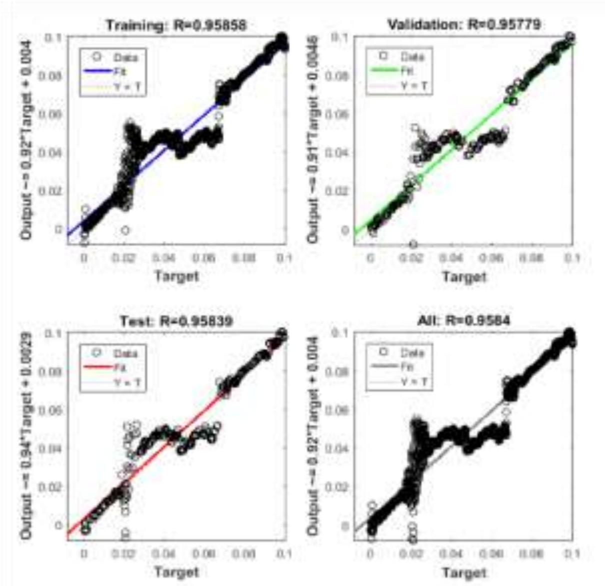

Figure 14 – Regression analysis graph for A – G fault detection

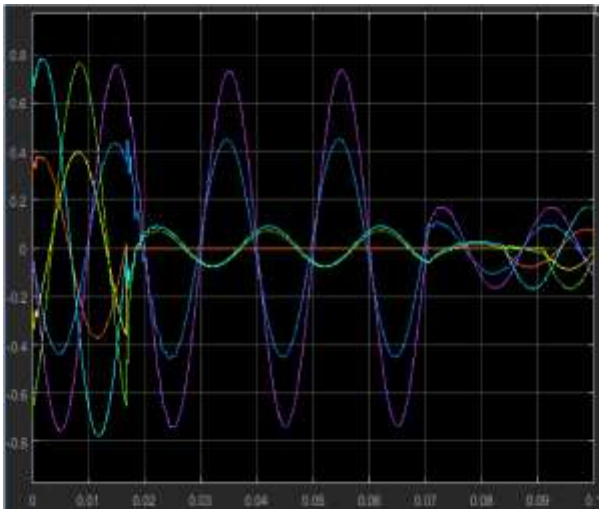

Figure 15: Phase AB – Ground three phase fault voltage and current signal waveform

This waveform illustrates the amplitudes of the voltage and current when phase AB – Ground fault occurred on the transmission line.

