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Artificial Neural Network & Wavelet Transform for Identification and Classification of Faults in Electrical Power System

Rajveer Singh[1]
[1]*Asstt. Prof. Deptt. of Electrical Engineering, Jamia Millia Islamia, New Delhi, India.*

Abstract
In a distributed Electrical Power System Faults are the major problem for regular supply to the consumers. A low impedance fault in electrical power distribution system is distinguished by a non-linear and unstable varying fault current due to type of fault. In this combined approach of Wavelet and Artificial Neural Network is used for identification and classification of all types of faults in power distribution system. Wavelet transform identify the types of fault in the form of change in energy in the current waveform and ANN used for classification of faults. IEEE 13-Bus system and 17 bus actual radial distribution system is used to test and verifying the results. The proposed method is implemented and tested in Matlab®/ Simulink environment.
Keywords—Fault Identification, Wavelet transform, ANN, Electrical distribution system, fault classification.

I. INTRODUCTION

In modern electrical power system either transmission system or distribution power system carries a large amount of power and is very complicated system. Fault identification and type of fault is necessary for fast clearance and restoration of supply to improve the power quality.

Fuzzy logic based technique for fault type and identification in electrical distribution system need both voltage and current signals to analyse the system and fault inception angle also [1]. Fault classification technique for power system in case of shunt faults are used for multiple transmission lines [2]. In case of high impedance fault where the fault current is very low and can-not detected easily by the protection equipments, this situation also increased the complexity of the protection system [3-4]. Identification of fault which based on a decision tree method, identifies the fault types (i.e., L-G, L-L, L-L-G and L-L-L faults), the drawback in this method is that it cannot identify the phase or phases involved in this fault [5]. In electrical power system load is changing in nature and more sensitive to power quality disturbances. The supply of electricity for consumers with the superior quality is a major concern today. A novel approach to detect and locate power quality disturbance in distributed power system combining wavelet transform and neural network is proposed in [6]. Faults in electrical distribution system are classified as temporary or permanent. Temporary faults in overhead lines are usually caused by lightning where automatically restored of service within millisecond. Faults by objects falling on the overhead line are permanent [7]. Till today three approaches are used in the industry for fault analysis these are Classical Symmetrical Components, Phase Variable Approach and Complete Time Domain Simulations [8], but symmetrical components based

techniques do not provide accurate result for power distribution systems.

This proposed method is very accurate and can easily detect the faults in the distribution system and can classify all 10 types of faults i.e., AG, BG, CG, AB, BC, CA, ABG, BCG, CAG and ABC (3-Φ) symmetrical fault. The advantage of this proposed method is that it utilises only three line currents.
The proposed technique is tested in IEEE-13 bus and 17 bus local feeders with the help of MATLAB®/ Simulink.

II. FAULT IDENTIFICATION BY WAVELET

In this proposed method the discrete wavelet transform is used for fault identification in electrical power distribution system, and obtained result from wavelet transform used as input to ANN model for fault classification.

A. WAVELET TRANSFORM

The wavelet transform analysis has emerged recently as a powerful tool for signal processing in different applications, particular for electrical power system. The discrete characteristics of wavelets can be employed to exact the information and effective analysis of the signals with complex frequency-time plane. Moreover, the wavelet analysis can accommodate uniform and non uniform bandwidths both. The bandwidth which is higher, make it possible to implement the wavelet analysis through different levels of decimation in a filter bank [9].

The wavelet transform of a signal does not change the information content present in the signal. The Wavelet Transform gives a time-frequency representation of the signal. Wavelet Transform uses many resolution techniques by which different frequencies are analysed with different resolutions. The Wavelet Transform, signal at higher frequency, gives good time resolution and poor frequency resolution, while the signal at low frequency, the Wavelet Transform gives good frequency resolution and poor time resolution.

