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Three phase transmission lines fault identification and location using multilayer artificial neural network

[1]Yakubu, B. and [1]Yau, A .
[1]*Department of Electrical and Electronic Engineering, Federal Polytechnic Mubi, Adamawa State, Nigeria*

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Corresponding author
Yakubu, B.
babangidayakubu01@gmail.com

Abstract:
Transmission lines are very important components of electric power infrastructure that connect generating stations and the load centres located over large geographical areas. Consequently, identification of the type of fault and their respective location is crucial to guarantee adequate protection of the power system lines. Various fault identification and classification techniques have been developed by different researchers. This paper is based on fault classification and location using artificial neural networks (ANN). A multilayer Feed-forward network was employed along with a back-propagation algorithm for each of the three phases in the Fault diagnostic process. The 245km Gombe - Yola 330kV transmission line was modeled and various fault types were simulated to obtain data for training. Analysis of neural networks with varying numbers of hidden layers and neurons per hidden layer has been carried out to validate the choice of the neural networks architecture and topology. Simulation results revealed that the faults detector has correctly differentiated between normal and faulty conditions on all the test data samples. Similarly, the classifier has achieved over 95% accuracy in classifying the fault type. More specifically, the location of all the five main categories of line faults; Line-Ground (L-G), Line-Line(L-L), Double Line-Ground (L-L-G), Three phase fault(L-L-L) and Three phase-Ground(L-L-L-G) were determined with a marginal error of between 0,02518%(62m) to 2.5% (6.125 km) overall minimum and maximum values respectively. This demonstrates the effectiveness of the proposed ANN based method towards achieving satisfactory transmission network fault diagnosis. As a possible extension to this work, a comparative study using other forms of neural network schemes such as RBF, SVM and ANFIS should be carried out so as to further ascertain the effectiveness of the proposed method.

Keywords: *Feedforward network, Learning algorithms, Levenberg marquardt, Supervised learning*

1. Introduction

The fundamental requirement of any electrical power system is the continuity of service with a high degree of reliability. One of the most important factors that hinder the continuous supply of electric power is fault in the power system [1]. A fault is defined as any significant changes in the system quantities and is therefore declared when a disturbance in voltage, current or frequency in the power signal has affected the proper functioning of the consumer equipment [2]. Fault protection on transmission lines has been predominantly based on the amplitude or phase comparison of one or two sinusoidal quantities using either an electromechanical or solid-state devices. These methods involve phase or magnitude comparisons of voltage and current or their differences [3, 4]. Typically, the distance relaying using impedance-based algorithm is one common protection method employed on transmission lines [5]. However, various conditions such as remote in-feed currents, fault-path resistance, arcing resistance, asymmetrical d.c- offsets, and shunt capacitance etc. degrade their performance. Also, the concept of traveling wave (TW) and Discrete Wavelet Transform (DWT) have been used as a fast fault identification techniques, but the required associated protective devices must withstand the heavy over current that flows during the fault period, which requires large size and capacity and therefore complex and costly [6, 7, 8].

In present day power system, in order to improve the transient stability, high speed fault detection is necessary. According to Saha, *et al.* [9] the rotational kinetic energy introduced into a power system during a fault is proportional to the square of the fault clearance time therefore, high speed clearance of fault close to large sources of generation will reduce the system acceleration more than any other form of dynamic control which can be applied only after the system is being accelerated. Thus timely fault clearance is very critical from the view point of improving transient stability and system reliability.

Due to uncertainty of line parameter affecting variables such as; line length, changes in fault inception angles and unknown fault resistance, coupled with the complex structure of the transmission network, several fault location techniques inaccurate. The artificial intelligence (AI) techniques are good at simulating human thinking process and one of the major (AI) based techniques used in power systems is the ANN. This is a high speed fault clearance technique that has the ability to adapt dynamically to system operating conditions. The ANN based method is simple to apply, unlike other AI based techniques, the ANN approach is non-algorithmic and requires no explicit description of the problem to be studied [10-13]. Neural computers are not programmed using the conventional computational algorithms rather, the network learns to adapt through the adjustments of its weights and biases [14, 15, 16]. There are many ANN-based techniques employed in power systems such as; the Finite Impulse Response Artificial Neural Network (FIRANN) method, the technique uses the impulse response of voltages and currents which limits its applications [17]; the Adaptive Neuro-Fuzzy Inference System (ANFIS), this technique has an inherent disadvantage of providing only frequency information of signal [18]. This paper presents an efficient and reliable protection method capable of performing satisfactorily under various system operating conditions and different electrical network parameters, ANNs can exhibit excellent qualities such as normalization and generalization capability, immunity to noise, robustness and fault tolerance. Thus, the declaration of fault made by ANN-based fault detection method is not affected by variations in system parameters [19, 20]. Evidence from the reviewed literature seems to suggest that such an approach has not been utilized for the Gombe – Yola transmission network.

1.1 Faults in Power Transmission Lines

A fault-proof system is neither practical nor economical, a fault in power system is an interruption to the normal flow of current in the circuit. Faults in power system can be transient or permanent, while transient faults are momentary and can disappear if power is disconnected for a short time and then restored, permanent fault are usually severe and can cause lasting damage to the transmission lines [19-21]. Before the advent of digital devices, transmission lines fault detection and location used to heavily rely on visual inspections of the faulted line resulting in long and tedious foot or aerial patrols.

1.2 The Artificial Neural Networks

The ANNs are mathematical abstractions designed to mimic its biological counterpart in order to imitate the capabilities of biological neural structures. McCulloch and Pitts [23] designed what is regarded as the first mathematical model of a neuron, it was later known as the McCulloch-Pitts model, essentially the Pitts model consists of a single neuron, which receives a set of inputs (P_1, P_2, …, P_R) as depicted in Figure 1, this set of inputs is multiplied by a set of weights (W_1, W_2, …, W_n). These weighted values are then summed and the output '**n**' is passed through an activation (transfer) function. The net output of the neuron 'α' is either 1 or 0 according to whether the weighted input sum is above or below the threshold value given by Equations 1 and 2 [23-25].

$$n = \sum_{i=1}^{N} W^T P + b \tag{1}$$

$$a = f\left(W^T P + b\right) = f(n) \tag{2}$$

Where $W = [W_1, W_2, W_3, \dots W_n]^T$ = weight vectors, $P = [P_1, P_2, \dots, P_n]$ = input vectors, b = constant bias value, f(n) = neuron activation function, n = summation of the weighted input signals with bias value and *a* = the net output of the neuron.