Figure 16– ANN training procedure for AB – G fault detection

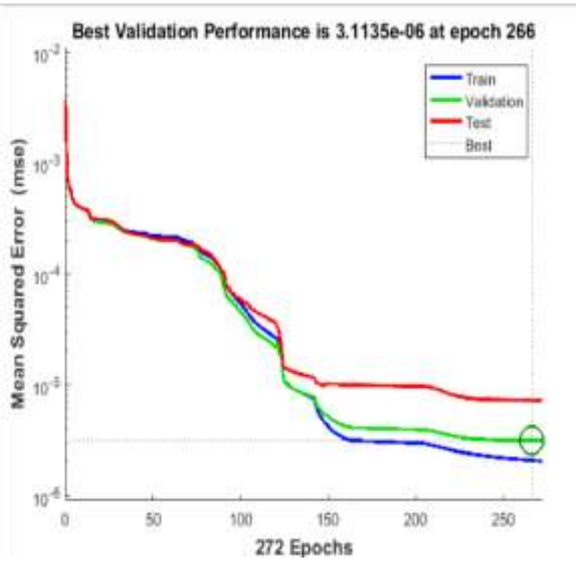

Figure 17 – Mean Square Error (MSE) graph for AB – G fault detection

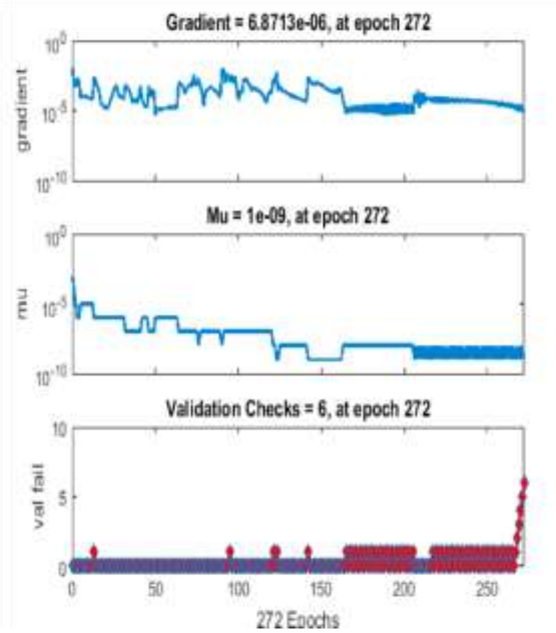

Figure 18 – Gradient and performance graph for AB – G fault detection

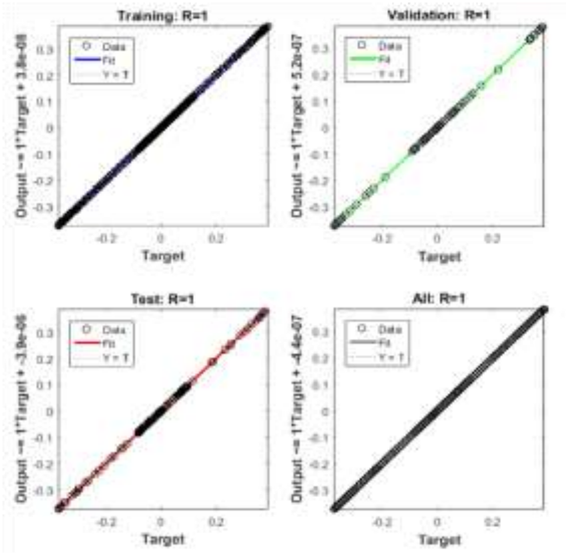

Figure 19 – Regression analysis graph for phase AB – Ground fault

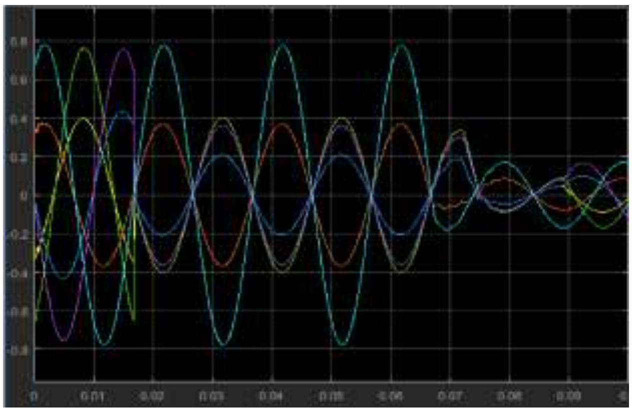

Figure 20: Phase A - B three phase fault voltage and current signal waveform

This waveform illustrates the amplitudes of the voltage and current when phase A – B fault occurred on the transmission line.

