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Transmission Line Protection Scheme for Fault Detection, Classification and Location Using ANN

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ABSTRACT: *A hybrid transmission lines protection scheme base on ANN is proposed in this paper. The hybrid transmission lines consists of two sections; overhead transmission line and underground cable. It uses the current and voltage measured from both terminal of the transmission line in the hybrid system. They are processed by the ANN to detect, classify and locate the faults. The data of voltage and current of that system has been handled by using a multi-layer feed forward neural network algorithm (MFFNN). The proposed scheme and the hybrid system is simulated using the Matlab program.*

Keywords : *transmission line fault detector, fault classifier, fault locator, MFFNN.*

I. INTRODUCTION

Transmission line is one of the most important components in a power system. Faults have higher possibility to happen at transmission lines rather than other power system components because it is exposed to the environment. These faults require fast restoration for the transmission line. As when a fault occurs on transmission line, it generates damage in the power system. So an accurate, fast and reliable method to detect, classify and locate the fault is needed to be established on the transmission lines to insure healthy power system.

When a fault strike a transmission line, it causes serious damaged due to its hazardous currents passed through short circuit. As it is important to detect the faults fast to protect the power system from severe damage which cause a great lose in the service. So several methods had been used to detect, classify and locate fault on transmission lines. These methods are mainly can be divide as conventional methods and intelligent methods. Conventional methods have many algorithms to locate the fault which can be dividing as three categories: one-terminal, two-terminals and multi-terminal algorithms.

One-terminal fault algorithms uses voltage and current measurements from one terminal of the line to calculate the reactance of the faulty line [1-2]. Two numerical algorithms used only one-terminal current signals as input data to estimate the location of phase to ground faults [3]. However, the accuracy of these algorithms is adversely affected by the fault type, fault resistance, and source impedances. Refs. [4-7] presented a fault detection and location algorithms using voltage and current measurements from two terminals of the line, these measurements can be synchronized by using phasor measurement units (PMUs) or global position system (GPS) [4-5], or unsynchronized ones [6]. However, this method requires the parameters of the transmission lines to estimate the location, which in reality; the electrical parameters of lines are not known with great precision. Multi-end methods are used for fault-location of multi-terminal transmission lines. Voltage and current measurements taken from all of the terminals are utilized to firstly identify the faulted section and next locate the fault [4], [7]. The accuracy of this method is affected by the load flow, fault resistance, and source impedance.

Intelligent methods which use Artificial Neural Network (ANN), fuzzy and Support Vector Machine (SVM) algorithms were presented in [8-19]. The fuzzy technique was used to compare the output signals of the fuzzy model with the real measurements available in the process [8-10]. The ANN algorithms applied in different power system to locate fault in transmission lines [11-15]. ANNs were used to locate faults in double circuits transmission lines [13], series compensation transmission lines [14], and in EHV transmission line [15]. The ANN has different function such as Elman recurrent network [11], multi-layer backpropagation [12]. The SVM method was used to protect the transmission lines in [16-18]. The original input space in SVM is mapped into a high dimensional dot product space called feature space in which the optimal hyperplane is determined to maximize the generalization ability of the classifier. The SVM algorithm was applied to protect the mutli-terminal transmission lines [17], and series compensated system [18]. Hilbert-Huang transformation (HHT) and SVM were adopted to distinguish different types of power system faults. Downtime is determined by using

HHT. Through analysis of the fault current signal [19]. Fuzzy methods were sensitive to system frequency changes. This makes the ANN method and the SVM method is better than the fuzzy in the protection applications. As also using the ANN method gives an accurate locates to the fault as trained more than the conventional methods.

In this paper, a multi-layer feed forward neural network algorithm (MFFNN) is proposed to detect, classify and locate the faults in nonhomogeneous transmission lines consists from overhead transmission line and underground cable. The detection, classification and the location module for that system will be designed tested in this paper.

II. OVERHEAD LINE CONNECTED CABLE MODEL

A three phase 132 kV power system consists of 80 km overhead transmission line connected to 30km underground cable between two equivalent sources. This system is used to test and validate the proposed method for hybrid system protection. The single line diagram of the modeled power system is shown in Fig. 1.