The wavelet transform decomposes transients into a series of wavelet components, each of which corresponds to a time domain signal that covers a specific octave frequency band containing more detailed information. Such wavelet components used to detect, localize, and classify the sources of transients. Hence, the wavelet transform is feasible and practical for analyzing power system transients. The discrete wavelet transform (DWT) is normally implemented by Mallat's algorithm, its formulation is related to filter bank theory. Wavelet transform is due to this technique, which can be efficiently implemented by using only two filters, one high pass (HP) and one low pass (LP) at level (k). The results are down-sampled by a factor two and the same two filters are applied to the output of the low pass filter from the previous stage. The high pass filter is derived from the wavelet function (mother wavelet) and measures the details in a certain input. The low pass filter on the other hand delivers a smoothed version of the input signal and is derived from a scaling function, associated to the mother wavelet [10]. The basis function (mother wavelet) is a dilated at low frequency and compressed into high frequencies, so that large windows are used to obtain the low frequency component of the signal, while small window reflect discontinuities.

$$Wf(m,n) = 2\text{^}(-m/2) \int f(t)\Phi(2^{-m}t-n)dt \tag{1}$$

Where m is frequency, n is time. In practice wavelet series are in equation (2).

$$f(t) = \sum_{k=-\infty}^{k=\infty} c_k \Phi(t-k) + \sum_{k=-\infty} \sum_{k=-\infty}^{\infty} d_{ik} \Phi(2^i t - k) \tag{2}$$

$$\Phi(x) = \sqrt{2}\ \textstyle\sum_n h_0 \Phi(2x-n) \tag{3}$$

Where $\Phi(x)$ is scale function and h_0 is the low pass filter coefficient.

$$\Phi(x) = \sqrt{2}\ \textstyle\sum_n h_1 \Phi(2x-n) \tag{4}$$

Where $\Phi(x)$ is wavelet function and h_1 is high pass filter coefficient. In fig. 1 Mallat's wavelet tree is shown.

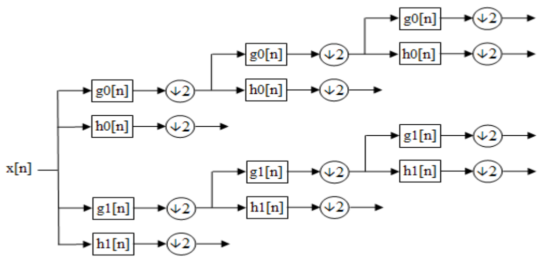


Fig 1. Signal decomposition (Mallat's wavelet tree).

Where, X[n] is the discrete signal.

III. Modeling of Three Phase Distribution System Using Matlab/Simulink

Fig. (2) shows IEEE-13 bus radial distribution system, as an example to compare the result from 17 bus radial distribution local feeder as shown in fig.(3). The data for IEEE-13 bus system are given in [11]. In the system shown in fig. (2) line to ground fault is applied at bus number 632 and only three line currents measured and analyse at main substation at bus number 650.

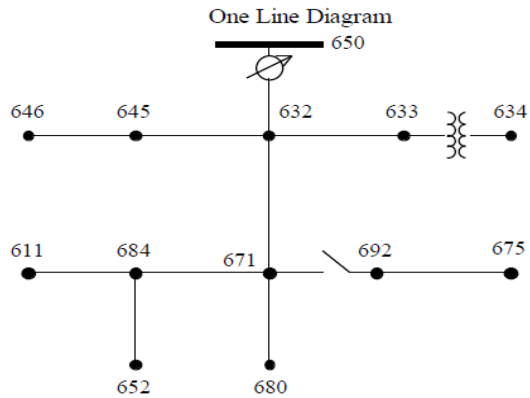


Fig. 2. IEEE 13 Bus Standard System.

Considering the same faults as in IEEE-13 bus system is duplicated on 17 bus radial feeder of distribution power system at bus S_3 shown in fig.(3). The three line currents Ia, Ib and Ic have been measured at the substation as shown in fig.(3). The current waveforms for single line to ground fault (say A-G) and for double line to ground fault (say AB-G fault) are simulated in Matleb / Simulink as shown in Fig.(4) and Fig.(5) respectively.