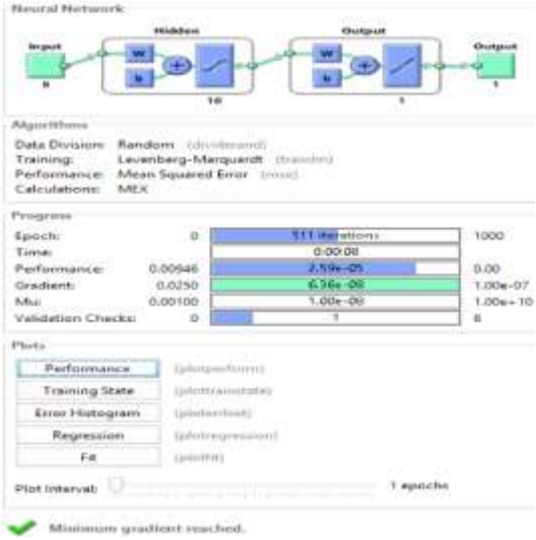

Figure 21 – ANN training procedure for A - B fault detection

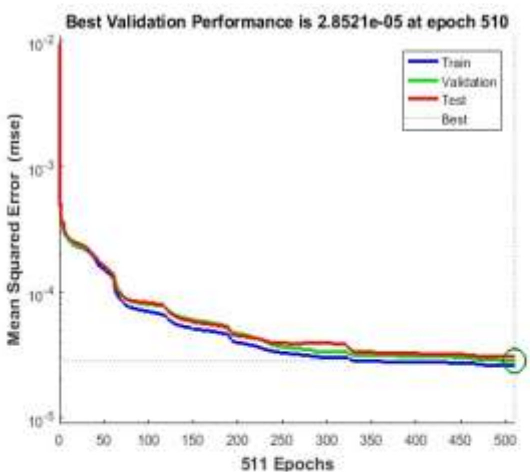

Figure 22 – MSE performance graph for A – B fault detection

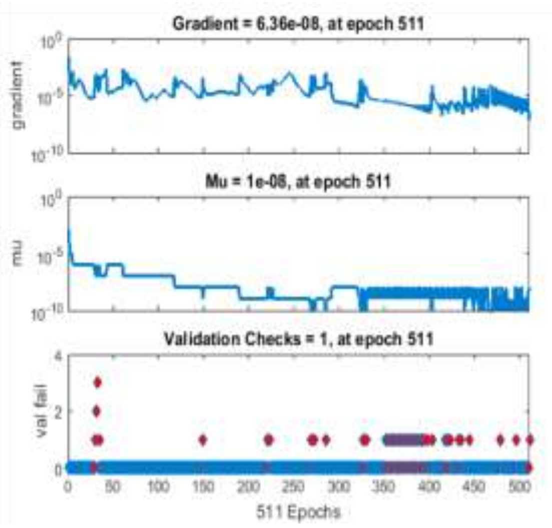

Figure 23 – Gradient and validation graph for A – B fault detection

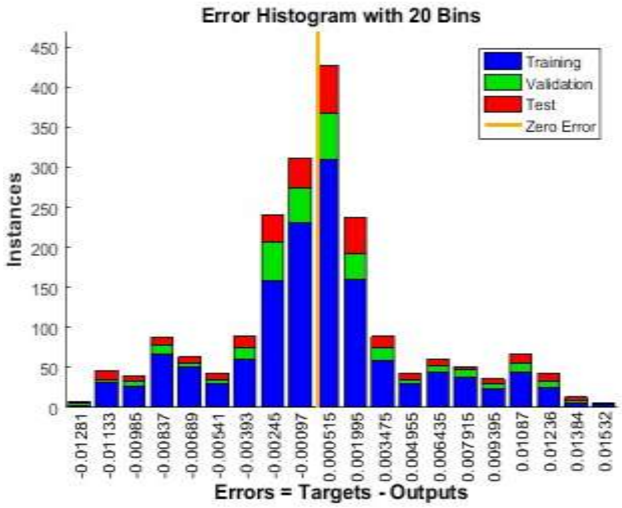

Figure 24 – Error Histogram for A – B fault detection

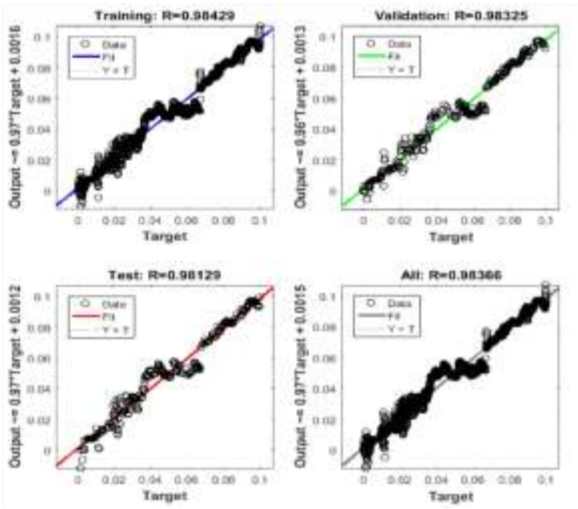

Figure 25 – Regression analysis graph for A – B fault detection

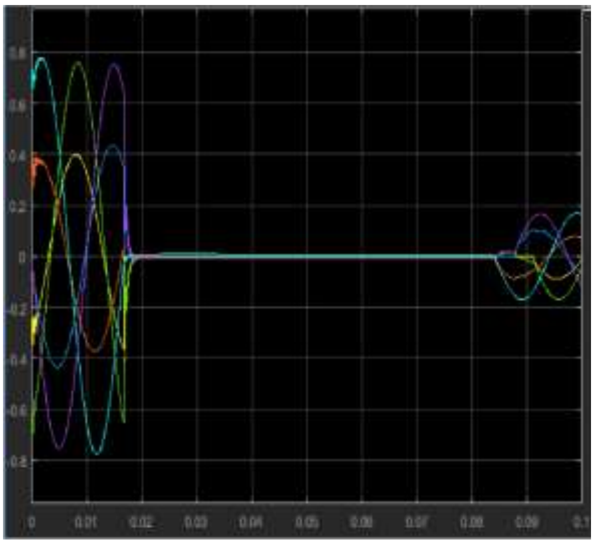

Figure 26: Phase ABC three phase fault voltage and current signal waveform

This waveform illustrates the amplitudes of the voltage and current when phase ABC fault occurred on the transmission line.

