

## Artificial Neural Network Method for Fault Detection on Transmission Line

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**ABSTRACT:** This research work examined the detection of various kinds of fault that occurs on the electric power system transmission line using artificial neural network (ANN). A typical 132KV real line data (parameters) from Enugu transmission line station was used to model the power system transmission line in MATLAB R2010a. Simulations were performed on the power transmission line modelled with real and generated line parameters and obtained graphical results for both parameters. The two versions of parameters were also used to train and simulate the ANN network architecture selected for each stage of the detection. The results obtained show that, three line – ground, three line – line, three double line – ground and one three phase faults occurred in the system. Performance and regression analysis graphs of output versus target also show the convergence of the network output with respect to the target values and the best line of fitting of the network. Simulation results have been provided to demonstrate that artificial neural network based methods are efficient in detection faults on transmission lines and achieve satisfactory performances.

**KEYWORD:** Artificial neural network, transmission line, matlab Simulink, simpowersystem

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Date of Submission: 23-02-2019

Date of acceptance: 14-03-2019

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### I. INTRODUCTION

The increasing complex nature of modern power system transmission system requires that, a reliable and effective power system protection scheme is installed for fast operation in protecting the transmission line.

Considering the complex nature of the modern transmission system, one of the factors that hinder the continuous operation of this transmission line is faults. These faults are categorized into transient, persistent, symmetrical and unsymmetrical faults.

Moreover, they are inevitable and must be detected and cleared within the shortest possible time to avoid damaging of the electrical power system equipment or power outage. The faults must be cleared quickly so as to restore electric power to the isolated area.

The protection of the transmission line requires that, the fault must be detected and cleared using various devices such as, relay, circuit breaker, current transformer, voltage transformer etc.

Hence some of the important challenges for the incessant supply of power are detection, classification and location of faults. Faults can be of various types namely transient, persistent, symmetric or asymmetric faults and the fault detection process for each of these faults is distinctly unique in the sense, there is no one universal fault diagnosis technique for all these kinds of faults. The High Voltage Transmission Lines are more prone to the occurrence of these faults than the local distribution line, because, there is no insulation around the transmission line cables unlike the distribution lines. The reasons for the occurrence of a fault on a transmission line are due to the following, momentary tree contact, a bird or an animal contact with the cable or due to other natural reasons such as thunderstorms or lightning.

Fault diagnosis techniques can be broadly classified into the following categories:

- Impedance measurement based methods
- Travelling-wave phenomenon based methods
- High-frequency components of currents and voltages generated by faults based methods
- Intelligence based method

From quite a few years, intelligent based methods are being used in the process of fault detection and location. Three major artificial intelligence based techniques that have been widely used in the power and automation industry are:

- Expert System Techniques
- Artificial Neural Networks
- Fuzzy Logic Systems

Among these available techniques, Artificial Neural Networks (ANN) has been used extensively in this thesis for fault diagnosis on electric power transmission lines. These ANN based methods do not require a knowledge base for the location of faults unlike the other artificial intelligence based methods [1] [2].

## II. METHODOLOGY

Tests was done on figure 1 which is a single three phase transmission line system having two generators. Phasor voltage and current are assumed to be available from both ends of a single transmission line.

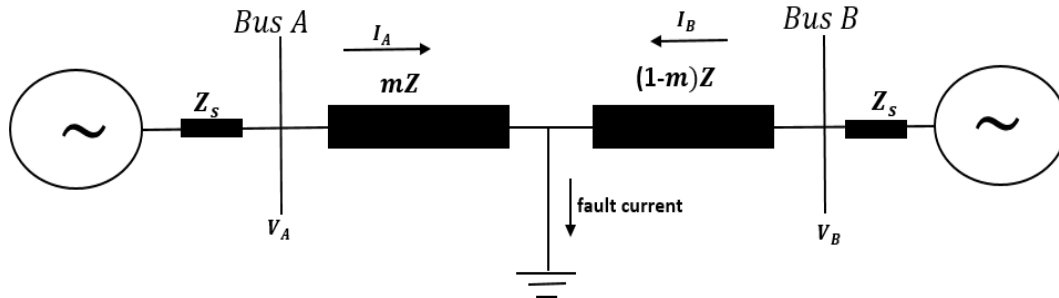


Figure 1: Faulted three phase transmission line

When faults occurred, recorded phasor voltages and currents were taken from both ends. Algorithms of the artificial neural network method written in MATLAB were used. Different fault types were made to occur at different locations on transmission lines. Fault voltages and fault currents were taken and given as input to MATLAB for detection of the fault.

The transmission lines of length 300Km were modeled in SimPowerSystems. The current samples waveform was given as input to MATLAB.