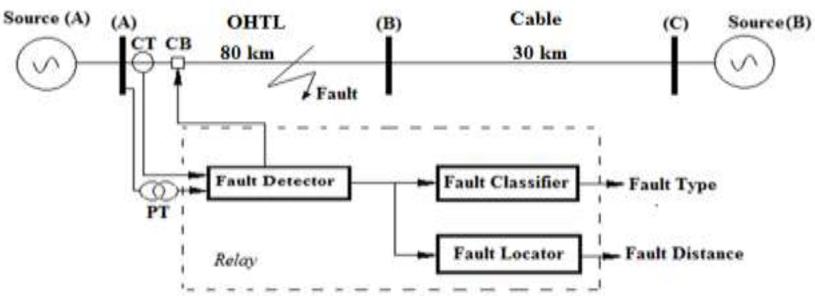


Fig.1: Single line Diagram of the system under study

The measurement devices are located at bus A. Different parameters and conditions such as fault location, inception time and pre-fault power will be changed to obtain training patterns belonging to a wide range of different conditions of the power system. Faults including high amount of resistance, up to 20, were also considered. The total patterns which generated for training the proposed neural networks are 1844 patterns. Table 1 contains the variable parameters values used to generate training and test patterns for the proposed ANNs of the fault detector, classifier and locator.

Table 1: Parameter settings for generating training patterns

Fault location L_f (km)	15, 35, 55, 75, 85, 95, 105
Fault inception time Θ_f (deg)	0, 60, 90, 150, 270, 330
Fault resistance R_f (Ω)	0, 10, 20
Source voltage V_A ,V_B (pu)	0.9, 1, 1.1
Source capacitance S_A, S_B (MVA)	250
Source angles δ_A , δ_B (deg)	5, 10
Fault types	Three phase, phase to ground, phase to phase fault.

III. INPUT SELECTION OF THE PROPOSED NETWORKS

The voltage and current waveforms are the most available information in power systems. Therefore, the sampled normalized voltage and current signals measured at the relay location were considered as the input information to the proposed ANNs. This paper uses consecutive samples of the three phase currents and phase voltages measured by PTs and CTs as the inputs to the proposed ANNs. Pre-processing of the input data is a useful method to reduce the dimensionality of the input data set.

To ensure that the network is able to detect, classify, and locate the fault, three phase voltage and current waveforms were sampled at a rate of 20 samples/cycle. The appropriate data window length is also a major factor which should be considered. It was decided to cover the information of one fourth of the cycle of the voltage and current inputs. Thus, each phase voltage and current was represented by its 5 consecutive samples. Data strings of 5 consecutive samples of each signal sampled at 1 kHz as shown in Fig. 2.

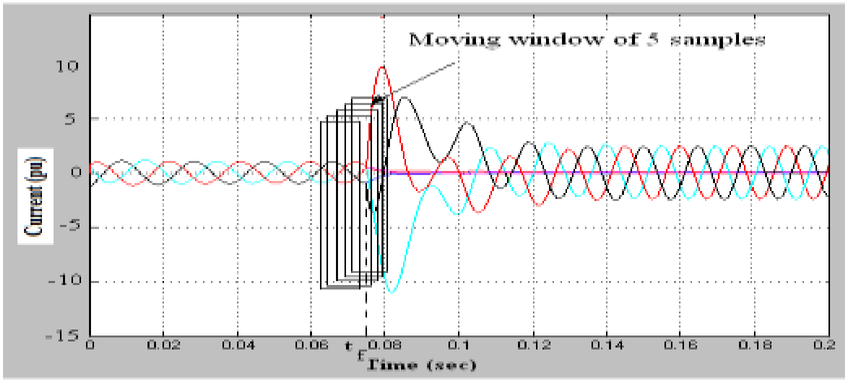


Fig. 2: Moving data window of five samples used as the inputs to the ANN

IV. DESIGN PROCEDURES OF THE PROPOSED ANNS

A Multi feed forward networks (MFNN) have been designed to act as fault detector, classifier, and locator modules of a transmission line relaying system. The design process of the MFNN fault detector, classifier, and locator can be summarized in the flow chart shown in Fig. 3. It illustrates the main steps of the design of the proposed MFNN for fault detection, classification and location for the hybrid transmission line.