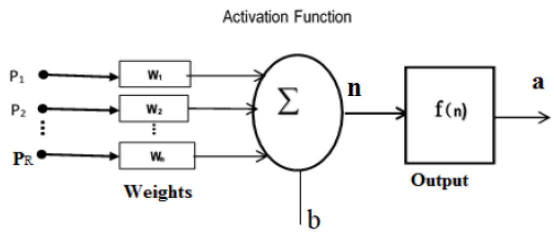

Figure 1: An artificial neuron model

1.2.1 The ANN architectures

The computational properties of isolated neurons is enhanced when many of these elements are combined together in order to obtain an increased computational power of a network structure. There are various forms of ANN structures such as the multi-layer perceptron (MLP), radial basis function (RBF), multilayer feedforward neural network (MFNN), etc. [26, 27].

1.2.2 Multilayer feedforward neural networks

A Multilayer Feedforward Neural Network (MFNN) is the most widely used neural network architecture for function approximation, pattern classification and linear mapping problems [28, 29]. The multilayer neural networks have intermediate units called a hidden layers between the input and output layer. The general structure of a feed-forward ANN is shown in Figure 2.

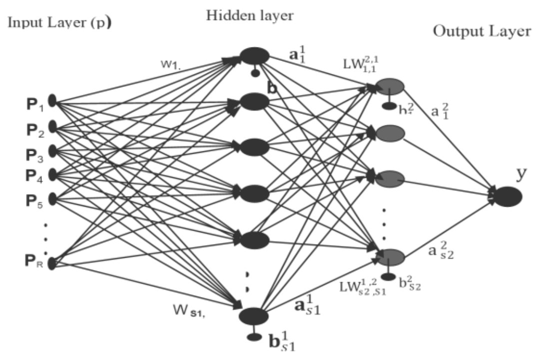

Figure 2: A Typical structure of a multilayer feedforward neural network

Each unit (neuron) is a processor that produces an output by performing a simple non-linear operation on its inputs [30]. The feedforward networks have a simple and a well-defined learning algorithm, the computation process in the *ith* layer of a MFNN can be described by Equation 3 [31].

$$\mathrm{a}^{(\mathrm{i})} = \mathrm{f}^{(\mathrm{i})}\left(W^{(i)}\mathrm{g}^{(\mathrm{i})} + b^{(i)}\right) \tag{3}$$

Where $g^{(i)}$ = gradient vector between the (i-1) th and the i th layer of the network.

$$W = \begin{vmatrix} w_{1,1}w_{1,2}\ldots w_{1,R} \\ w_{s,1}w_{s,2}\ldots w_{s,R} \end{vmatrix}$$ = weighing matrix between the (*i*-1) th and the *i* th layer,

$$a^{(i)} = \begin{bmatrix} a_1^{(i)} \\ a_2^{(i)} \\ . \\ . \\ . \\ a_R^{(i)} \end{bmatrix}$$ = Signal vector at the output of the *i*th layer,

$$b = \begin{bmatrix} b_1 \\ b_2 \\ . \\ . \\ . \\ b_i \end{bmatrix}$$ = Bias vector to i_{th} layer neurons,

1.3 Learning in Neural Networks.

The ability of neural networks to adaptively fine-tune its parameters is called learning or by training the ANN. Examples of supervised learning rules includes; the perceptron learning, error back propagation and the Levenberg Marquardt learning algorithms. The schematic structure of feedforward error back propagation algorithm is illustrated in Figure 3 [32].

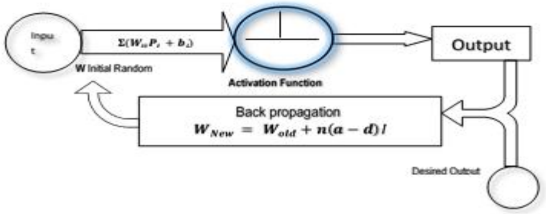

Figure 3: Structure of a supervised learning for feedforward ANN

1.3.1 The feedforward error back propagation learning algorithm

The error back propagation algorithm is a numerical procedure for finding the minimum of the error function. In this learning rule, weights and biases are adjusted by error-derivative (delta) vectors back propagated through the network [33, 34]. The three stages involved in training the Feedforward Error Back propagation neural network (FBPN) include:

1.3.1.1 The Feedforward Phase.

During the feedforward stage each input neuron receives a signal (P_i) and broadcast it to each hidden layer neuron ($Z_1 \ldots Z_P$). Each hidden neuron computes its net activation (a_i) given by Equations 1 and 2. The computed output is transmitted as input to all neurons in the layer above (output neurons). Each output neuron sums its weighted input and computes its net activation output according to Equations 4.

$$\mathrm{Y}_{\mathrm{j}} = \frac{1}{n}\sum_{n}^{m} W_{jk} a_j b_j \; ;$$

$$\mathrm{Y}_{\mathrm{k}} = f(y_i) = \frac{1}{1 + \exp(\sum_{n}^{m} W_{jk} a_j + b_j)} \tag{4}$$

1.3.1.2 Error Back propagation Stage

Each output neuron compares its net response with target values to determine the associated error function (e). The total sum of the error output E_i represents sum of all the quadratic errors of the network of nodes in each layer given by the expression in Equation 5.

$$E_i = \frac{1}{2}\sum (t_k - y_k)^2 \tag{5}$$

Equation 6 is the gradient descent algorithm for the calculation of error information or error factor. Hence the error factor δ_k is determined which is propagated back from the output layer to the hidden [35].

$$\nabla E_i = \left(\frac{\partial E_i}{\partial W_{11}}, \frac{\partial E_i}{\partial W_{21}}, \ldots, \frac{\partial E_i}{\partial W_{np}} = \delta_k \right) \tag{6}$$

Similarly error information factor δ_j is computed for each hidden layer units to be used in weight adjustment but not propagated back to the input layer as shown in Equation 7.

$$\delta_j = \frac{\partial E_j}{\partial W_j} = \left(t_k - t_y\right)\frac{\partial E_i}{\partial W_j} \tag{7}$$

1.3.1.3 Calculation and adjustment of weights

The changes in weight and bias terms are calculated using the error factors given by the expressions of Equations 8.

$$\Delta W_j = -\alpha \delta_j P_j ; \Delta b = -\alpha \mathrm{A} \delta_j \tag{8}$$

Where α is the proportionality constant or learning rate.