### B. Modelling the Power Transmission Line System

A 132 kV transmission line system has been used to develop and implement the proposed strategy using ANN. Figure 2 shows a one-line diagram of the system that was used throughout the research. The system consists of two generators for 132 kV each located on either ends of the transmission line along with a three phase fault simulator used to simulate faults at various positions on the transmission line. The line has been modeled using distributed parameters so that it more accurately describes a very long transmission line. The parameters in per units are shown below[3].

Frequency =50Hz, Real Power = 87.7MW, Reactive Power = 21.4MVAR, Apparent Power = 90.27MVA, Line Voltage = 132KV, Line Distance = 96KM

$R_1 = 0.0114pu$ ,  $R_0 = 0.2466pu$ ,  $L_1 = 0.0009pu$ ,  $L_0 = 0.0031pu$ ,  $C_1 = 0.1343pu$ ,  $C_0 = 0.0859pu$ ,  $Z_1 = 0.2603pu$  and  $Z_0 = 0.2601pu$ .

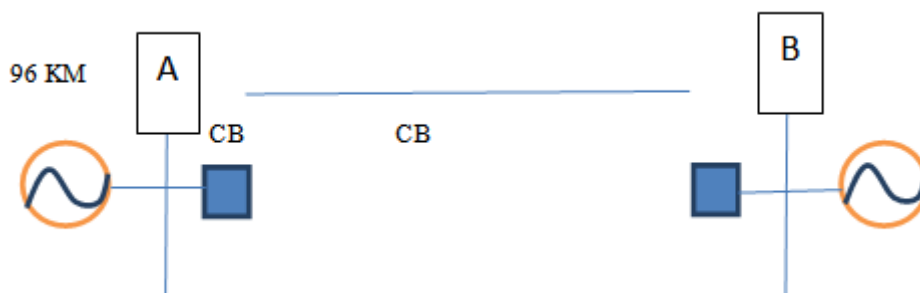


Figure 2: One-line diagram of the studied system

This power system was simulated using the Sim Power Systems toolbox in SimulinkMatlab. A snapshot of the model used for obtaining the training and test data sets is shown in figure 3 in which  $Z_P$  and  $Z_Q$  are the source impedances of the generators on either side. The three phase V-I measurement block is used to measure the voltage and current samples at terminal A. The transmission line (line 1 and line 2 together) is 96 km long [3].

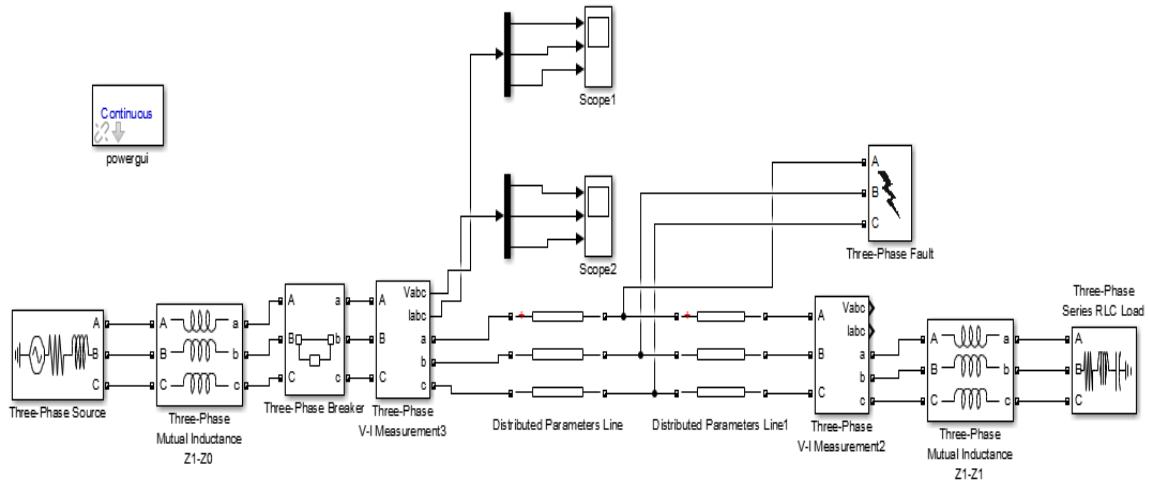


Figure 3: Snapshot of the studied model in SimPowerSystems.

Figure 3 is a transmission line diagram modeled using Matlab 2010. It contains Simulink blocks for three phase power source, three phase circuit breaker, three phase voltage /current measurement, two line and a three phase series RLC load. It also contain a Simulink block for three phase fault which is used to for the simulation of various unbalanced fault. Each of the unbalanced fault type was simulated and per unit voltage and current values for both normal and faulty conditions of the line where obtained during the simulation. The values of the three-phase voltages and currents are measured using the three phase measurement Simulink block, modified accordingly and are ultimately fed into the neural network as inputs. The SimPowerSystems toolbox has been used to generate the entire set of training data for the neural network in both fault and non-fault cases [5].