4.1. A MFNN based fault detection module (FD)

The function of the MFNN based fault detector module (FD) is to differentiate between two states; normal and fault state on the TL. The process of generating input patterns to the FD is depicted in Fig. 3.

Many different neural network structures, having 30-inputs and one outputs but with different number of neurons in their hidden layers were considered and trained. MFNN trained with the back propagation algorithm in general learns faster when the sigmoid activation function is symmetric than when it is non-symmetric. The values of the outputs during network performance will be analog between 0 and 1. Therefore one of the outputs of the MFNN is mapped to a value of 1 and the other output is mapped to 0.

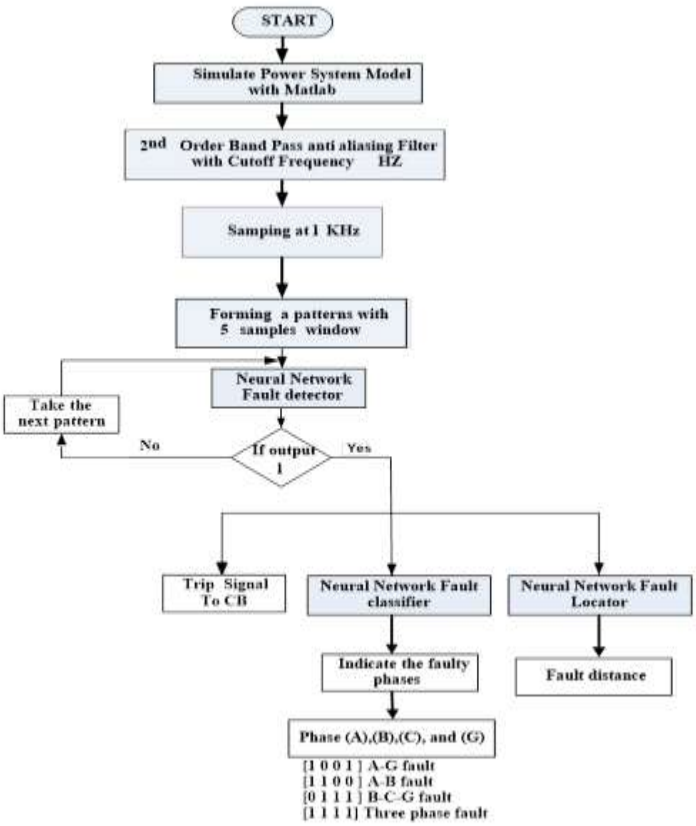


Fig 3: Flow chart of the proposed protection algorithm

Various networks considered were trained with Bp algorithm. The criterion for determining the number of neurons in each hidden layers was based on a combined consideration of the training error and speed. In this paper, several tests were performed to determine the optimum number of hidden neurons based on the mean square error (MSE) and number of training epochs. Moreover, different training functions were examined for convergence. The network which showed satisfactory results, while not having a big size had 30 inputs, 15 neurons in first hidden layer, 10 neurons in second hidden layer and one output neurons. The MFNN structure of the fault detector is (30-15-10-2). It shown in Fig. 4. The sigmoid transfer function was used for hidden and output layers and this function can be expressed as:

$$\varphi(s) = \frac{2}{1+e^{-2s}} - 1 \qquad (1)$$

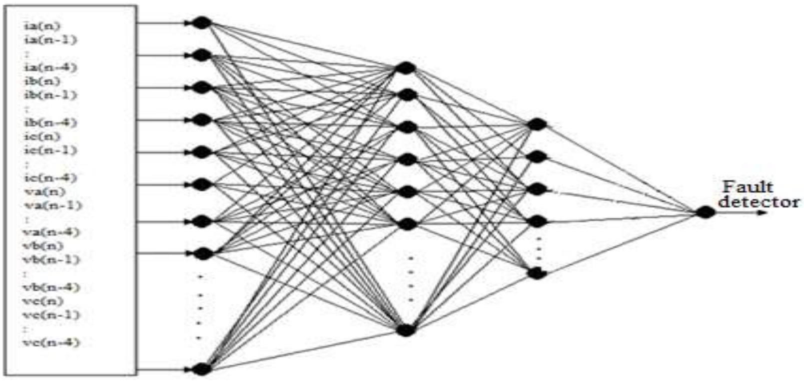


Fig. 4: Structure of MFNN fault detector (FD)