Finally the weights and biases are updated accordingly as described by Equation 9 [36].

$$W_{jk}^{new} = W_{jk}^{old} + \Delta W_{jk} \text{ and}$$

$$b_{jk}^{new} = b_{jk}^{old} + \Delta b_{jk} \tag{9}$$

2. Materials and Methods

Figure 4 shows the single line diagram of the Jos/Gombe/Yola 330kV transmission network consist of the primary transmission feeders, buses, power transformers and the associated 132kV sub-transmission network [37].

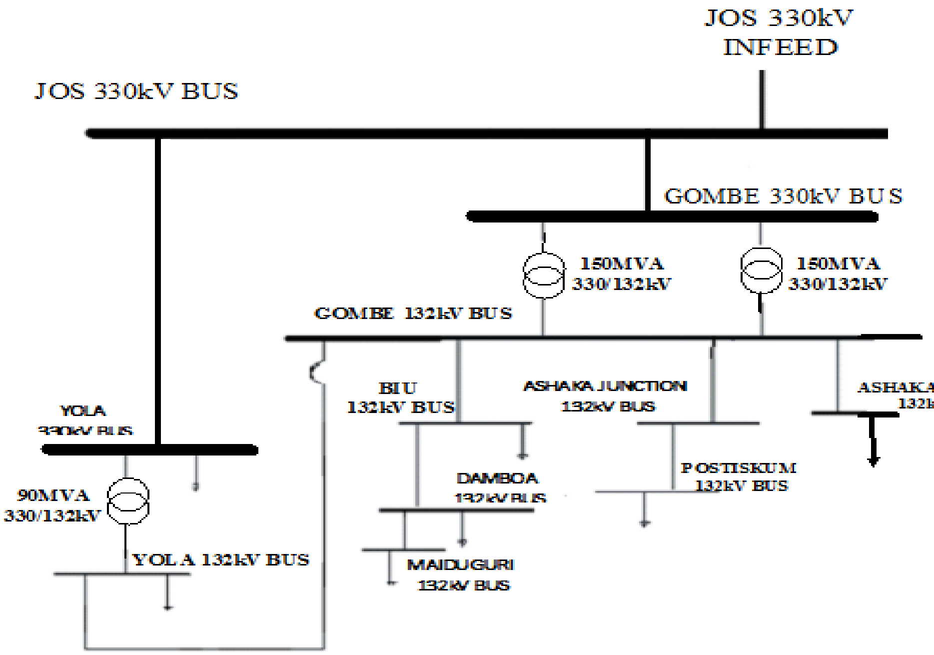

Figure 4: Single line diagram of Gombe 330/132kv transmission network

2.1 Transmission Line Model

The Gombe to Yola 330kV, 50 Hz, 245 km, three phase, single circuit transmission line was modelled using the power system BLOCK SET together with the Simulink and SimPowersystems toolboxes of MATLAB 2013 version. The network data was obtained from [38] and was used as input to design and build the model. The twelve fault types on a line with various values of fault resistance, inception angles and locations were simulated to generate the fault data for current and voltages. The faults simulated are: Line to Ground (LG), Line to Line (LL), Line to Line to Ground (LLG), Line to Line to Line (LLL) and Line to Line to Line Ground (LLLG). The Simulink model used consist of the three phase fault simulator block, three-phase V-I measurement blocks set, the Data Acquisition block and the Goto blocks as shown in Figure 5. The fault data obtained were scaled to remove redundancy and to reduce the training computation time. These data form the training and validation inputs/output data sets to the neural network presented in Table 1.

