American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-10, Issue-01, pp-01-10
www.ajer.org
Research Paper Open Access

A Comparative Analysis of Artificial Neural Network- Based Power Transmission Line Fault Classifiers

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ABSTRACT : *Transfer of large blocks of power is economically done between using overhead transmission lines which are prone to undue interruption of continuous flow known as fault. There are various types of fault and proper diagnoses of the type of fault helps to have a quick restoration of power flow. Hence a fault Classifiers with high accuracy, specificity and sensibility is needed. This paper compares the performance of FFNN classifier and Elman classifier using Leverberg Marquadrt as training technique and compare using training parameters, sensitivity, accuracy and specificity as performance metrics. FFNN gives a better result and more satisfactory..*

KEYWORDS*: Fault ; classifier; Faults, Transmission line; Elman Network*

Date of Submission: 26-12-2020 Date of acceptance: 06-01-2021

I. INTRODUCTION

Fault in the context of this research work, is a defect on transmission line, responsible for discontinuity of electricity flow along a predetermined path [1]. Faults cannot be completely avoided in transmission lines since a portion of these faults also occur due to natural reasons, which cannot be controlled by humankind [2]. It was observed that planned outages on the transmission lines, recorded the highest value of only 7% while, the remaining 93% were due to either forced outages or emergency or urgent outages as a result of fault occurrence, [3]. This suggested that the reliability of the network is very low due to fault occurrences and handling, resulting in very low efficiency and disruption in the lives of the citizenry. Faults are usually taken care of by devices that detect the occurrence of a fault and eventually isolate the faulted section from the rest of the power system [4]. There are various types of fault and proper diagnoses of the type of fault helps to have a quick restoration of power flow [5]. Classifiers of faults must therefore have high accuracy, specificity and sensibility to detect and classify faults at the shortest possible time, so as to shorten fault rectification time and manage resources well; this makes the power system more reliable. Neural network based classifiers are able to achieve this.

A neural network is a parallel system, capable of resolving paradigms that linear computing cannot. They are used for applications where formal analysis is difficult or impossible such as pattern recognition and nonlinear system identification and control [2]. A neural network when created, has to be configured which is done using training function. Artificial neural networks may probably be the single most successful technology in the last two decades, which has been widely used in a large variety of applications. [6]. There are various types of neural network due to the neuron model and the architecture, which describe how a network transforms its input into an output. The model and the architecture places limitations on what particular neural network can compute or address a particular problem. Some of the examples include Feed Forward Neural Network (FFNN), Self - Organizing Map (SOM), Hopfield Neural Network, Radial Basis Function (RBF) Network and Elman network. [7]

Artificial neural network (ANN) can be applied to fault detection and classification effectively because it is a programming technique capable to solve the nonlinear problems easily [8]. Therefore, this paper compares the functionality of two types of ANN for fast and reliable fault detection and classification. The various processes of modelling, training, simulations and testing were also implemented on 330 kV transmission network. The ANN based algorithm was developed for recognition of these faulty patterns. The performance of the proposed algorithm was evaluated by simulating the various types of ground faults, to perform fast and correct classification for different combinations of faulty conditions.

II. DESCRIPTION OF THE TEST CASE STUDY

The necessary parameters of the transmission line conductors useful for its modeling were obtained from Transmission Company of Nigeria, Osogbo. The relay on the line has a small memory and does not give the fault type, sometimes when it trips for fault. Therefore, the 330 kV transmission line was represented by distributed line parameters with frequency dependency considered for accurate description of a long transmission line for modelling. A three phase fault simulator was used to simulate faults at various positions on the transmission line.

III. SYSTEM METHODOLOGY AND DESIGN

a. Feed- forward neural network

The feed forward neural network type is a simple neural network type where synapses (connections) are made from an input layer to zero or more hidden layers and ultimately to an output layer. There is no feedback connection involved in the network and hence the information travel is unidirectional, they are the most widely used neural networks. Figure 1. [4] shows a simple structure of a two-layered feed-forward network.