Training set consists of about 1340 pattern representing different conditions of power system, so that a wide range of possible cases is included:

The output layer is capable to minimize the MSE of the MFNN to a final value less than 1.65e-5 within 34 epochs. The MSE training error convergence diagrams for the MFNN using "trainlm" training function is shown in The MSE training error convergence diagrams in Fig. 5.The training performance of the proposed MFNN is depicted in Fig. 6.

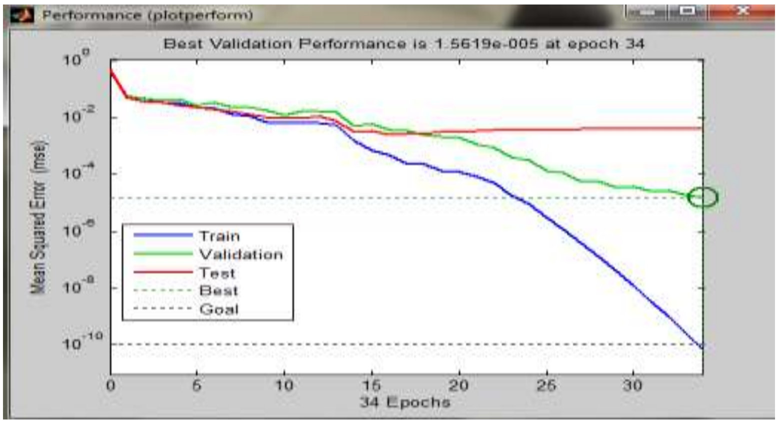


Fig. 5: MSE Training convergence of the MFNN

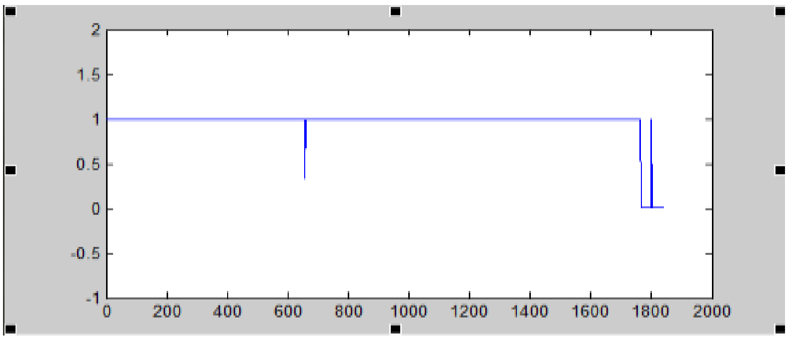


Fig. 6: Training Performance of Output

4.2: Fault classification module (FC)

The inputs to the FC are 6-inputs (3-current and 3-voltage) both are represented by 5 samples, making a total of 30 inputs. The FC has three layers with activation function tan-sigmoid for the hidden layers, and also tan-sigmoid for the output layer. The output layer has 4 neurons to represent the faulty phases and the ground for example a single phase (b) to ground has an output equal to [0 1 0 1], and double phase to ground (c-a) has an output equal to [1 0 1 0].

The MFNN forming the FC uses the three phase currents and the three phase voltage of the TL. The FC module is represented by Fig. 7.

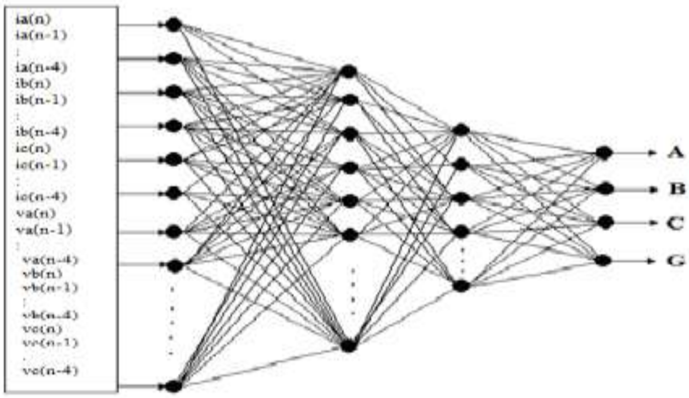


Fig.7: Structure of MFNN fault classifier

The output layer is capable to minimize the MSE of the MFNN to a final value less than 1.45e-10 within 45 epochs. The MSE training error convergence diagrams for the ANN using "trainlm" training function is shown in The MSE training error convergence diagrams in Fig. 8.