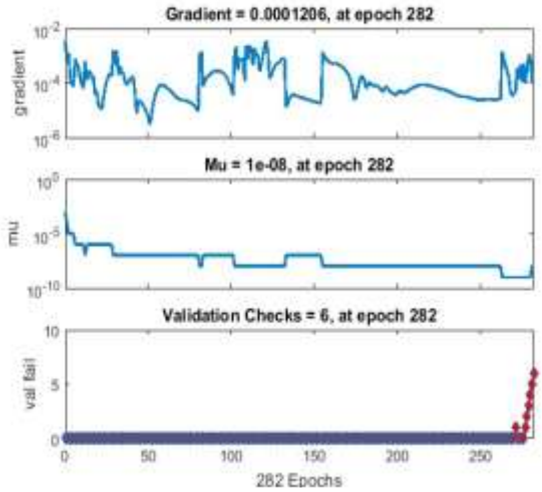

Figure 27 – ANN training procedure for ABC fault detection

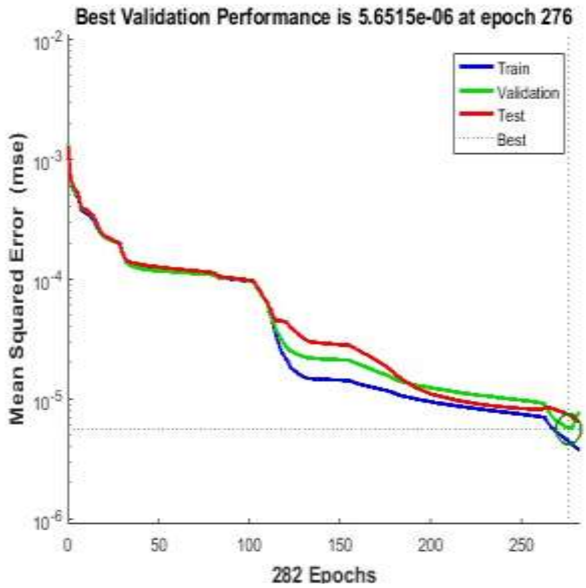

Figure 28 – MSE Performance graph for ABC fault detection

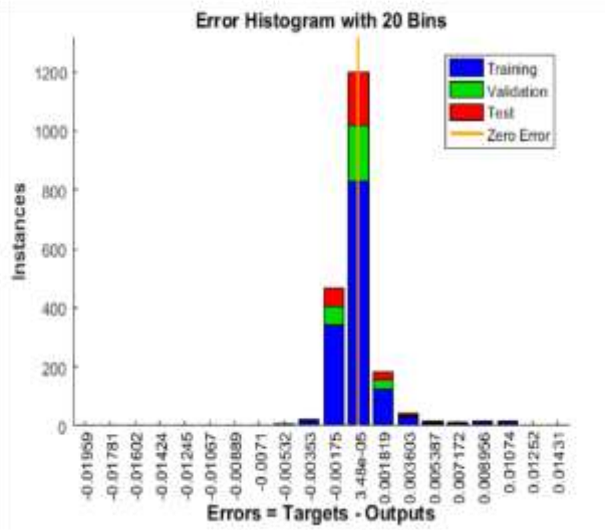

Figure 29 – Error histogram for ABC fault detection

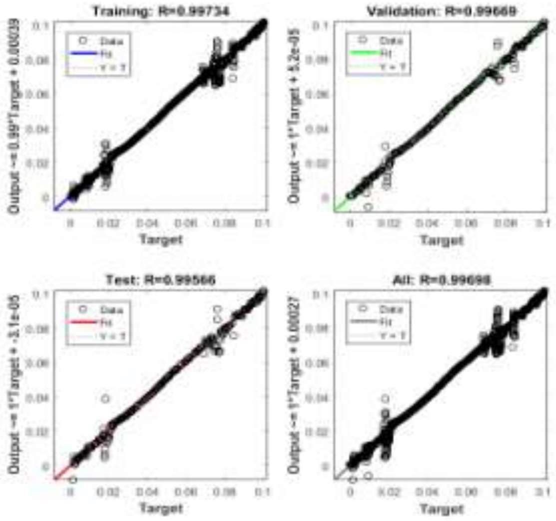

Figure 30 – Regression analysis for ABC fault detection

Fault Detection Using Simulation Data

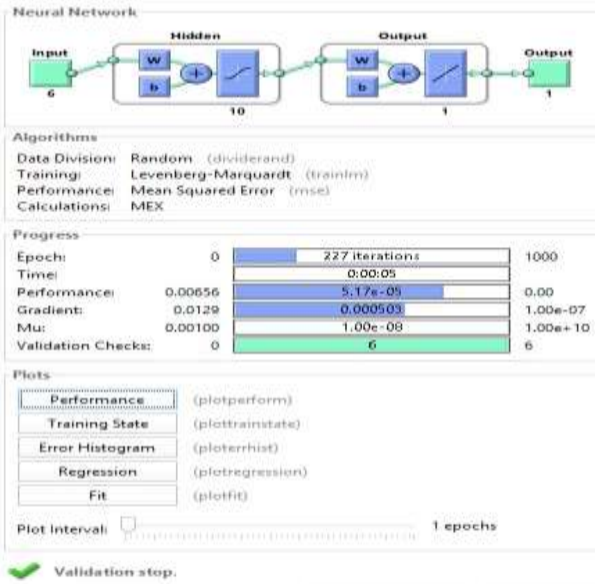

Figure 31 – ANN training procedure for A – G fault detection

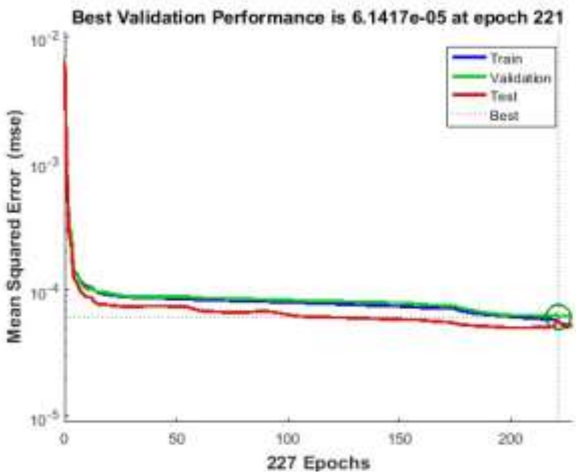

Figure 32 – MSE performance graph for A – G fault detection

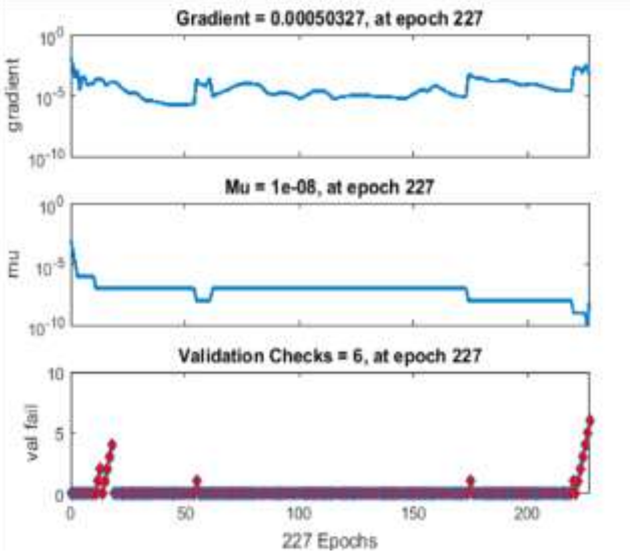