Faults can be classified broadly into four different categories namely:

- Line to ground faults
- Line to line faults
- Double-line to ground faults
- Three-phase faults

### III. FAULT DETECTION

The inputs of the network selected for the detection of fault are the three phase currents ( $\mathbf{I} = \{I_a I_b I_c\}^T$ ) and voltages ( $\mathbf{V} = \{V_a V_b V_c\}^T$ ) of the line obtained as a raw data and a generated data from the Transmission line communication unit Enugu (TRANSCO) and MatlabSimpowersystem respectively. The real and the generated per unit values of phase voltage and current were sampled with the target values into the input neurons of the selected ANN, trained and produced outputs of different types of fault detected on the transmission line.

### IV. DATA PRE-PROCESSING

A reduction in the size of the neural network improves the performance of the same and this can be achieved by performing feature extraction. By doing this, all of the important and relevant information present in the waveforms of the voltage and current signals can be used effectively. The per unit voltage and current samples of all the three phases obtained through the simulation of the modeled transmission line using matlab 2010 for both normal and faulty conditions were used for the simulation, training and testing of the neural network automatically selected by the ANN training algorithm for the fault diagnosis.

### V. TRAINING PROCESS

Two important steps in the application of neural networks for any purpose are training and testing. The first of the two steps namely training the neural network is discussed in this section. Training is the process by which the neural network learns from the inputs and updates its weights accordingly. In order to train the neural network we need a set of data called the training data set which is a set of input output pairs fed into the neural network. Therefore, we teach the neural network what the output should be, when that particular input is fed into it. The ANN slowly learns the training set and slowly develops an ability to generalize upon this data and will eventually be able to produce an output when a new data is provided to it. During the training process, the neural network's weights are updated with the prime goal of minimizing the performance function. This

performance function can be user defined, but usually feed forward networks employ Mean Square Error as the performance function and the same is adopted throughout this work.

As already mentioned in the previous chapter, all the voltages and currents fed into the neural network are scaled with respect to the corresponding voltage and current values before the occurrence of the fault.

For the task of training the neural networks for the different stages, sequential feeding of input and output pair has been adopted. In order to obtain a large training set for efficient performance, each of the ten kinds of faults has been simulated at different locations along the considered transmission line [6].

Apart from the type of fault, the phases that are faulted and the distance of the fault along the transmission line, the fault resistance also has been varied to include several possible real-time fault scenarios.

## VI. TESTING PROCESS

As already mentioned in the previous section, the next important step to be performed before the application of neural networks is to test the trained neural network. Testing the artificial neural network is very important in order to make sure the trained network can generalize well and produce desired outputs when new data is presented to it.

There are several techniques used to test the performance of a trained network, a few of which are discussed in this section. One such technique is to plot the best linear regression fit between the actual neural network's outputs and the desired targets. Analyzing the slope of this line gives us an idea on the training process. Ideally the slope should be 1. Also, the correlation coefficient ( $r$ ), of the outputs and the targets measures how well the ANN's outputs track the desired targets. The closer the value of ' $r$ ' is, to 1, the better the performance of the neural network. Another technique employed to test the neural network is to plot the confusion matrix and look at the actual number of cases that have been classified positively by the neural network. Ideally this percentage is a 100 which means there has been no confusion in the classification process. Hence if the confusion matrix indicates very low positive classification rates, it indicates that the neural network might not perform well. The last and a very obvious means of testing the neural network is to present it with a whole new set of data with known inputs and targets and calculate the percentage error in the neural networks output. If the average percentage error in the ANN's output is acceptable, the neural network has passed the test and can be readily applied for future use.

The Neural Network toolbox in Matlab divides the entire set of data provided to it into three different sets namely the training set, validation set and the testing set. The training data set as indicated above is used to train the network by computing the gradient and updating the network weights. The validation set is provided during to the network during the training process (just the inputs without the outputs) and the error in validation data set is monitored throughout the training process. When the network starts over fitting the data, the validation errors increase and when the number of validation fails increase beyond a particular value, the training process stops to avoid further over fitting the data and the network is returned at the minimum number of validation errors. The test set is not used during the training process but is used to test the performance of the trained network. If the test set reaches the minimum value of MSE at a significantly different iteration than the validation set, then the neural network will not be able to provide satisfactory performance.

For the purpose of fault detection, various topologies of Multi-Layer Perceptron have been studied. The various factors that play a role in deciding the ideal topology are the network size, the learning strategy employed and the training data set size.