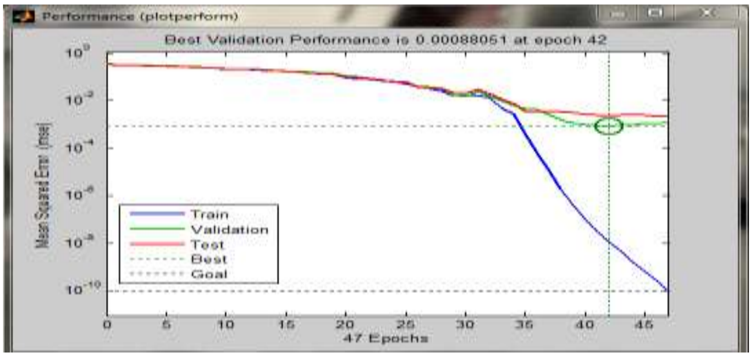
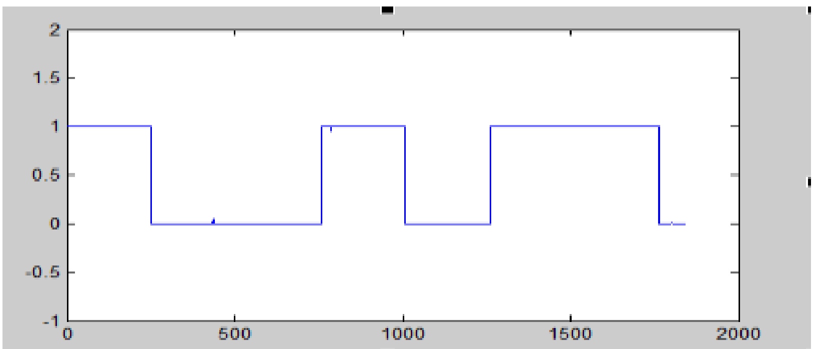
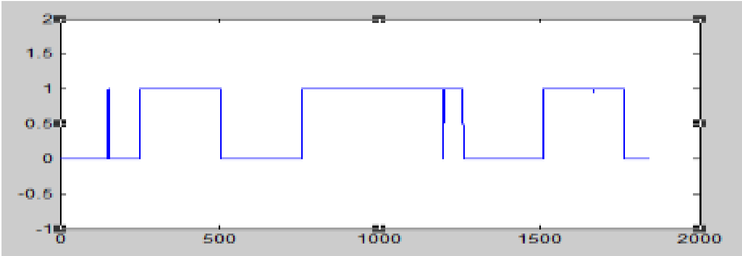


Fig.8: MSE Training convergence of the ANN

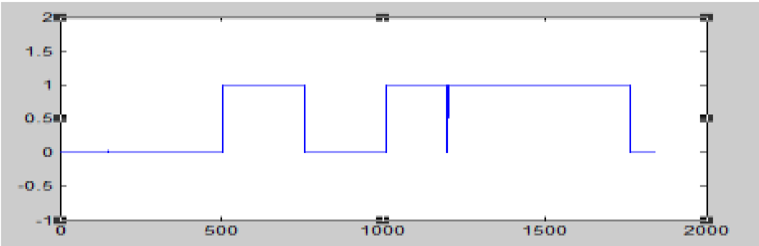
The number of neurons in the hidden layers was determined after a series of trials. It was found that 10 neurons in the first hidden and 8 in the second hidden layer. The training performance of the proposed ANN is depicted in Fig. 9.