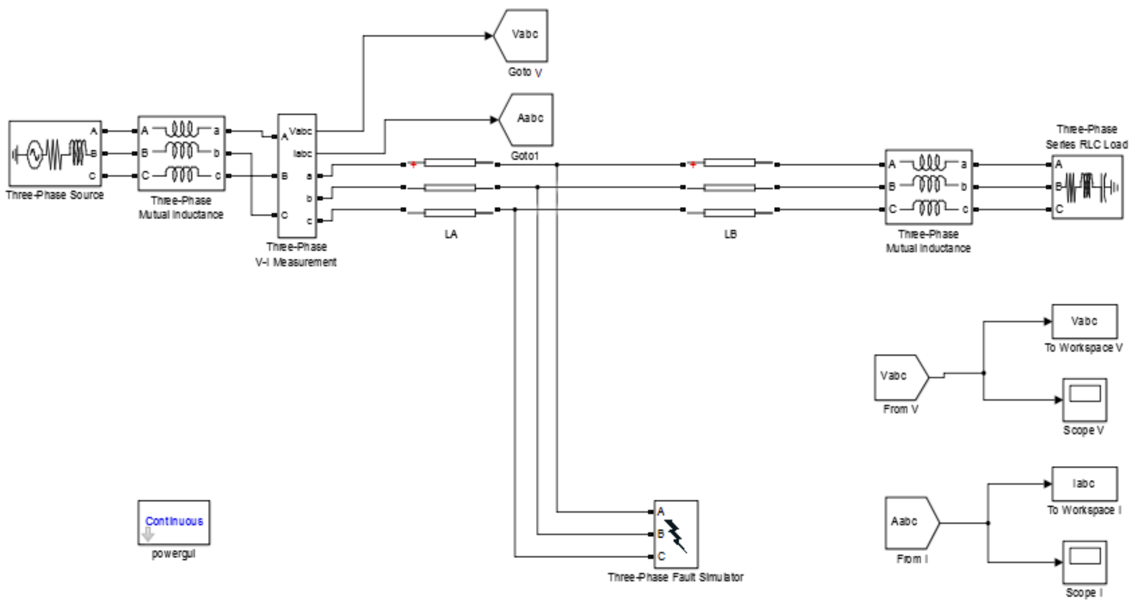

Figure 5: Simulink model of the network studied

Table 1: Sample of input/output data to the neural network

S/N	Input Elements						Detect	Fault Type	Fault Dist.
	V_R/V_R(pf)	V_B/V_B(pf)	V_Y/V_Y(pf)	I_R/I_R(pf)	I_B/I_B(pf)	I_Y/I_Y(pf)	0 or 1	RBYN	(Km)
1	1.1032	1.0052	0.9395	2.2712	0.3472	1.2198	1	1001	2.5
2	0.9546	0.9624	0.9677	1.2616	-1.3129	0.8274	1	0101	5
3	1.0007	0.9179	0.8605	1.0480	1.0966	1.0605	1	0011	7.5
4	1.0909	1.0086	0.9526	3.3182	-3.6449	0.9989	1	1100	10
5	0.6927	0.7408	0.7735	0.9981	-1.2527	0.2484	1	0110	12.5
6	1.3250	0.8593	0.5423	2.1942	1.0005	1.7966	1	1010	15
7	1.0755	0.9777	0.9088	3.3682	-3.8333	1.0234	1	1101	17.5
8	0.7566	0.7585	0.7598	1.2261	-2.1253	0.5199	1	0111	20
9	1.2969	0.8361	0.5122	2.5561	0.5937	1.5995	1	1011	22.5
10	1.0788	0.7373	0.4973	3.3709	-3.7966	1.0646	1	1110	25
11	1.0705	0.7561	0.5346	3.3712	-3.8374	1.0661	1	1111	27.5
12	1.0000	1.0012	0.9998	1.0000	1.0000	1.0000	0	0000	30

2.2 Selection of ANN Architectures.

Several multi-layer feed forward neural network structures were experimented, as there is no hard-and-fast rule for network selection, a number of simulations were carried out to determine a suitable network structure and learning strategy, the architecture that best minimizes the mean square error (MSE) was selected for each application [39, 40,]. Table 2 shows that (6 -20-5-3- 1) architecture has the lowest MSE of 1.359e-07 and a running time of 9.7 seconds is chosen. Figure 6 depicts a snapshot of the Matlab training window for the 6-20-5-3-1 configuration indicating that 45 epoch was required to achieve the least MSE of 0.0000001359.

Table 2: Performance of Different Architectures using trainscg Algorithm

Neural Network Architecture	MSE	Iterations/Time (sec.) (s)
6 - 20 - 5 - 3 - 1	1.3592e-07	45 epochs,9.7
6 - 20 - 5 - 1	2.2493e-04	39 epochs,7.1
6 -10- 1	1.7495e-06	50 epochs,6.3
6 - 5 - 1	2.2237e-06	46 epochs,3.5

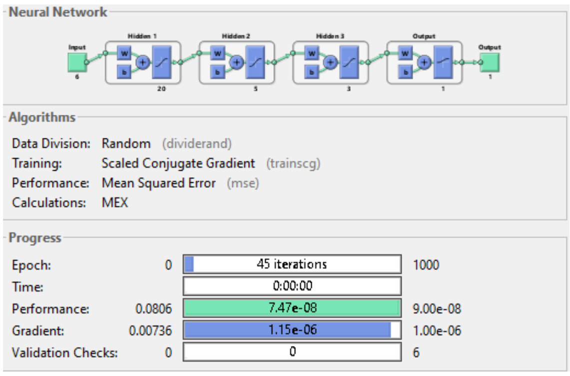

Figure 6: Neural Network Training Interface

2.3 Training and Validation of ANN Structures

To train the ANN, the training data sets were fed into the neural network. The ANN learns and develops an ability to generalize upon training. The network inputs are fault voltages and currents values, while the outputs are the fault condition, the type of fault and the location of the fault. A total of 12 fault cases were simulated at 98 different locations (245km ÷ 2.5 km). Varied values of fault resistance were also included to imitate real-time fault scenarios as follows: 0.25, 0.5, 0.75, 1, 5, 10, 25, and 50 Ω. The performance of the trained network was also validated for various types of training errors using different types of ANN evaluation tools which includes; the confusion matrix, linear regression plot, error histogram and the Gradient and validation performance plot [41, 42].

3. Results and Discussion

In every case, a test data set was applied to the trained and validated ANN model to detect, classify and locate faults on the transmission lines at reasonable accuracy.

3.1 Fault Detection

The fault detector is subjected to a new but similar data set consisting of fault scenarios never used during the training phase. Figure 7 shows the confusion matrix diagram for the training, testing and validation phases, in which the last cell in blue indicates the percentage of correctly classified in all cases. The results obtained demonstrate the ability of the network to detect the occurrence of a fault. It can be seen that the chosen neural network has 100% accuracy in fault detection.

Figure 7: Confusion Matrix for Fault Detection

The structure of the fault detection network consisting of 6 neurons in the input layer, 3 hidden layers with 20, 5 and 3 neurons respectively and one neuron in the output layer is shown in Figure 8.

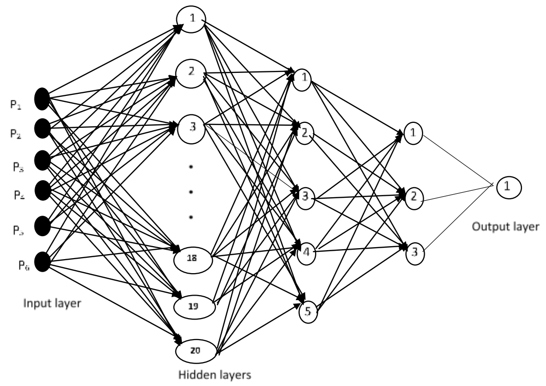

Figure 8: Architecture of the Fault Detection ANN (6 – 20 – 5 – 3– 1)

3.2 Fault Classification

Data for fault classification was organized into two matrices, the input matrix and the target matrix. The Neural Network should classify, in each case, if a specific phase(s) is involved in a fault scenario or not. The combinations generate eleven different categories of faults as illustrated in Table 3 [43, 44].