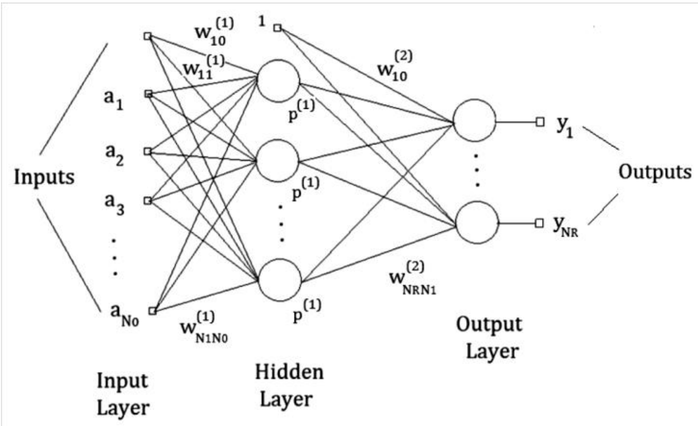

Figure 1: Structure of a two-layered feed-forward network. [4]

First, the network was trained by feeding learning patterns into the solution and by adjusting the weights according to some learning rules known as the supervised learning, unsupervised learning and reinforcement learning. The supervised learning or training has both the inputs and the expected target values known prior to the training of ANN. We then applied this technique to fault detection and classification in a power system.

b. Elman network

Elman network is a recurrent network made up of two back propagation network, with the addition of a feedback connection from the output of the hidden layer to its input. These recurrent connections give the network memory and allow the network to learn to recognize and generate temporal patterns, as well as spatial patterns [9]. The architecture of Elman network is shown in Figure 2. The Elman neural network is capable of providing the standard state-space representation for dynamic system.

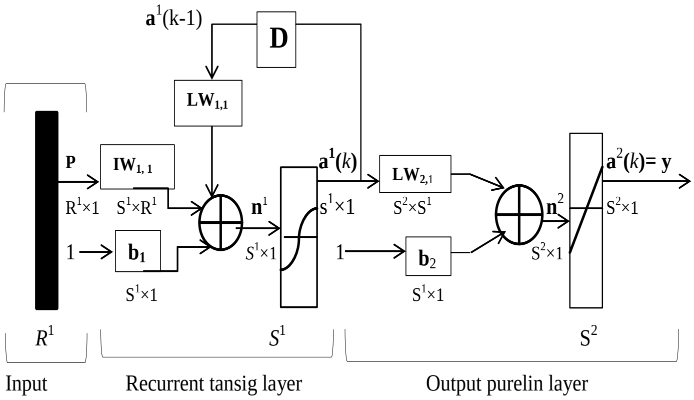

Figure 2: The architecture of Elman

The context units are initially set to some value. Both the input units and context units activate the hidden units; the hidden units then feed forward to activate the output units. This constitutes the forward activation. Output so obtained is compared with target output and back propagation of error is used to adjust the connection strength incrementally .In other words, the weights was set utilizing a prior knowledge by feeding learning patterns into the solution and by adjust the weights according to some learning rule.

IV . PROBLEM FORMULATIONS

Following the method as shown in the flowchart in Figure 3, we have the following processes

a. **Data Input**

The input is the simulated data obtained from high voltage transmission line Simulink model and are analyzed for eight types of faults and no fault conditions. One hundred (100) set of data were obtained for each of the cases mention. The neural network is based upon the total six numbers of inputs, i.e. the voltages and currents of respective three phases. The neural network is trained by using these six inputs. The total number of outputs of the neural network is four in numbers, i.e. three phases A, B, C and fourth is ground of three phase transmission line. Samples of voltages and currents simulated by MATLAB version 2016a were used as input for an ANN network as shown in Figure 3.

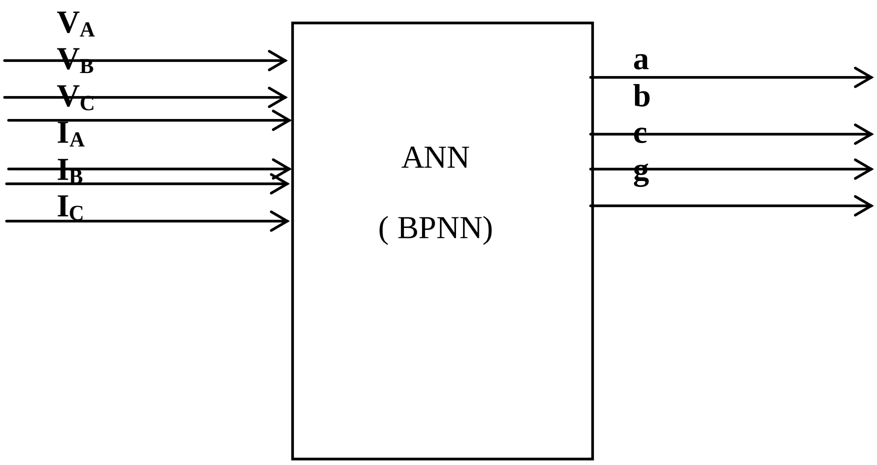

Figure 3: 6-input-4-output ANN for fault detection and classification

b. **Data Preprocessing**

The data obtained was normalized as a preprocessing operation. The normalized value of Line ‘a’ voltage and current are given in Equation 2 and 3 as;

$$V_{an} = \frac{V_a - V_{a\,min}}{V_{a\,max} - V_{a\,min}} \quad 1$$

$$I_{a\,n} = \frac{I_a - I_{a\,min}}{I_{a\,max} - I_{a\,min}} \quad 2$$

The data set was divided into two set, 60 sets for training and testing (train data) and 40 sets for testing and evaluating performance (test set).