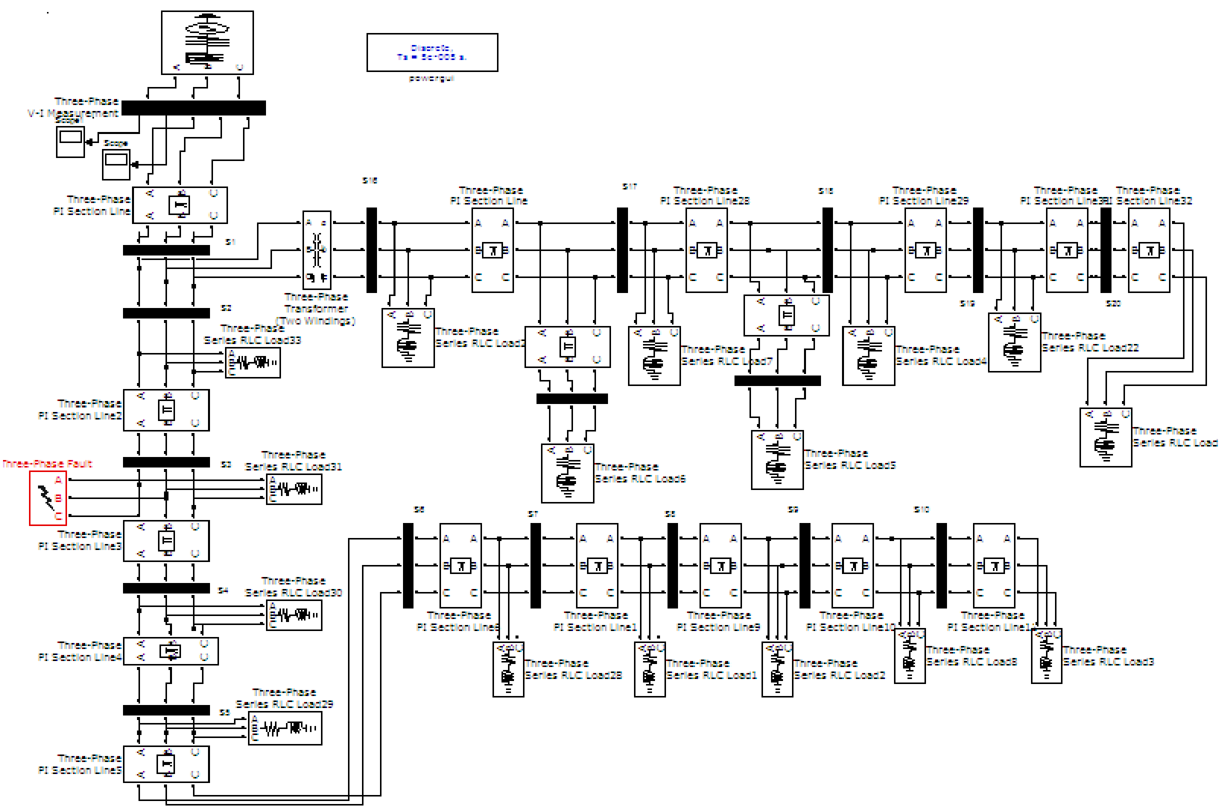
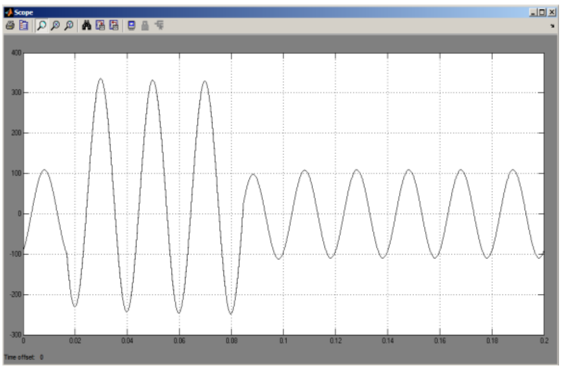
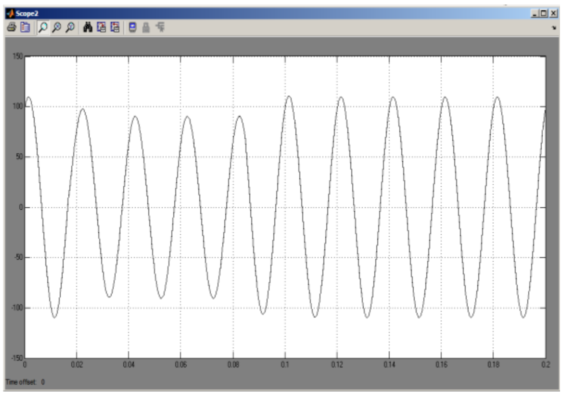