Table 3: The Classification Network Truth Table

Fault Type	Classifier output			
	Phase A	Phase B	Phase C	Ground G
A-G	1	0	0	1
B-G	0	1	0	1
C-G	0	0	1	1
A-B	1	1	0	0
B-C	0	1	1	0
A-C	1	0	1	0
A-B-G	1	1	0	1
B-C-G	0	1	1	1
A-C-G	1	0	1	1
A-B-C	1	1	1	0
A-B-C-G	1	1	1	1

Table 4 shows that the network with (6-10-35-35-35-4) architecture has the lowest MSE of 0.010617. Similarly, Figure 9 and Figure 10 also reveal that the (6-10-35-35-35-4) architecture has the lowest MSE of 0.010617. This result shows that the output tracks the targets for all data sets with an R-value of over 0.95 for the entire test data set indicating a good fit.

Table 4: Performance of various neural network architectures for fault classification

Neural Network Architecture	MSE	Coefficient of Correlation(R)
6 -10-5-4	0.016481	0.97504
6 -10-5-5-4	0.015982	0.97775
6 - 10-35-35-35-4	0.010617	0.97821
6 -10-20-35-35-4	0.011831	0.9778

Figure 11 depicts the snapshot of the developed ANN model in Simulink Toolbox. Figure 12 shows the structure of the fault classifier network with 6 neurons in the input layer, 4 hidden layers with 10, 35, 35, 35 neurons respectively and 4 neurons in the output layer.

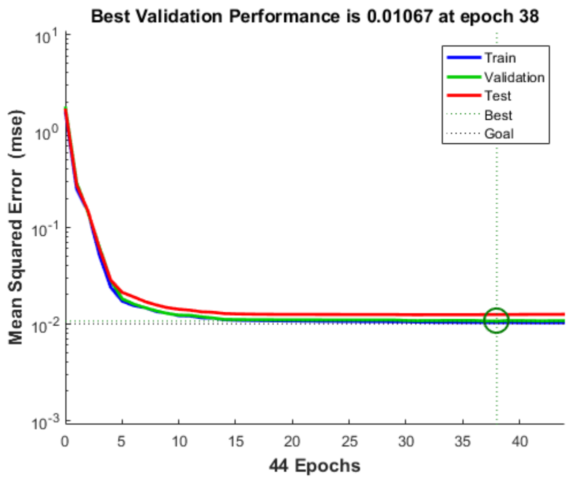

Figure 9: Performance Plot of the Classifier Network Configuration (6-10-35-35-35-4)