c. Creating Networks

There was a consideration of two networks for comparism purpose. These are; BPNN supervised trained FFNN network with two hidden layers of 18 neurons in the first hidden layer and 15 neurons in the second hidden layer and Elman network of the same configuration (6-18-15-4) were chosen. Both were trained with Levenberg-Marquardt optimization technique.

d. Training Networks

The training data set was used to train the two networks:

The FFNN network adjusts the weights and bias to attain the thresholds stated for the various types of fault or no fault situation. The validation set is provided by the network during the training process (this implies the inputs data without the outputs) and the error in validation data set is monitored throughout the training process.

Elman network on the other hand, is much due to the backward feed that makes it a recurrent network. It takes longer time to process weight and biases. It can also be noted that the different structures has their MSE values close to zero with 6-18-15-4 structure with the least value. The Elman network was also trained using the Levenberg-Marquardt (trainlm) algorithm. The result of the training performance as well as its evaluation by performance matrices was compared with that of FFNN.

e. Testing the Networks

The Mean Square Error (MSE) tells how efficient the training of the neural networks is, and the MSE for each output in each iteration is calculated by;

$$MSE = \frac{1}{N}\sum_1^N (Ei - Eo)^2 \quad 3$$

where N is number of iterations, Ei is actual output and Eo is output of the model.

The correlation coefficient 'R' for training, validation and testing was also used as evaluation for training effectiveness. When 'R' is very close to 1 and there is similarity between testing and validation curves, it indicates efficient training.

V. RESULTS

A satisfactory training performance was achieved by the neural network with the 6-18-15-4 configuration (6 neurons in the input layer, 2 hidden layers with 18 and 15 neurons in them respectively and 4 neurons in the output layer) as shown in Table 1 and Plate 1a & b. It gives the higher correlation and low mse for both elman network and FFNN.

Table 1: Comparism of FFNN classifier and Elman Classifier

	FFNN Classifier				Elman Classifier			
Structure	**Number of iterations**	**Training Mean Square Error**	**Correlation Coefficient**	**Training time (sec)**	**Number of iterations**	**Training Mean Square Error**	**Correlation Coefficient**	**Training Time (sec)**
6-38-4	38	0.47	0.79	4.28	28	0.21	0.86	11.00
6-55-4	42	0.69	0.93	7.60	27	0.57	0.86	5.09
6-12-10-4	37	0.12	0.93	5.48	37	0.13	0.94	19.66
6-14-10-4	34	0.60	0.85	5.45	45	0.10	0.95	32.73
6-15-18-4	38	0.10	0.95	3.28	36	0.21	0.88	81.80
6-18-15-4	47	0.08	0.97	7.00	41	0.10	0.95	87.71
6-20-18-4	34	0.67	0.85	11.34	31	0.11	0.94	101.47
6-6-2-3-4	43	0.60	0.74	6.46	54	0.41	0.77	4.74
6-5-5-31-4	34	0.37	0.82	5.90	44	0.42	0.79	155.13