Figure 33 – Gradient and validation graph for A – G fault detection

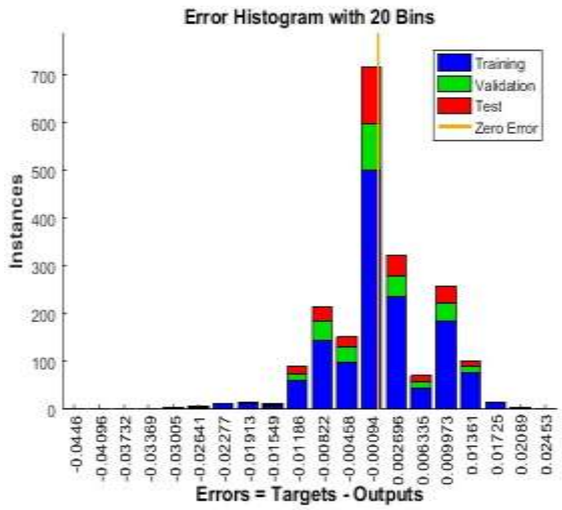

Figure 34 – Error histogram for A – G fault detection

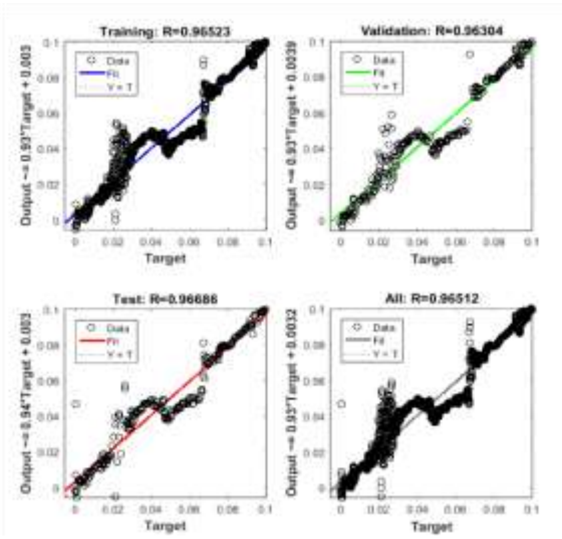

Figure 35 – Regression analysis graph for A – G fault detection

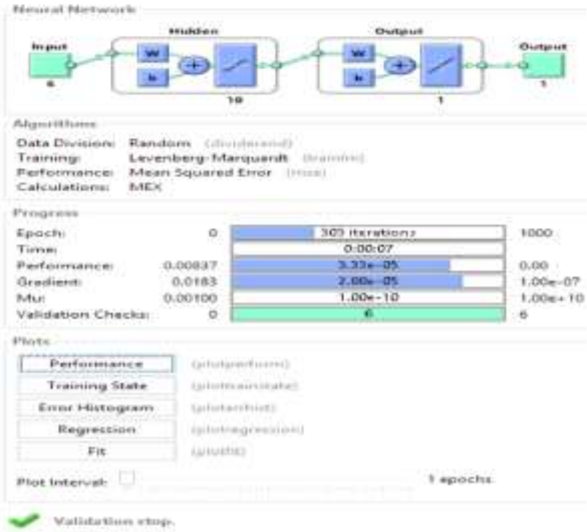

Figure 36 – ANN training procedure for AB – G fault detection

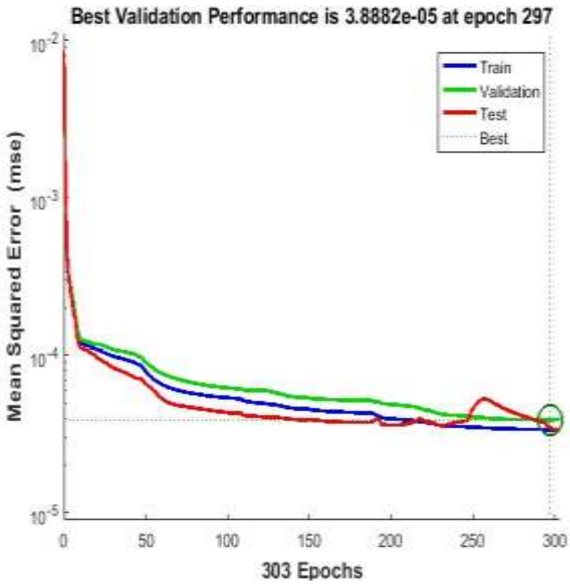

Figure 37 – MSE performance graph for AB – G fault detection

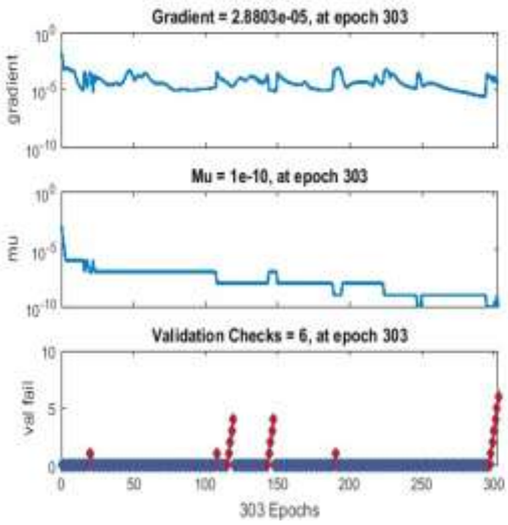

Figure 38 – Gradient and validation graph for AB – G fault detection

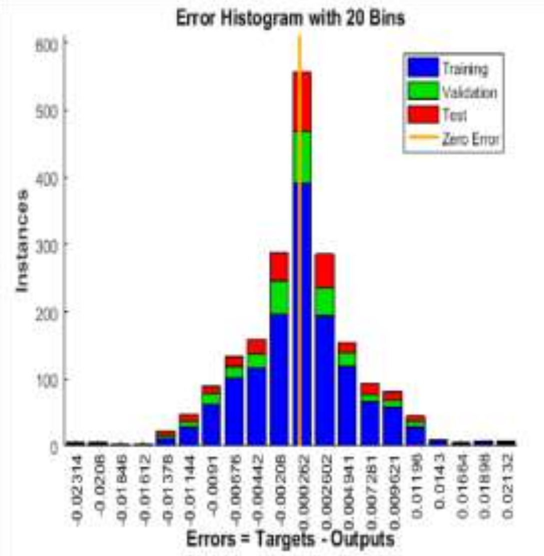

Figure 39 – Error histogram for AB – G fault detection

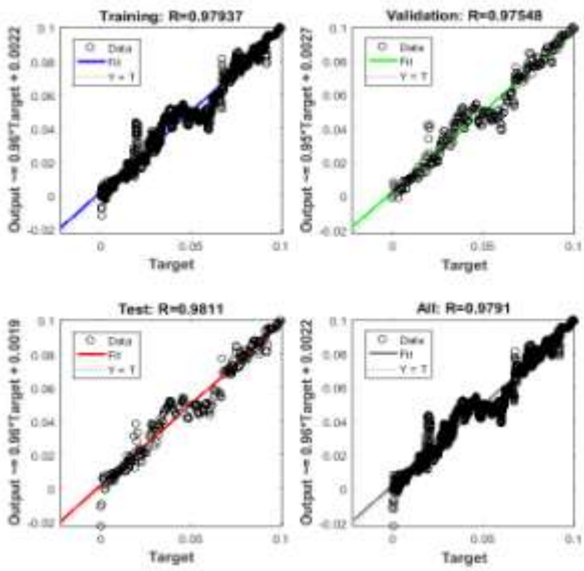