(a) Training performance of output (1)



(b) Training performance of output (2)

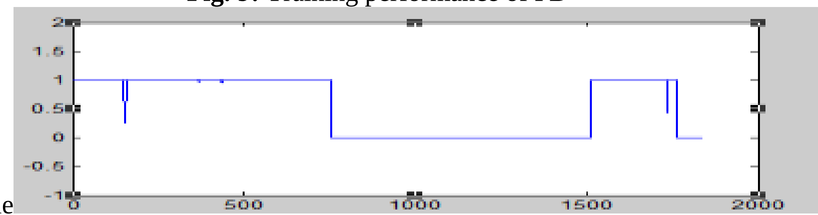


(c) Training performance of output (3)

(d) Training performance of output (4)

Fig. 9: Training performance of FD

module



4.3 Fault location module (FL)

The MFNN fault locator (FL) is to locate faults in our transmission line. The FL is activated when a fault is detected by the fault detector (FD). The MFNN forming the FL uses the magnitudes of the voltage and current phasors corresponding to the post-fault fundamental frequency (50 Hz) as inputs to the MFNN.

The ANN forming of the FL uses three phase current and voltage of the TL. The FL module is represented in Fig. 10.

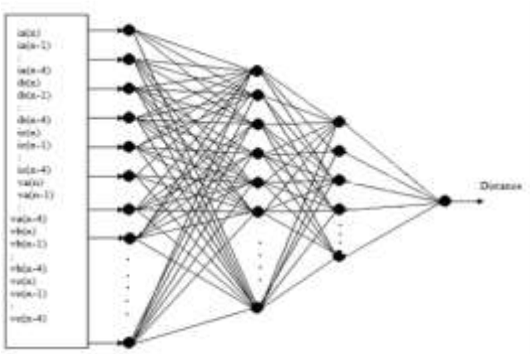


Fig. 10: Structure of ANN fault detector (FC)

The FL module was tested with set of independent test patterns to cover different distance along the line in different types of faults using three modules one for single phase faults, one for double phase faults, and the last one for three phase fault. The training set contested about 756 pattern representing in both cases of single and double line faults, and about 252 pattern representing for three phase fault.

The output layer is capable to minimize the MES of the MFNN to a final value less than 3.05e-3 within 36 epochs for single phase faults, less than 2.47e-4 within 47 epochs for double phase faults, and less than 1.192e-7 within 32 epochs for three phase fault. The MSE training error convergence diagrams for ANN using "logsig" training function is shown in The MSE training error convergence diagrams in Fig. 11.

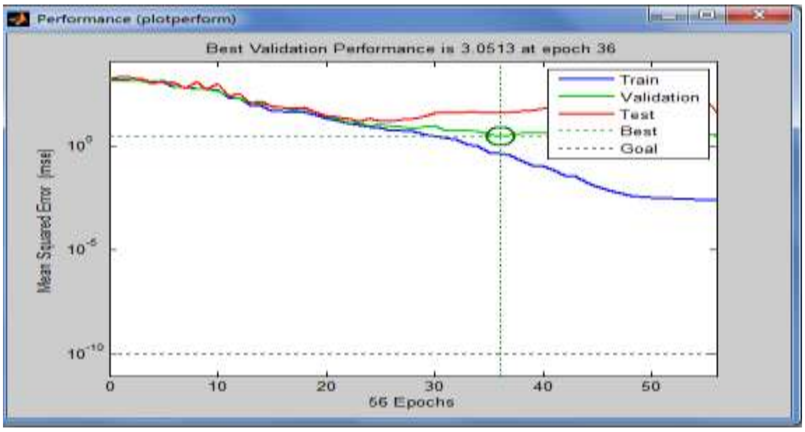


Fig.11: MSE Training convergence of the MFNN for single phase faults

The number of neurons in the hidden layer was determined after a series of trials. It was found that 12 neurons in the first hidden and 8 in the second hidden layer in the module of single phase faults.