After an exhaustive study, the back-propagation algorithm was chosen as the ideal topology. Even though the basic back-propagation algorithm is relatively slow due to the small learning rates employed, few techniques can significantly enhance the performance of the algorithm. One such strategy is to use the Levenberg-Marquardt optimization technique. The selection of the apt network size is very vital because this not only reduces the training time but also greatly enhances the ability of the neural network to represent the problem in hand. Unfortunately there is no thumb rule that can dictate the number of hidden layers and the number of neurons per hidden layer in a given problem [6] [7].

**Table 1** – Per unit values of the phase voltages and currents of the transmission line generated during simulation.

S/No	Input values						Fault types
1	$V_a$	$V_b$	$V_c$	$I_a$	$I_b$	$I_c$	
2	0.5000	0.5000	0.5000	0.1500	0.1500	0.1500	No fault
3	0.4200	0.4800	0.4100	0.7750	0.1200	0.1250	A – G
4	0.4800	0.4500	0.4300	0.1480	0.6850	0.1050	B – G
5	0.4300	0.4200	0.4100	0.1480	0.1250	0.5150	C – G
6	0.5000	0.4800	0.4800	0.8200	0.7000	0.1200	A – B
7	0.4800	0.5200	0.4900	0.1480	0.8480	0.8000	B – C
8	0.5200	0.4800	0.4700	0.8700	0.1480	0.9250	C – A
9	0.4700	0.4600	0.4700	0.2200	0.1050	0.1250	A – B – G

10	0.4200	0.5000	0.4600	0.1480	0.1450	0.1650	B – C – G
11	0.4800	0.4300	0.4000	0.2000	0.1480	0.1450	C – A – G
12	0.4000	0.4500	0.4900	0.2200	0.1400	0.1490	A – B – C

**Table 2** – Per unit values of the phase voltages and currents of the transmission line obtained from Onitsha 132KV Transmission station.

S/N	Input values						Fault types
	V <sub>a</sub>	V <sub>b</sub>	V <sub>c</sub>	I <sub>a</sub>	I <sub>b</sub>	I <sub>c</sub>	
1	0.35	0.35	0.35	0.12	0.12	0.12	No fault
2	0.37	0.48	0.45	0.875	0.22	0.325	A – G
3	0.46	0.46	0.43	0.048	0.775	0.005	B – G
4	0.43	0.42	0.41	0.148	0.125	0.515	C – G
5	0.65	0.58	0.58	0.72	0.78	0.02	A – B
6	0.42	0.57	0.44	0.148	0.85	0.76	B – C
7	0.62	0.58	0.57	0.82	0.048	0.945	C – A
8	0.56	0.66	0.66	0.33	0.125	0.145	A – B – G
9	0.57	0.5	0.56	0.158	0.165	0.165	B – C – G
10	0.66	0.63	0.5	0.3	0.138	0.135	C – A – G
11	0.5	0.55	0.59	0.25	0.14	0.139	A – B – C
12							

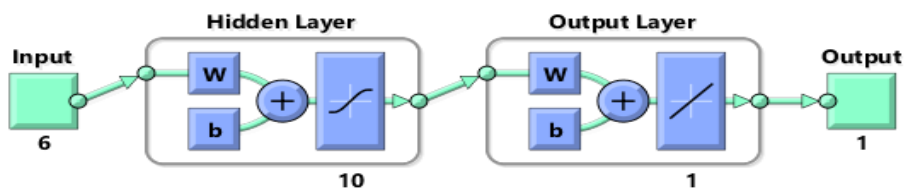
The per unit phase voltage and current used were generated values from the Matlab Simulink modeled transmission line diagram.

### VII. TRAINING THE FAULT DETECTION NEURAL NETWORK

In the first stage which is the fault detection phase, the network takes in six inputs at a time, which are the voltages and currents shown above in table 1 for all the three phases a, b and c (scaled with respect to the pre-fault values) for ten different faults and also no-fault case. Hence the training set consisted of about 1100 input output sets (100 for each of the ten faults and 100 for the no fault case) with a set of six inputs and one output in each input-output pair. The output of the neural network is just a yes or a no (1 or 0) depending on whether or not a fault has been detected. After extensive simulations it has been decided that the desired network has one hidden layer with 10 neurons in the hidden layer as shown in the figure 4.1 below. For illustration purposes, several neural networks (with varying number of hidden layers and neurons per hidden layer) that achieved satisfactory performance are shown and the best neural network has been described further in detail.

### VIII. RESULTS AND ANALYSIS

The Figure 4 shows the chosen neural network 6-10-1 contains 6 neurons in the input layer, 1 hidden layer with ten neurons in it and one neuron in the output layer.