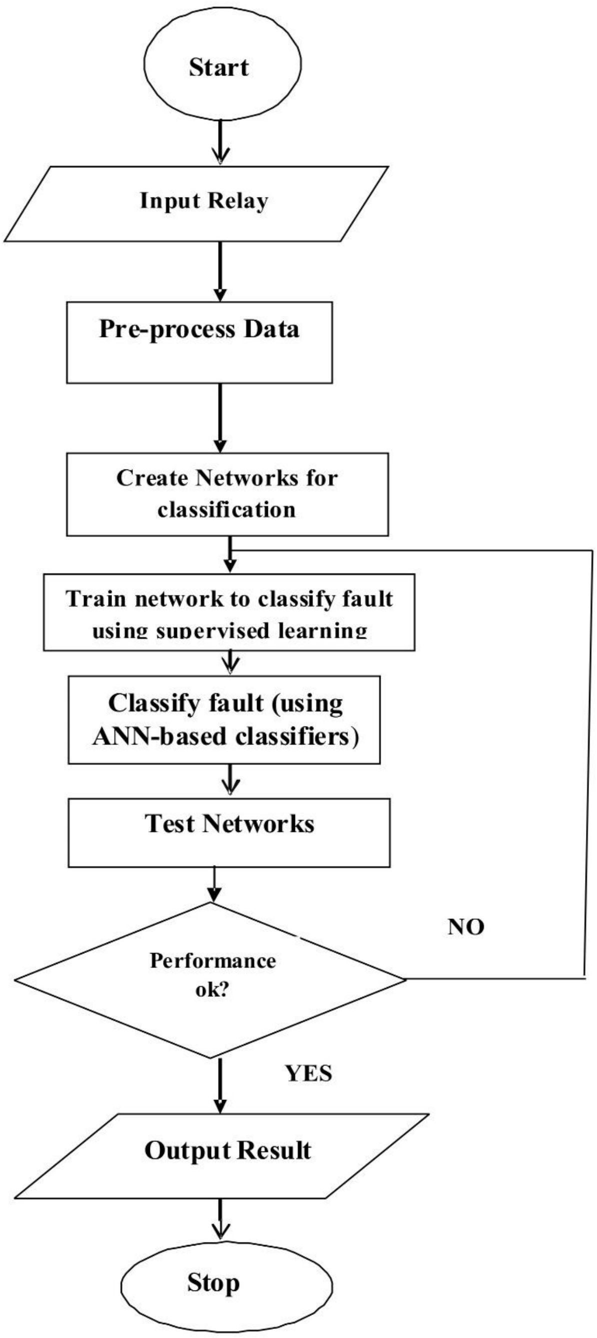

Figure 4: Flow chart for ANN-based fault classifiers

The overall MSE of the trained FFNN doing training is 0.08, which is the closest to zero, and 0.10 for Elman network compared to other configurations tested. Hence, 6-18-15-4 was chosen as the ideal ANN for the purpose of fault detection and classification. The ANN-based model (6-18-15-4) for the classifiers is shown in Plate 1A & B. the performance plot of both network during training is shown in Figure 5 (A) & (B)