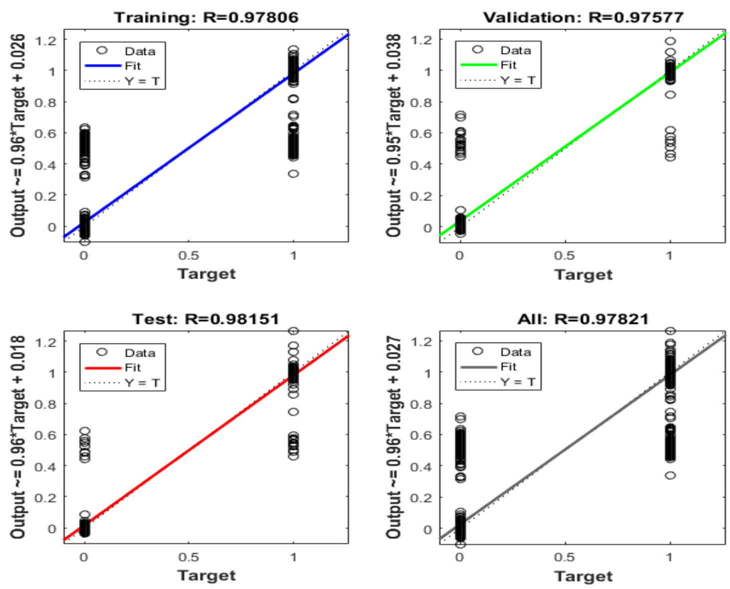

Figure 10: Regression fit for (6-10-33-35-35-4) Configuration

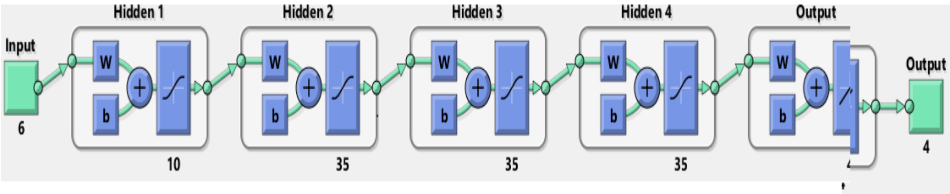

Figure 11: Model of the classifier network training window interface

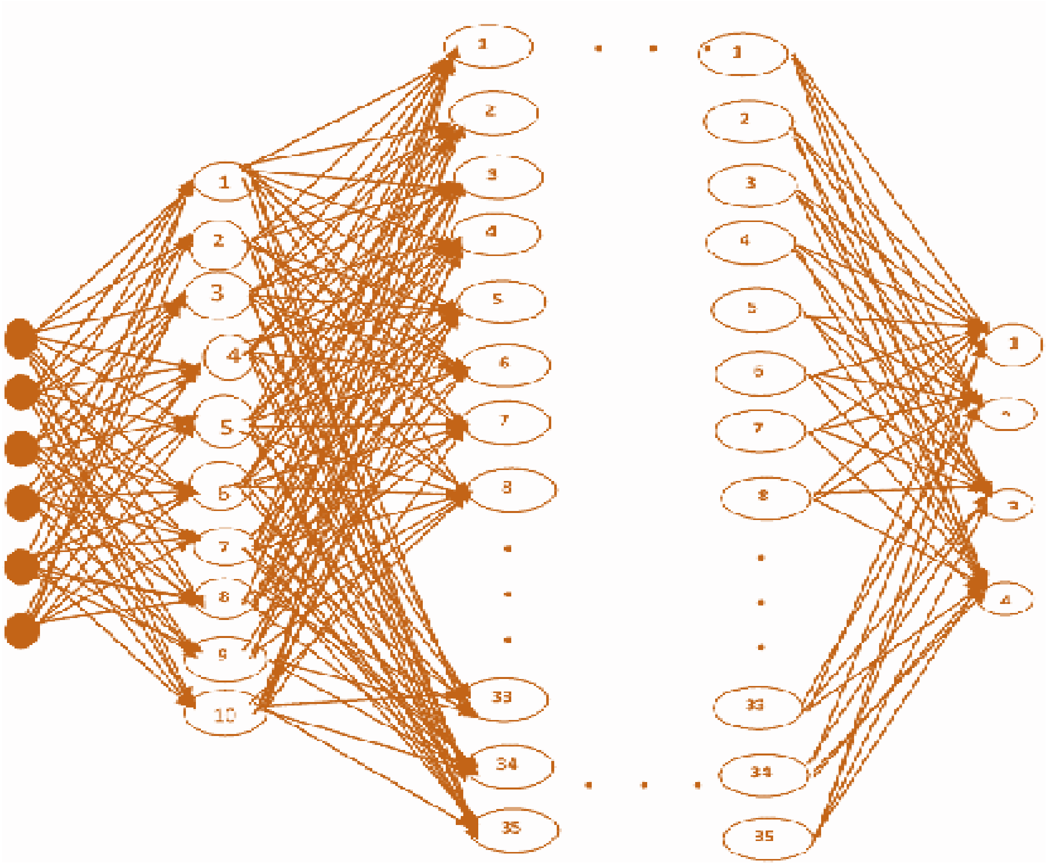

Figure 12: Structure for Fault Classification (6- 10 -35 – 35 – 35 -4) Network

3.3 Fault Location

The last stage of the fault diagnosis is to pinpoint the location of different kind of faults on the transmission lines. After training and validation, the ANN fault distance locator is tested by presenting samples of faults which have not been used during training process.

3.3.1 Single Line to Ground Fault

Test results for a single phase to ground fault is shown in Table 5(a). The first two columns gives actual location and measured distances and while the third is the % errors respectively. The error values and the respective percentage error in fault location are defined by the expressions of Equation 10:

$$\text{Error} = (\text{e}) = |\text{Actual location - Desired location}|(km)$$

$$PercntageError = \frac{e}{L} \times 100\% \qquad (10)$$

Table 5(b) reveals that the minimum, maximum and mean error values. Figure 13 shows the results of the test, it can be seen that the maximum percentage error is around 0.3714 percent. This performance demonstrates the ability of the fault locator network to generalize and react to new data.

Table 5(a): % Error against Distance for Single Line to Ground (L-G) Faults

S/N	Actual Location (Km)	Measured Distance (Km)	% Error
1	20	20.91	0.371429
2	25	25.29	0.118367
3	60	60.21	0.085714
4	73	73.14	0.057143
5	95	95.25	0.102041
6	166	166.3	0.122449
7	183	183.2	0.081633
8	212	212.7	0.285714

Table 5(b): Summary of Errors (L-G) Faults between Actual and Measured Distances

S/N	Statistic	% Error	Error Value (Km)
1	Min Value	0.057143	0.14
2	Max. Value	0.371429	0.91
3	Mean Value	0.1673%	0.41

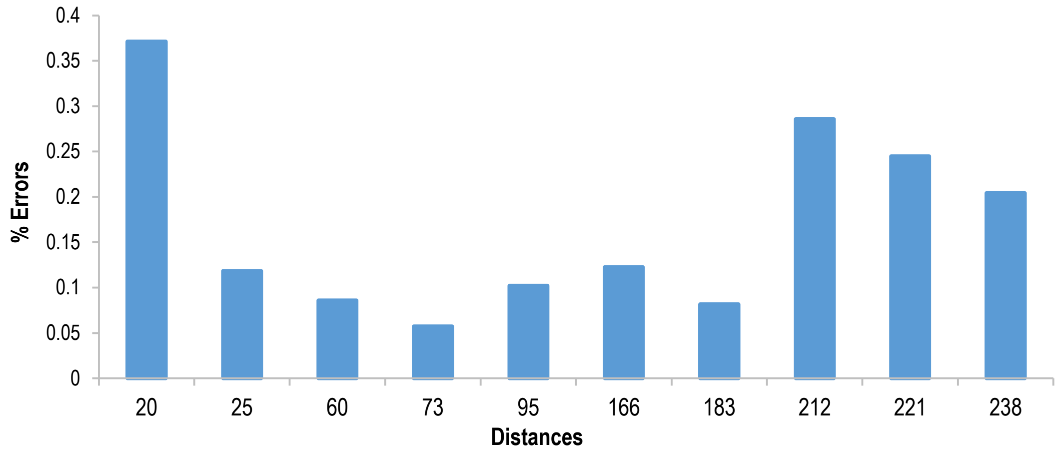

Figure 13: Percentage error vs. distance plot single line to ground faults

Figure 14 shows the topology of the Line-to ground fault location neural network has 6 neurons in the input layer, 2 hidden layers with 10 and 5neurons and 1 neuron in the output layer.

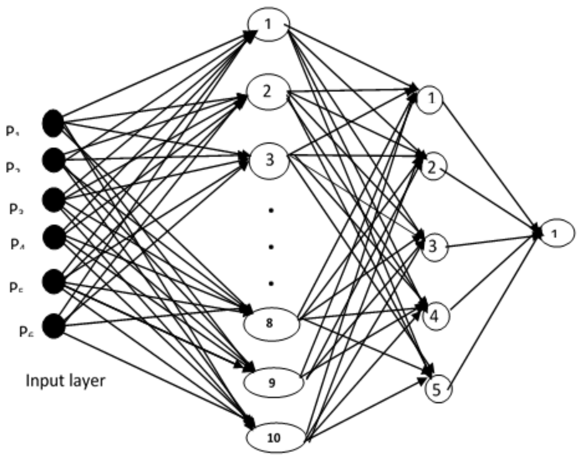

Figure 14: The ANN Structure for Single Phase to ground Fault (6- 10 -5 – 1)

3.3.2 Line- to-Line (L-L) Faults

The three line –to-line faults of (A-B, B-C, and A-C) were simulated at every 2.5km interval for the entire line length. A total of 98×3×8 = 2352 faults cases were generated and tested on the selected (6–30 –10 – 1) network architecture. In each case, the % error between the actual output and the measured value was calculated.