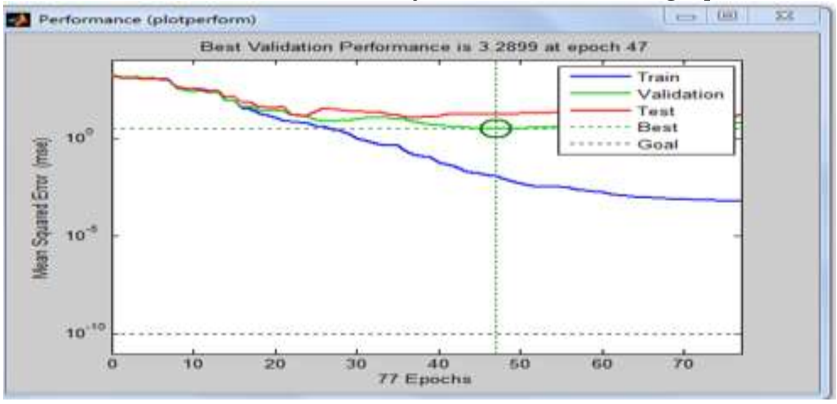


Fig. 12: MSE Training convergence of the ANN of double phase faults.

The number of neurons in the hidden layer was determined after a series of trials. It was found that 15 neurons in the first hidden and 12 in the second hidden layer in the module of double phase faults.

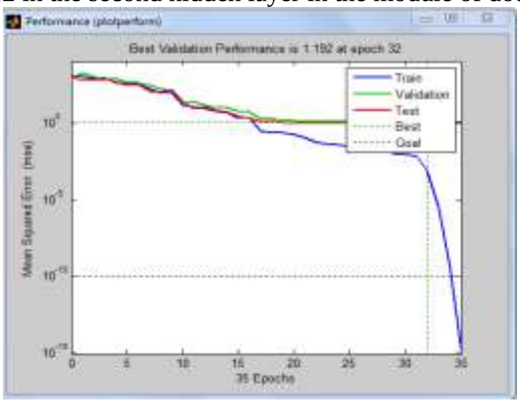
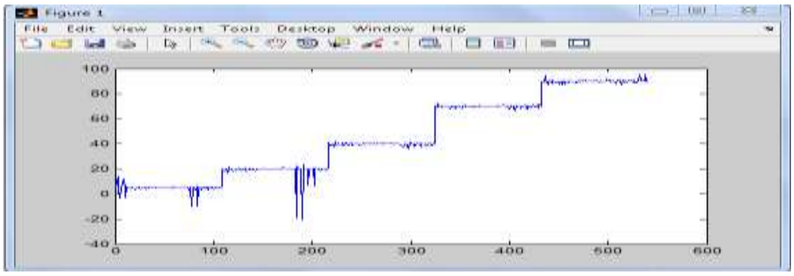
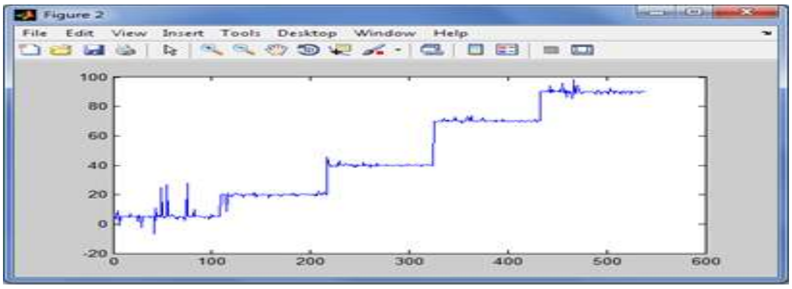


Fig.13: MSE Training convergence of the ANN of the three phase fault**.**

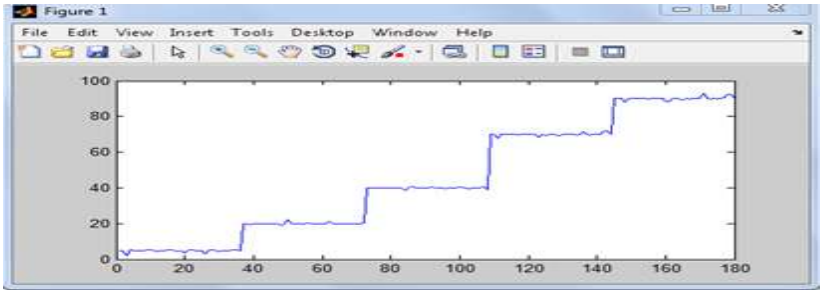
The number of neurons in the hidden layer was determined after a series of trials. It was found that 10 neurons in the first hidden and 10 in the second hidden layer in the module of three phase fault. The training performance of the proposed ANN is depicted in Fig. 14.