**Figure 4:** BP neural network architecture chosen for fault detection 6-10-1

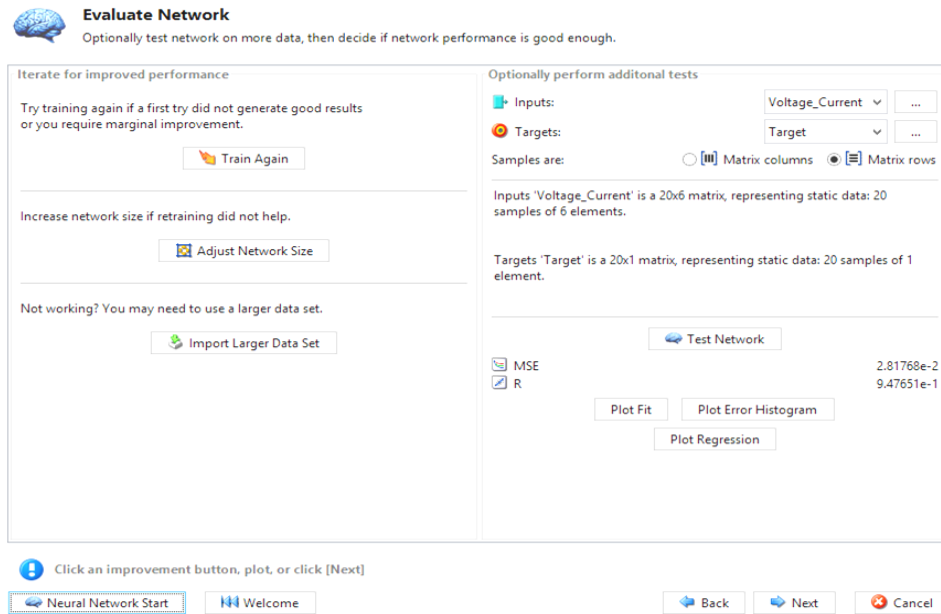


Figure 5: Training procedure of the matlab generated data for detection of fault

The overall MSE of the trained neural network for the detection of fault is actually  $2.81768 \times 10^{-2}$  by the end of the training process. Hence this has been chosen as the ideal ANN for the purpose of fault detection.

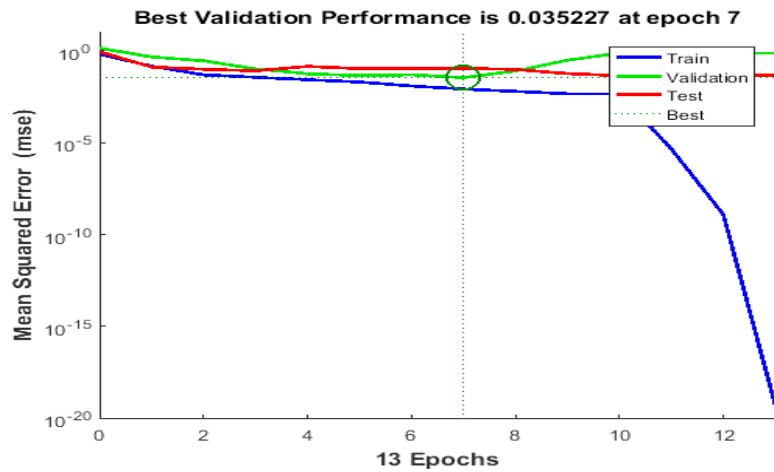


Figure 6: Mean-square error (MSE) performance graph of the chosen network for the generated data

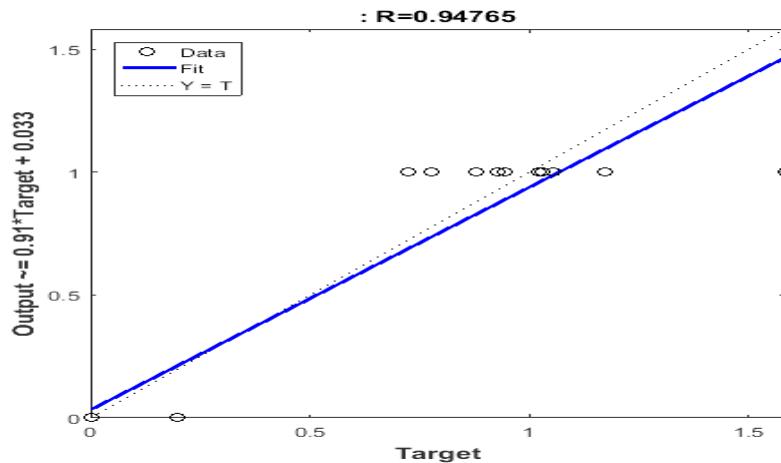


Figure 7: Regression analysis graph of the chosen neural network for fault detection using generated data