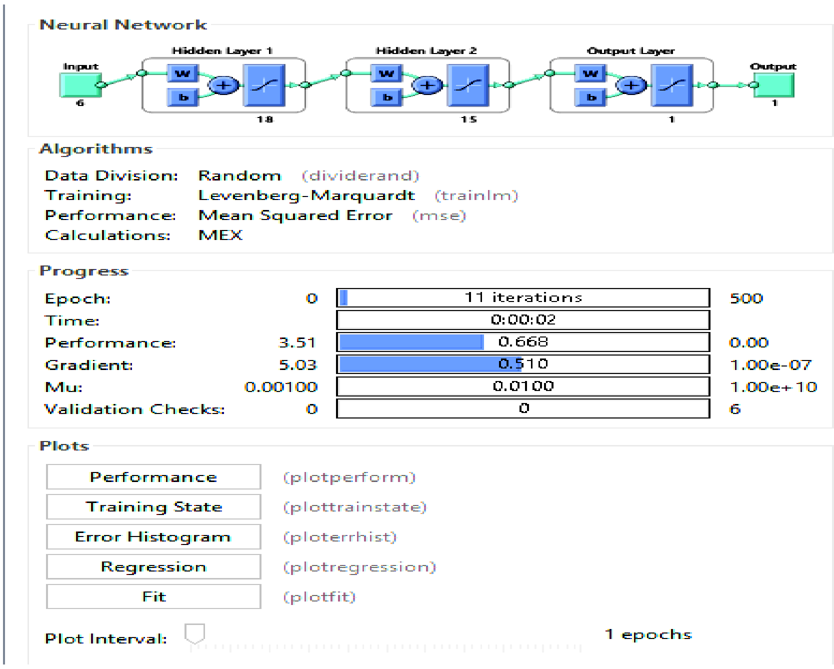

Plate 1 (A): Snapshot during ANN-based FFNN classifier

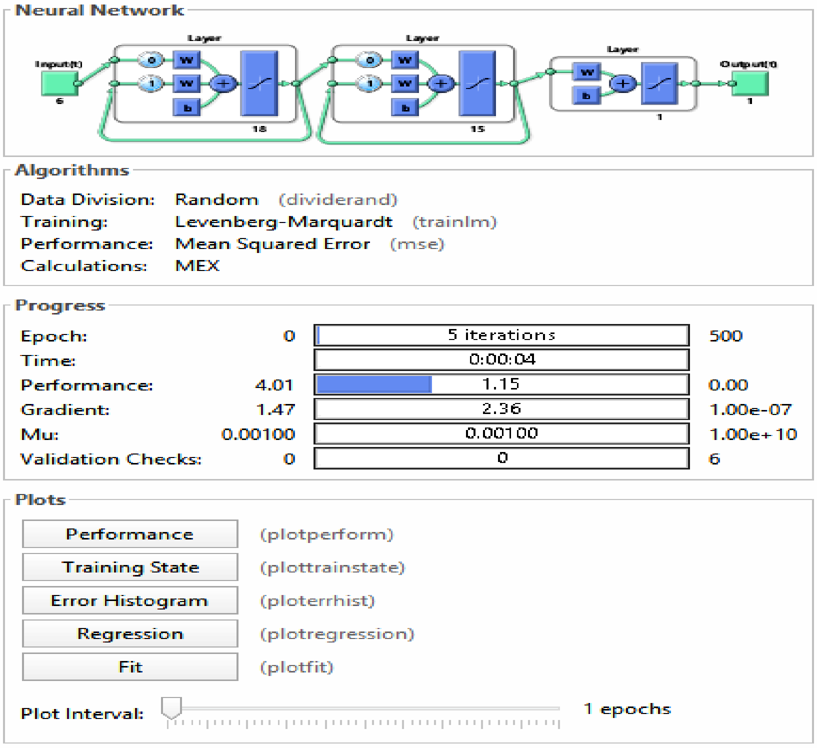

Plate 1 **(B):** Snapshot during ANN-based Elman classifier training session

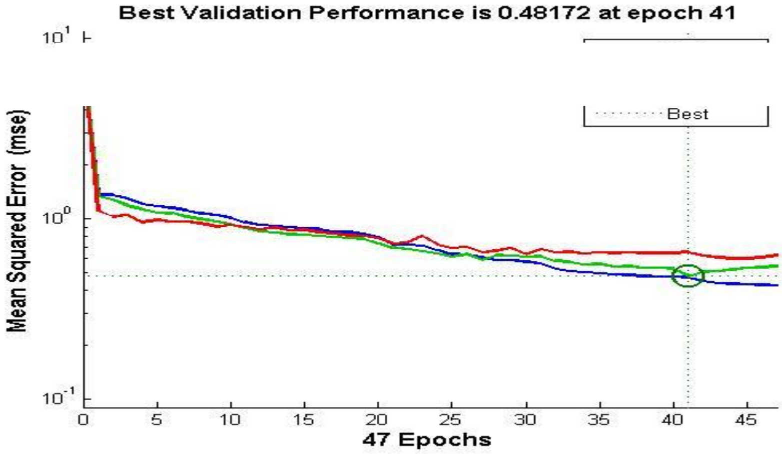

Figure 5 (A): Training performance plot of the FFNN 6-18-15-4

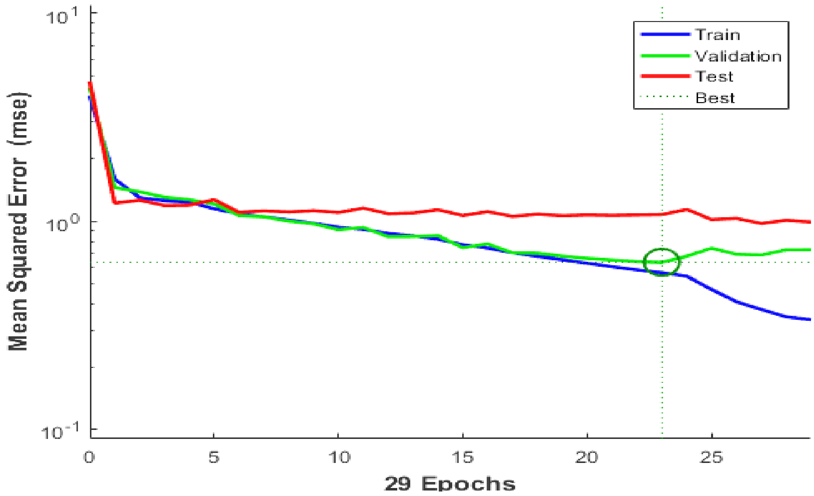

Figure 5(B): Training performance plot of the Elman network 6-18-15-4

Figure 6 shows the curve of regression Fit for the outputs versus targets of the proposed ANN. The correlation of the 6-18-15-4 ANN is 0.96836 for training which indicates very good correlation between the targets and the outputs.