Table 6: Statistics of Simulation Result the (L-L) Fault Location Neural Network

Statistic	(%)Error	Error Value (Km)
Min	0.02518	0.062
Max	1.749	4.3
Mean	0.7271	1.73

Figure 15 shows the results obtained, it can be seen that the maximum error is 1.749% (4.3Km) and a minimum of 0.02518% (62m) as presented in Table 6. Figure 15 shows the graphical representation of the test result, while Figure 16 represents the structure of the selected (6-30-10-1) neural network.

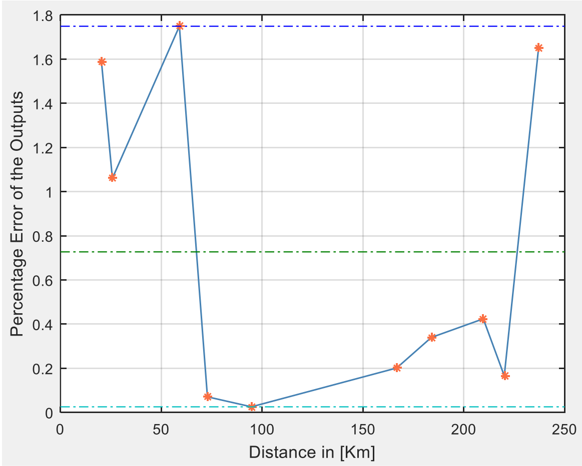

Figure 15: Percentage error vs. distance plot line – to - line faults

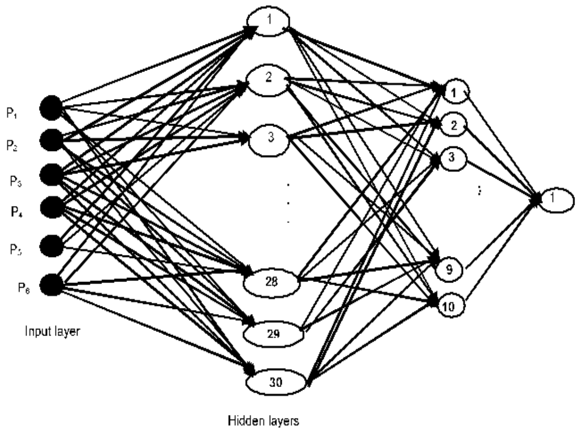

Figure 16: Chosen ANN structure for line-to-line faults (6-30 -10 – 1)

3.3.3 Double Line to Ground (L-L-G) Fault

To test performance of the trained network, new samples of the phase- to- phase- Ground faults have been simulated, by taking fault values with varying fault resistances at ten different locations on the transmission line (20, 25, 60, 73, 95, 166, 184, 212, 221 and 250) km. In each case, the percentage error between the actual output and the measured value has been calculated using Equation 10. Figure 17 shows the structure of the (6-20-3-

1) network. The test results of Figure 18 shows that the minimum and maximum error values of 0.061224% (149m) and 0.46939% (1.15Km) respectively.

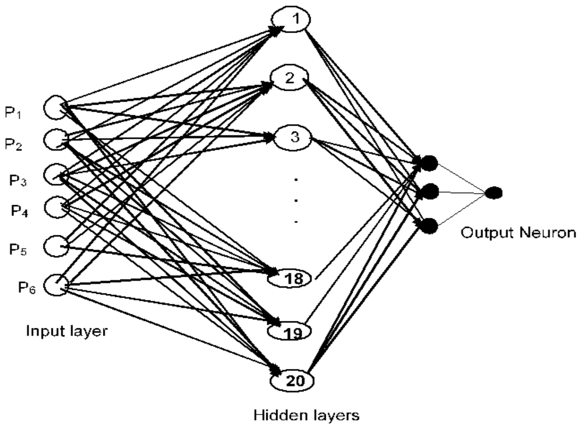

Figure 17: Structure for (L-L-G) faults (6-20-3-1) network

Similarly, Table 7(a) and 7(b) presents the summary for all test points respectively. Figure 19 gives an overview of the trained (6-20-3-1) Network, showing the training parameters; number of layers, training algorithm, training functions,training of epochs and so forth.

Table 7(a): Percentage errors as a function of distance double-line-ground faults

S/N	Actual Location (Km)	Measured Distance (Km)	Percentage Error
1	20	20.32	0.130612
2	25	25.72	0.293878
3	60	58.85	0.469388
4	73	72.85	0.061224
5	95	94.66	0.138776
6	166	166.7	0.285714
7	183	183.9	0.367347
8	210	209.7	0.122449

Table 7(b): Summary of errors for (L-L-G) faults between actual and measured distances

S/N	Statistic	% Error	Error value (Km)
1	Min Value	0.061224	0.15
2	Max. Value	0.46939	1.15
3	Mean Value	0.26449	0.65