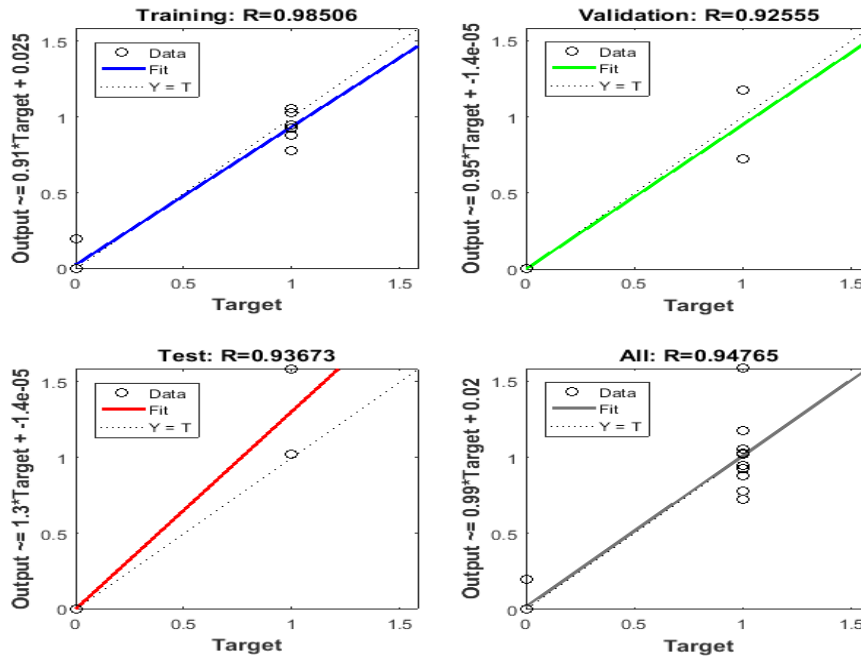


Figure 8: Overall Regression plot of the chosen neural network for detection using generated data

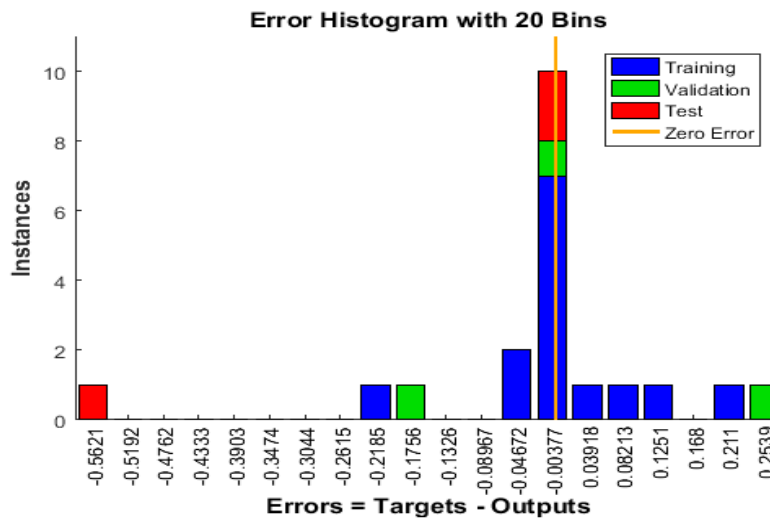


Figure 9: Histogram showing difference between the target and output value.