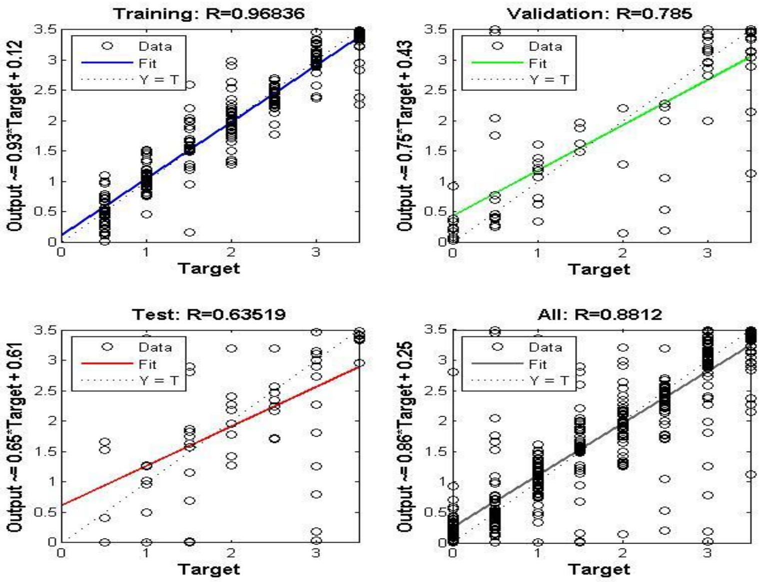

Figure 6: (A) Linear regression plot of FFNN classifier

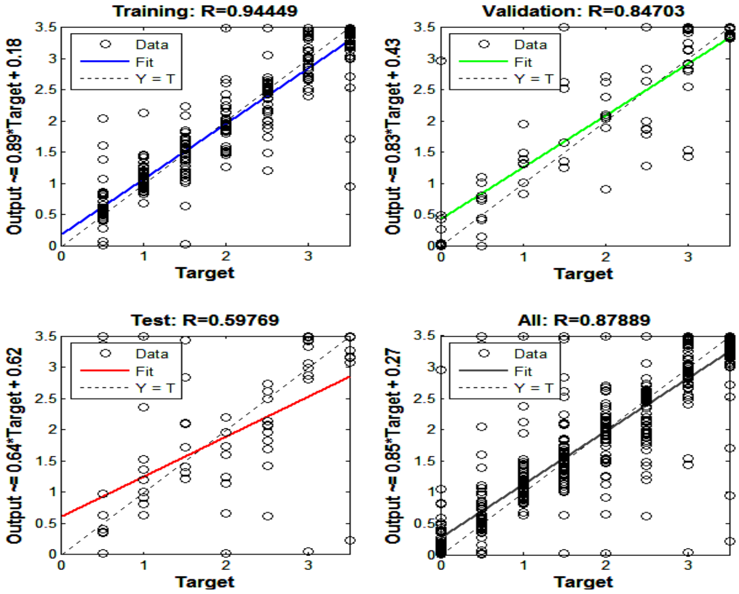

Figure 6 **(B):** Linear regression plot of Elman Classifier

VI. DISCUSSION

The ANN fault classifiers were tested with two data sets; training data set (60 for each fault conditions and no fault condition on the modelled transmission line). Table 3 shows the classification output when the training data set was used to test the network performance. It gave accurate classification of all types of fault. This shows that the network was well trained. [7], explains that the efficiency and best performance of a developed ANN and the optimum learning method can be estimated by using the final trained network by testing with testing dataset.

Owning to this fact, the test data set (consisting of 40 various fault records each for the 7 types of fault mentioned early and no fault conditions) was used to test the 6-18-15-4 ANN classifier. Various observations were made and its relevance to the efficiency of the neural network is determined using sensitivity, specificity, and accuracy as performance metrics. The performance of the network was tested based on its behaviour with the trained data set and the test data set.

The result obtained from FFNN training was compared with that of Elman as shown in Table 1, the network which has two hidden layers with 18 neurons in the first hidden layer and 15 neurons in the second gave the most favourable results. FFNN results was better than that of Elman. This is shown clearly in the bar chart of Figure 7, which shows the mean square error. The red bar showing the MSE of Elman Classifier while the blue shows the MSE of FFNN classifier which is lowest at 6-18-15-4 model and lower than that of Elman. Figure 8 also shows the training time for FFNN classifier training and Elman Classifier training. The red bar shows the training time of Elman Classifier while the blue shows the training time of FFNN classifier. It is seen for the bar-chart that FFNN classifier requires lesser training time compare to Elman Classifier. The last training parameter for comparism is the regression coefficient. FFNN classifier also has regression coefficients greater than that of Elman Classifiers which make them better. This is because a good regression coefficient will be near 1 and the 6-18-15-4 FFNN structure is the closest to 1. The bar-chart of Figure 9 shows the comparism between the regression coefficient of FFNN Classifier and Elman Classifier.