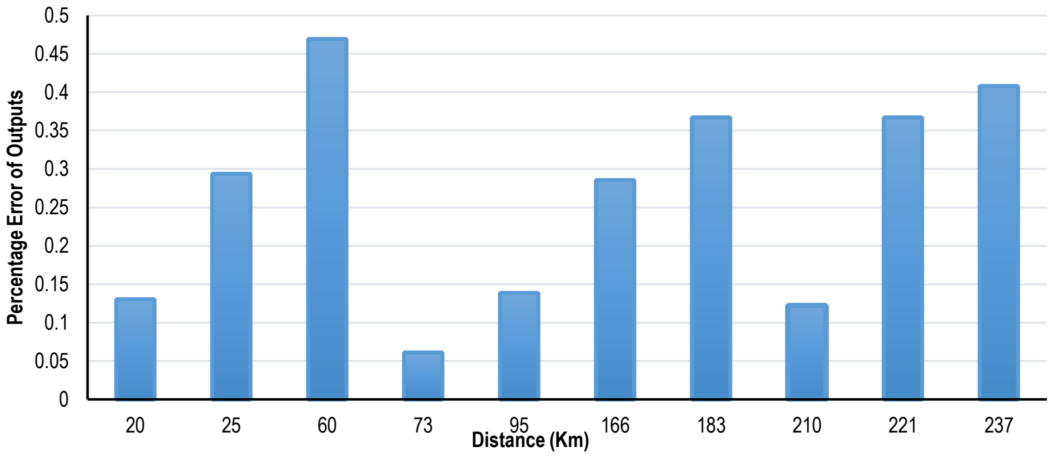

Figure 18: Percentage error vs. distance plot for double line to ground faults

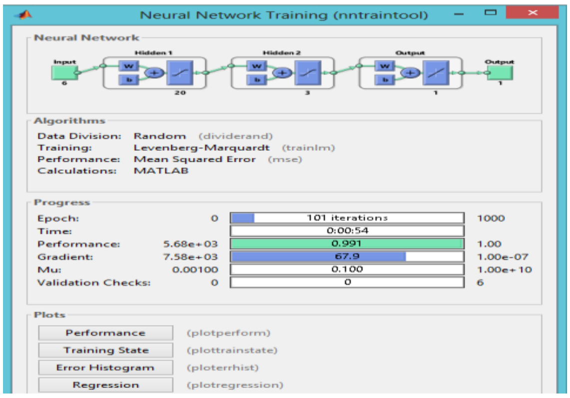

Figure 19: An overview of the ANN training window for the (L-L-G) fault

3.3.4 The Three Phase Fault Location

The trained ANN was tested by presenting new samples of faults data. Test results for the three phase faults locator is shown on Figure 20. From the graph, it can be seen that the errors in locating the three phase faults is between 0.1134% (277.8m) - 2.5% (6.125Km). Figure 21 gives an overview of the trained Network, which provides information on the training parameters.

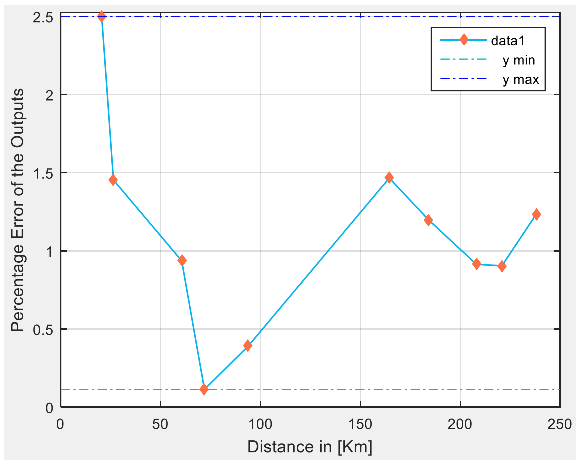

Figure 20: Testing error result for three phase faults locator

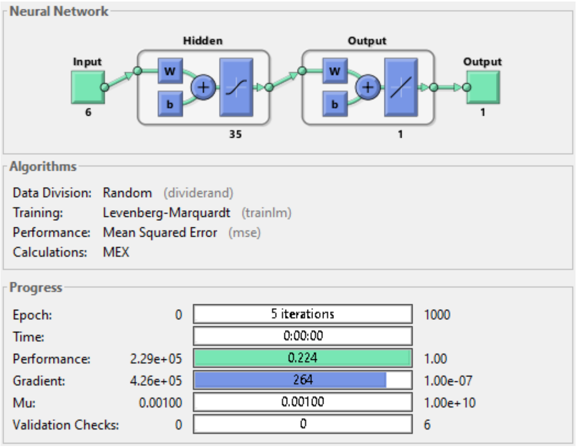

Figure 21: An overview for three phase faults location training window

3.4 Discussions of results

In this paper, the use of neural networks as an alternative method for the detection, classification and location of faults on transmission lines has been studied. The data employed are the three phase voltages and currents (scaled with respect to their pre-fault values) as inputs to the neural networks. In every case the data recorded is passed through the trained ANN model to first determine if there is a fault, the established faults are classified into the five main classes of (L-G, L-L, L-L-G, L-L-L, and L-L-L-G) and then lastly identify the most likely location of the fault. The determination of neural network architecture is a designer-defined process, in this paper a heuristic approach was adopted where several networks having various parameters were trained. The best performing network among was selected. More neurons require more computation, and they have a tendency to over fit the data when the number is set too high, but they allow the network to solve more complicated problems more efficiently. Four main training algorithms were used in all stages; trainscg, Trainlm, trainbr and trainrp. Trainscg had the best performance for the Fault detection phase. For fault classification, it can be seen from Table 4 that the (6-10-35-30-4) architecture had the lowest MSE of 0.010617 and was selected. The overall performance of the fault classification tool is excellent as 97% accuracy was achieved as indicated by the output/target correlation as shown on Figure. 10. The test performance results for the fault locator networks are as illustrated on Tables 5, 6(a), 6(b), 7(a) and 7(b) for all the four fault categories, also the plots of percentage error against distance for each kilometer has been presented. In all the cases errors has been marginal and within acceptable limit.

4. Conclusion

It has been shown that the Fault Detection, classification and location tool is able to perform satisfactorily to recognize and distinguish between healthy and faulty network. The fault classifier has been able to achieve over 95% accuracy in classifying which kind of fault has occurred. Similarly the fault locator is able to perform satisfactorily, with the highest possible error of 2.5% for a three phase close-in fault at a distance of less than 20km from source as shown in Figure 20.

Recommendations

As a possible extension to this work, the following suggestions and recommendation are proposed; a comparative study using other schemes such as RBF, SVM and ANFIS should be carried out so as to further ascertain the effectiveness of the proposed method and with the availability of high processing capacity modern computers, practical implementation of the scheme to confirm its practical usefulness to our power system is recommended.

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