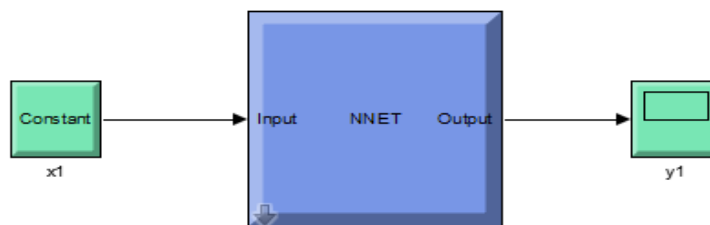


Figure 10: Mask ANN Simulink block diagram of the chosen neural network

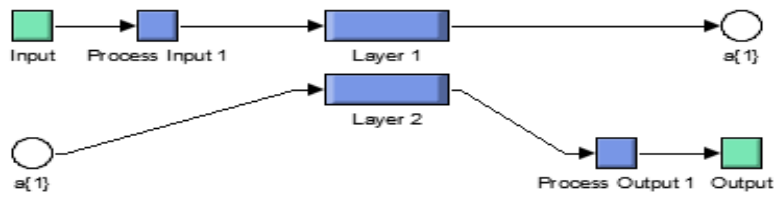


Figure 11: Unmask ANN Simulink block diagram of the chosen neural network

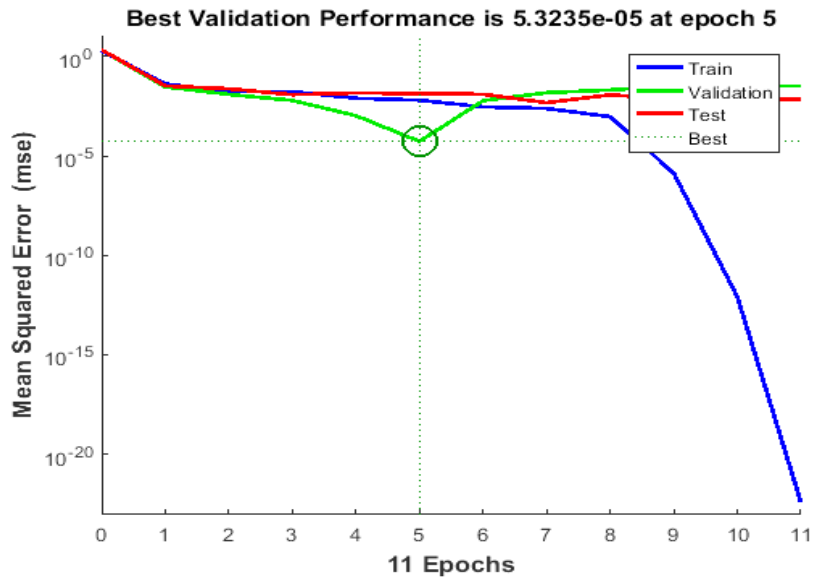


Figure 12: Mean-square error (MSE) performance graph of the chosen network for the real data

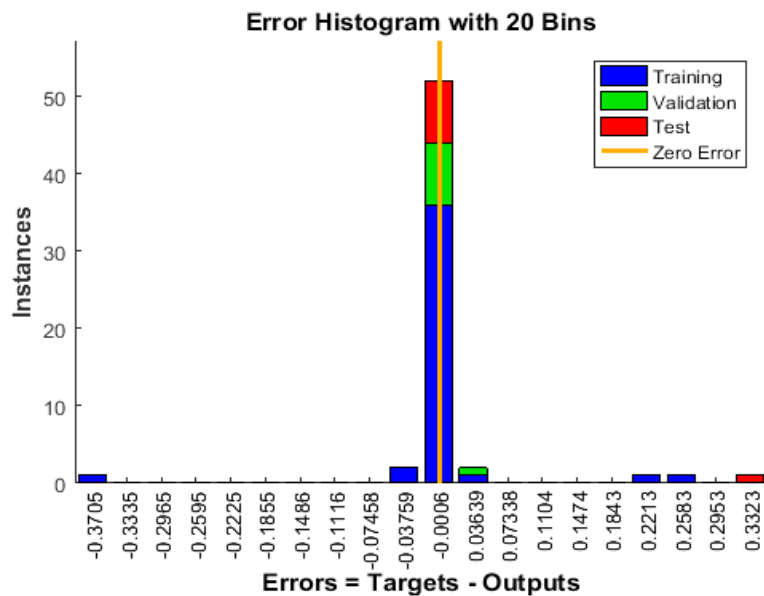


Figure 13: Histogram showing difference between the target and output value real data



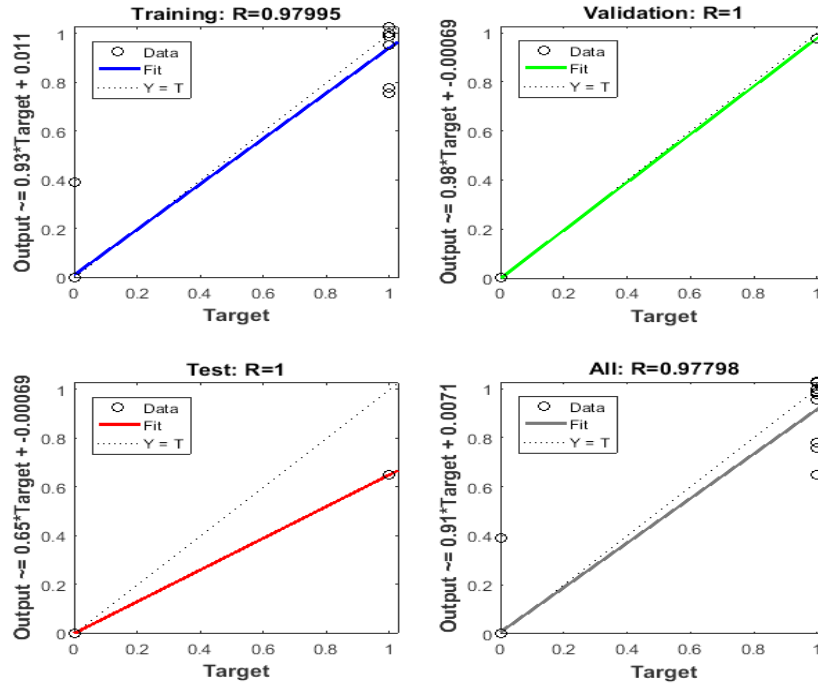


Figure 14: Overall Regression plot of the chosen neural network for detection using real data