The result of the evaluation metrics for the two classifiers was then compared. That is, the accuracy, specificity and sensitivity in Table 4.9. Results show that they both have the same sensitivity of 95%, but different accuracy and specificity when testing with test data set. It is shown that FFNN has a greater accuracy of 81.25% against 75% of Elman.

Table 2: Comparism of FFNN with Elman

Type of Classifier	Specificity	Sensitivity	Accuracy
Elman	95%	75%	71.47%
FFNN	95%	81.25%	78.57%

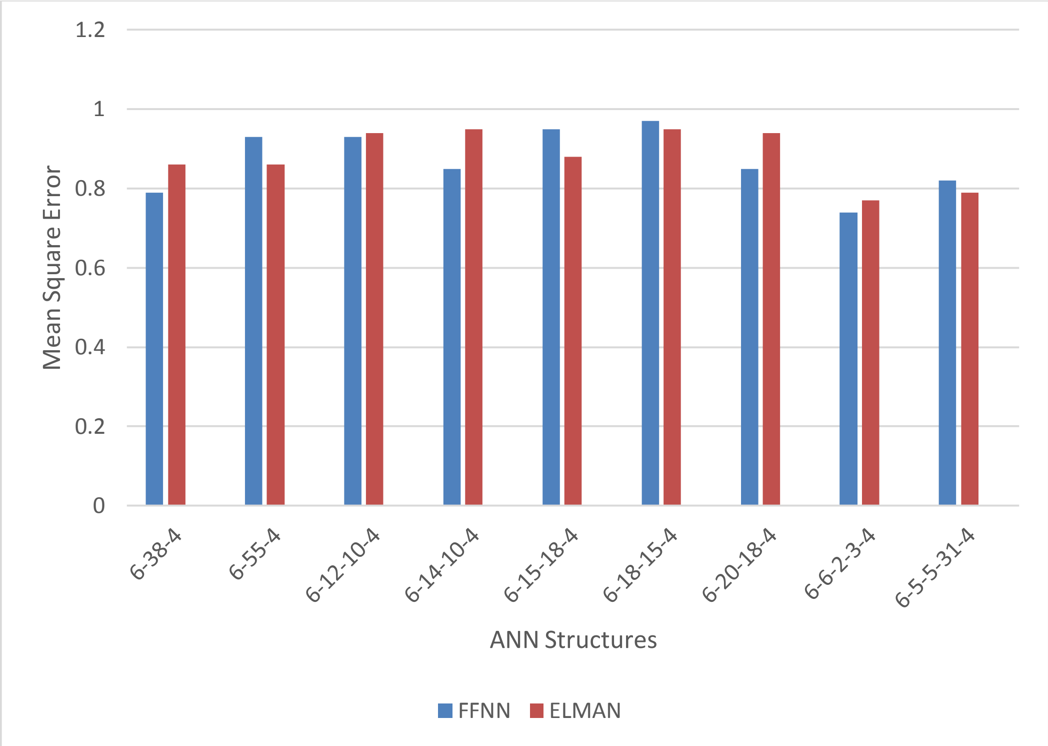

Figure 7: Bar-chart showing the Mean Square Error of FFNN and Elman Classifier Training