Figure 40 – Regression analysis graph for AB – G fault detection

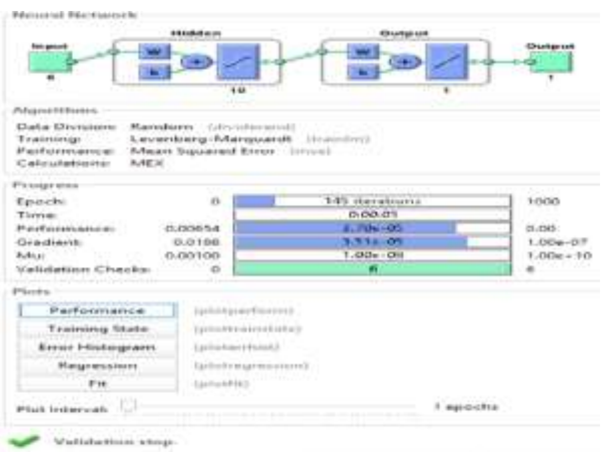

Figure 41 – ANN training procedure for A – B fault detection

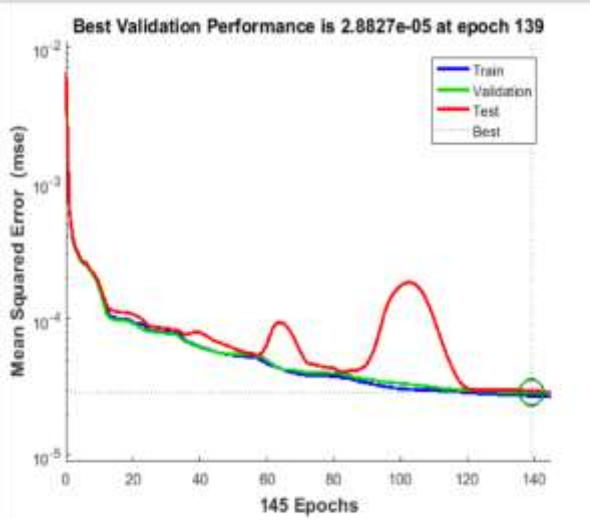

Figure 42 – MSE performance graph for A – B fault detection

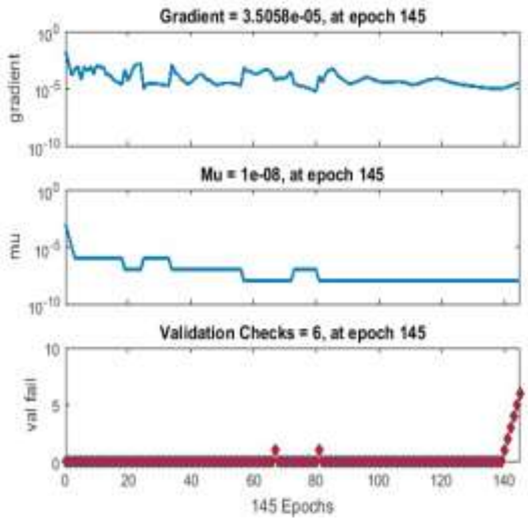

Figure 43 – Gradient and validation graph for A – B fault detection

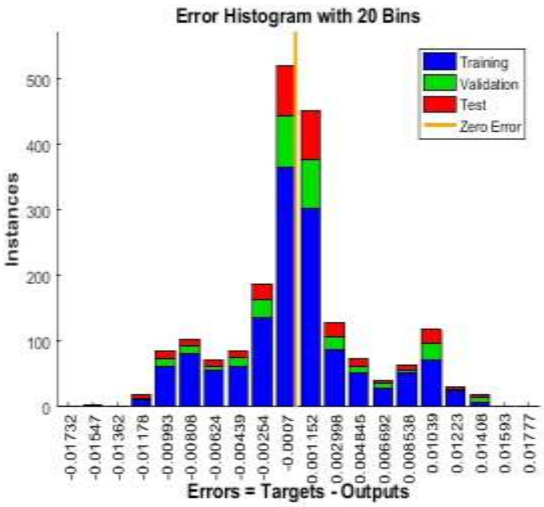

Figure 44 – Error histogram for A – B fault detection

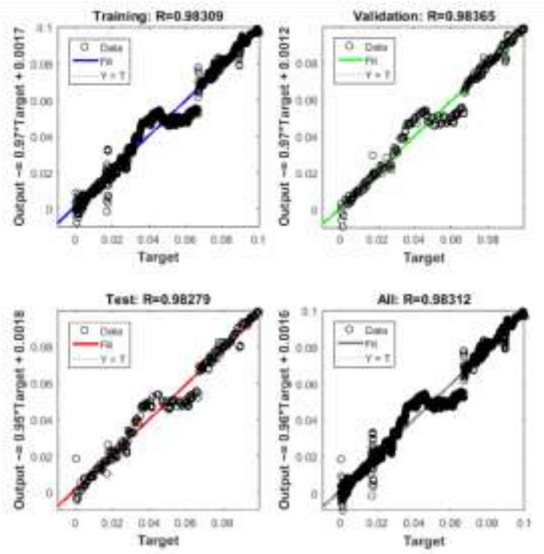

Figure 45 – Regression analysis graph for A – B fault detection

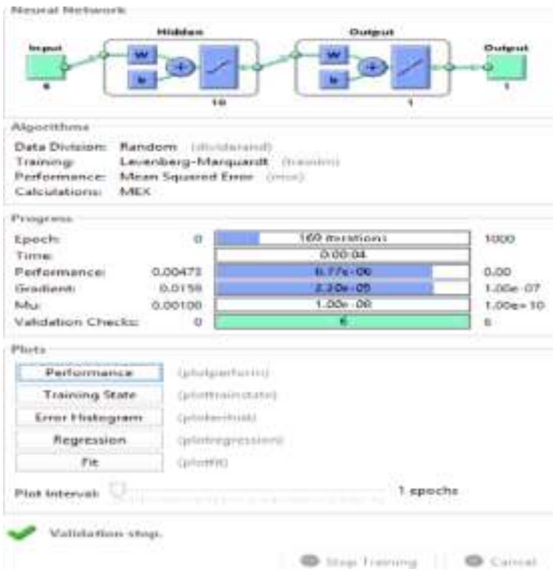

Figure 46 – ANN training procedure for ABC fault detection