(a) Training performance of single phase faults.



(b) Training performance of double phase fault.



(c) Training performance of three phase fault.
Fig.14: Training performance of FC module

V. TEST RESULTS OF THE PROPOSED MODULES

The proposed MFNN was trained off-line. Once the desired performance was achieved, the weights of the MFNN were frozen. In this paper, the proposed MFNN was tested with different independent test patterns and promising results were obtained for the FD, FC, and FL modules. The results of the testing performance are shown in the following sections.

5.1 FD module

Determination of the fault is not affected by the type and the location of the fault, fault inception time, and the presence of fault resistance. Table 2 shows results of different cases of fault the results show that the network correctly detects the faults for all the studied cases.

Table 2: Results of FD module tests.

Fault Point	**Fault Resistance**	**Fault Type**	**Fault Time Occurrence**	**Target Output**	*ANN Output*
At 30km	5(Ω)	a-b-c-g a-g a-b	0.1016 (s)	[1] [1] [1]	[1] [1] [1]
At 90km	12(Ω)	b-g a-b-c-g c-a	0.106 (s)	[1] [1] [1]	[1] [1] [1]

In all cases the MFNN fault detector is correctly detect the faults. The results show the stability of the ANN outputs under normal steady state conditions and rapid convergence of the output variables to the expected values under fault conditions. This clearly confirms the effectiveness of the proposed fault detector.

5.2 FC module

The FC module is activated by the fault detector module only in the event of a fault. The FC was subject to different types of faults at different distance on transmission line, to check its performance. Table 3 gives the results for faults at different fault locations, different fault types and different fault inception time.

Table 3: Results of FC module tests

Fault point	Fault Type	Fault Time Occurred	Target Output	*ANN Output*
At 40km	a-g	0.11 sec	[1 0 0 1]	[0.9998 0.0000 0.0002 1.0000]
	b-c		[0 1 1 0]	[0.0000 0.9999 0.9991 0.0000]
	a-b-c-g		[1 1 1 1]	[1.000 0.9985 1.0000 1.0000]
At 97km	c-g	0.11 sec	[0 0 1 1]	[0.0090 0.0000 1.0000 1.0000]
	a-b		[1 1 0 0]	[1.0000 0.9905 0.0000 0.0000]
	a-b-c-g		[1 1 1 1]	[1.0000 0.9987 1.0000 1.0000]

The results indicate that the FC is accurate robust and is not affected by the different pre-fault loading conditions, fault types, fault locations and inception angle. It can reliably and correctly respond to the faults very near to the neutral point.

5.3 FL module

The FL module is activated by the fault classification module only in the event of a fault. The FL was subjected to different types of faults at different distance on transmission line, to check its performance. Table 4 gives the results for faults at different fault location, different fault type.

Table 4: Results of FL modules tests

Fault Type	Fault Time Occurred	Target Output	ANN Output
a-g	0.108 Sec	[30] km	[32.7550] km
		[45] km	[45.6124] km
		[87] km	[83.8226] km
		[97] km	[97.2099] km
a-b	0.108 Sec	[25] km	[25.1214] km
		[53] km	[53.7728] km
		[93] km	[96.7320] km
		[102] km	[101.5823] km
a-b-c-g	0.108 Sec	[20] km	[18.6412] km
		[50] km	[51.0701] km
		[92] km	[94.7797] km
		[100] km	[102.8627] km

VI. CONCLUSION

This paper presents a scheme for transmission line protection using artificial neural network. The design of the MFNN for transmission line protection can be essentially treated as a pattern recognition problem. An efficient neural network based fault detector, classifier and locator have been proposed. The results demonstrate the ability of MFNN to generalize the situation from the provided patterns and to accurately indicate the presence of fault and locate it. The presented test results demonstrate the effectiveness of the three modules under a variety of fault conditions including fault types, fault location, fault inception angle, and different power system data.

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