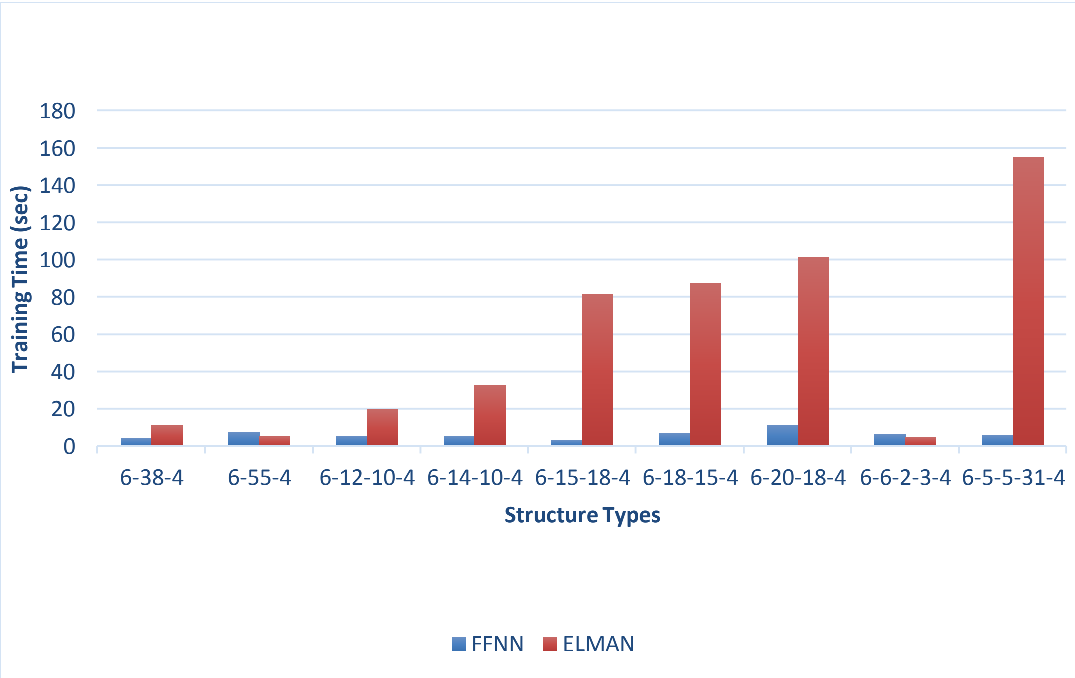

Figure 8: Bar-chart showing the training time of FFNN and Elman Classifier

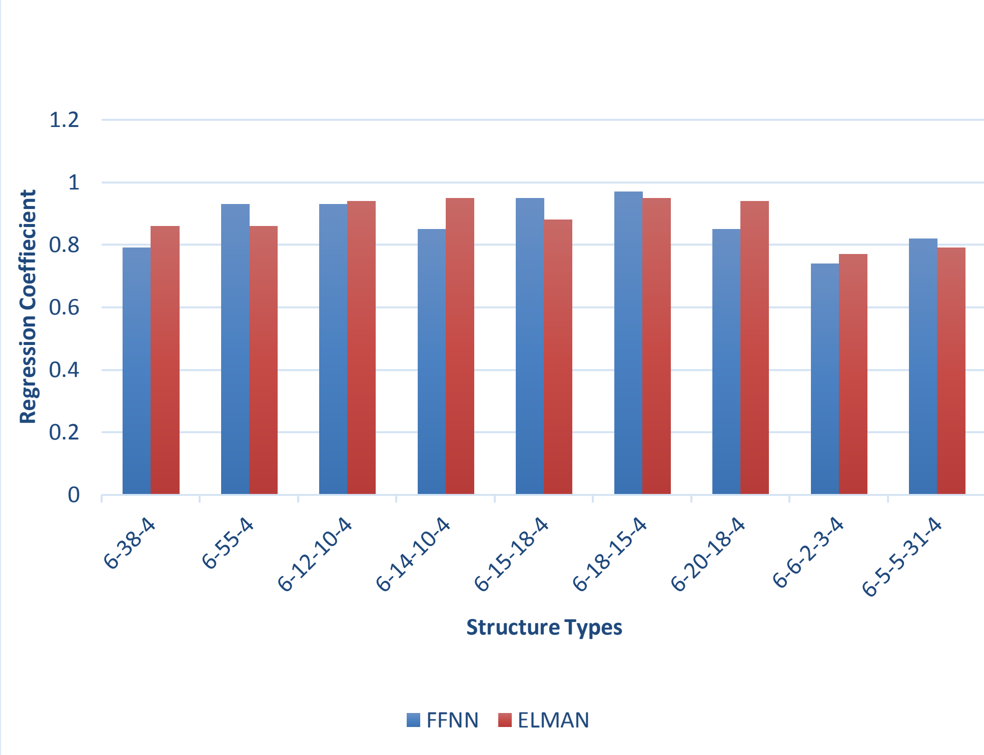

Figure 9: Bar-chart showing the Regression coefficients of FFNN and Elman Classifier Training

VII. CONCLUSION

This research work was able to compares the performance of FFNN classifier and Elman classifier to detect and classifier fault on transmission lines, using Leverberg Marquadrt as training technique and comparing their performance using training parameters, sensitivity, accuracy and specificity as performance metrics. FFNN gives a better result and more satisfactory. This research work agrees that ANN has wide scope that needs to be explored. The application of which will be of significant improvement to power system operations and planning.

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David Aborisade, et. al. "A Comparative Analysis of Artificial Neural Network- Based Power Transmission Line Fault Classifiers."*American Journal of Engineering Research (AJER)*, vol. 10(1), 2021, pp. 01-10.