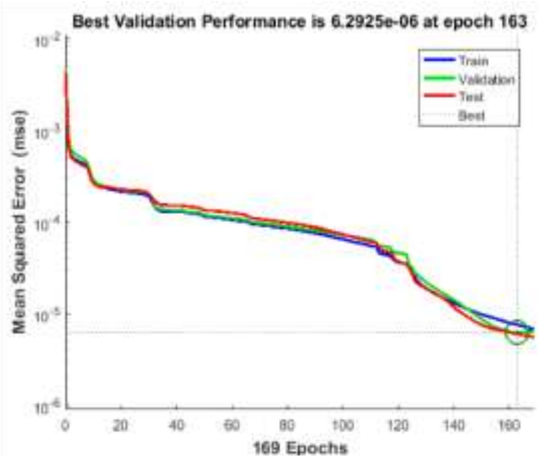

Figure 47 – MSE Performance graph for ABC fault detection

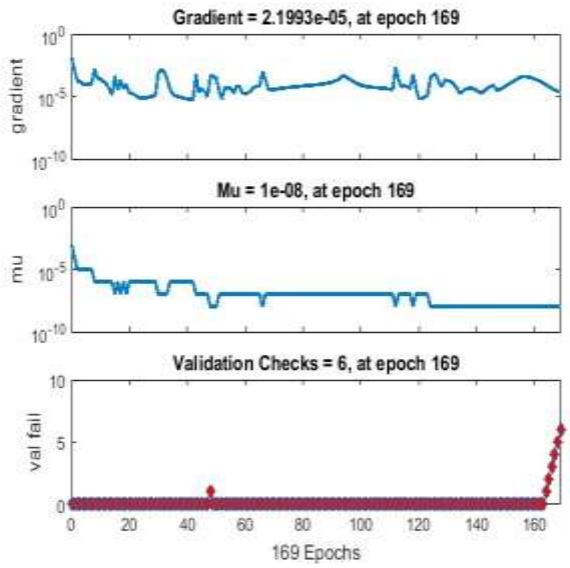

Figure 48 – Gradient and validation graph for ABC fault detection.

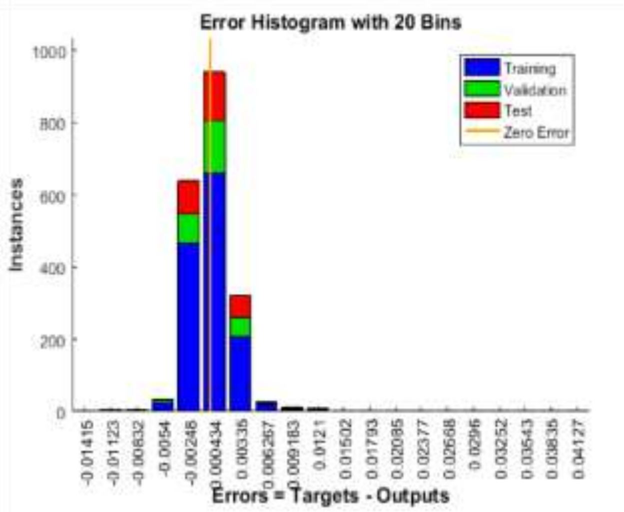

Figure 49 – Error histogram for ABC fault detection

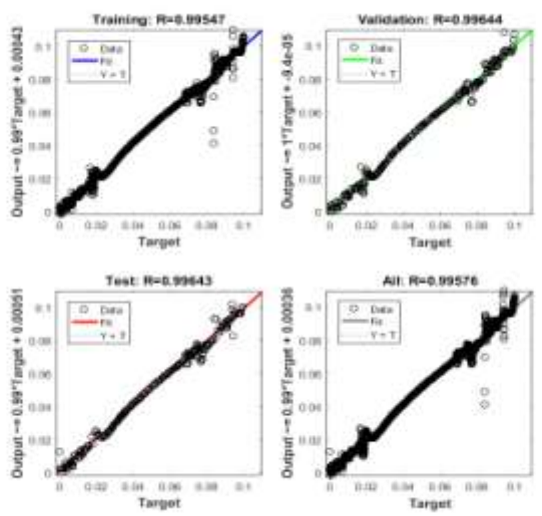

Figure 50 – Regression analysis graph for ABC fault detection

Table 3: ANN fault detection result using real data

S/NO	MSE (Performance)	Regression (R)	Gradient	Faults
1	7.0113×10^{8}	0.95840	6.7023×10^{8}	A – G
2	3.1135×10^{6}	1.00000	6.8713×10^{6}	AC – G
3	2.8521×10^{7}	0.98370	6.3600×10^{8}	A – B
4	5.6515×10^{-6}	0.99698	1.2060×10^{-4}	ABC

Table 4: ANN fault detection result using simulated data

S/NO	MSE(Performance)	Regression (R)	Gradient	Faults
1	6.1417×10^{5}	0.96512	5.0327×10^{4}	A – G
2	3.8882×10^{9}	0.97910	2.8803×10^{9}	AB – G
3	2.8827×10^{5}	0.98312	3.5058×10^{9}	A – B
4	6.2923×10^{4}	0.99576	2.1993×10^{9}	ABC

VII. CONCLUSION

The ANN does not require the impedance calculation on the line but per unit value phase voltages and currents are used. It can accept large amount of data, train it and give accurate result in a short time.
ANN is fast, accurate, simple and able to generate a program which when simulated or ran produces the entire results or tells more about the detail process of diagnosis.

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