### IX. TESTING THE FAULT DETECTION NEURAL NETWORK OBTAINED USING GENERATED DATA

Once the neural network has been trained, its performance has been tested by three different factors. The first of these is by plotting the best linear regression graph that relates the targets to the outputs as shown in Figure 4.7 and 4.11 for simulated and real data respectively.

According to the learning and training rule, if the regression R is 1 or approximately 1, it means there is no error difference or no much difference between the target and the output respectively. However, after the training of the ANN selected for the detection, the value of regressions obtained for both data types are 0.94765 and 0.97798, which is approximately 1. But the real data is closer to 1 than that of simulation with the difference of 0.03033.

Table 2: Comparison between the performance, regression of real and simulated data.

S/NO	DATA TYPE	PERFORMANCE VALUE (MSE)	REGRESSION VALUE
1	Real Data	5.3235e-5	0.97798
2	Simulated Data	0.035227	0.94765

This thesis has studied the usage of hybrid neural networks as an alternative method for the detection, classification and location of faults on transmission lines. The methods employed make use of the phase voltages and phase currents (scaled with respect to their pre-fault values) as inputs to the neural networks. Various possible kinds of faults namely single line-ground, line-line, double line-ground and three phase faults have been taken into consideration into this work and separate ANNs have been proposed for each of these faults.

All the neural networks investigated in this thesis belong to the back-propagation neural network architecture. A fault diagnosis scheme for the transmission line system, right from the detection of faults on the line to the fault location stage has been devised successfully by using hybrid artificial neural-network modules.

The simulation results obtained prove that satisfactory performance has been achieved by all of the proposed neural networks in general. As further illustrated, depending on the application of the neural network and the size of the training data set, the size of the ANN (the number of hidden layers and number of neurons per hidden layer) keeps varying. The importance of choosing the most appropriate ANN configuration, in order to get the best performance from the network, has been stressed upon in this work. The sampling frequency adopted for sampling the voltage and current waveforms in this thesis is just 720 Hz which is very low compared to what has been used in the literature (a major portion of the works in literature utilized 2 kHz – 5 KHz).

To simulate the entire power transmission line model and to obtain the training data set, MATLAB R2016a has been used along with the Sim Power Systems toolbox in Simulink. In order to train and analyze the performance of the neural networks, the Artificial Neural Networks Toolbox has been used extensively.

## **X. CONCLUSION**

The Artificial Neural Networks are indeed a reliable and attractive scheme for an ideal transmission line fault diagnosis scheme especially in view of the increasing complexity of the modern power transmission systems.

Back Propagation neural networks are very efficient when a sufficiently large training data set is available and hence Back Propagation networks have been chosen for all the three steps in the fault diagnosis process namely fault detection, classification and fault location.

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## **REFERENCE**

- [1]. Saha, M. & Rosolowski, E. (2010). "Fault Location on Power Networks. Springer Publications, vol. 114(3), pp. 24-36
- [2]. Saha, M. & Rosolowski, E. (2004). "A Method of Fault Location Based on Measurements from Impedance Relays at the Line Ends." Proceedings of the 8<sup>th</sup> International Conference on Developments in Power Systems Protection – DPSP, IEE, vol. CP500, pp. 176-179.
- [3]. Kezunovic, M. (2011). "A survey of Neural Net Applications to Protective Relaying and Fault Analysis." International Journal of Engineering Intelligence Systems for Electronics, Engineering and Communications, vol. 5(4), pp. 185-192.
- [4]. Kezunovic, M., Rikalo, I., & Sobajic, D. J. (1996). "Real-Time and Off-Line Transmission Line Faulty Classification Using Neural Networks." Engineering Intelligent Systems, vol. 10, pp. 57-63.
- [5]. Matlab 2015 version
- [6]. Lahiri, U., Pradhan, A. K., & Mukhopadhyaya, S. (2015). "Modular Neural-Network Based Directional Relay for Transmission Line Protection." IEEE Trans. On Power Delivery, vol. 20(4), pp. 2154-2155.

Okwudili O. E" Artificial Neural Network Method for Fault Detection on Transmission Line"  
International Journal of Engineering Inventions, Vol. 08, No. 1, 2019, pp. 47-56