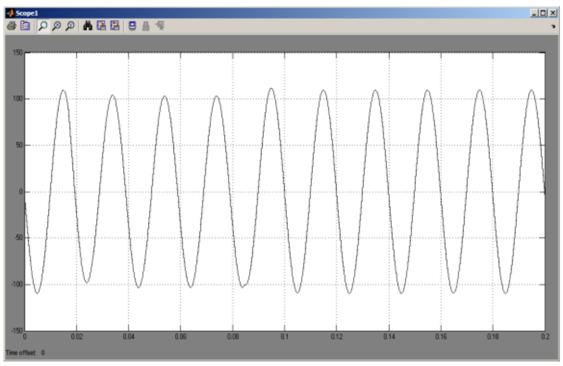
Fig. 3: 17 Bus 3 phase radial distribution system.



Line current Ia (amp)

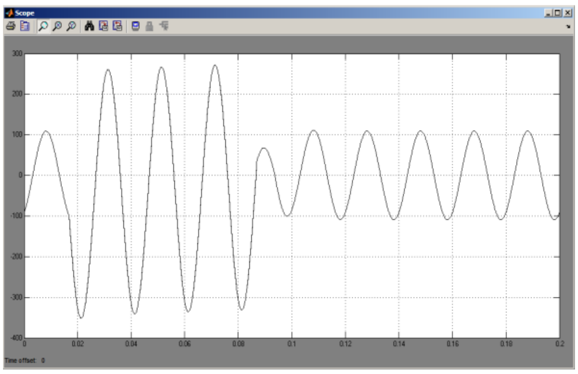


Line current Ic (amp)

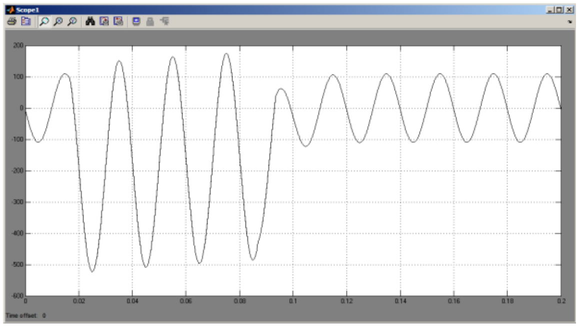


Line current Ib (amp)

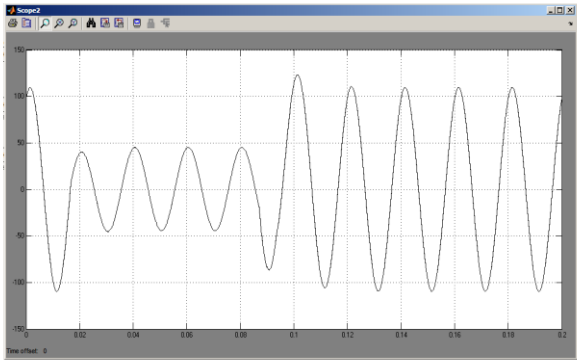
Fig.4: Current waveforms for L-G fault at Bus S3



Line current Ia (amp)



Line current Ib (amp)



Line current Ic (amp)

Fig.5: Current waveforms for LL-G fault at Bus S3

Table I Typical energy values of wavelet transform

Type of fault	Phase A	Phase B	Phase C	Ground (G)
	$*10^{11}$	**$*10^{11}$**	**$*10^{11}$**	**$*10^{11}$**
A-G	1.34181	0.00141	0.00188	0.10901
B-G	0.00277	1.32778	0.00182	0.10972
C-G	0.00249	0.00162	1.34248	0.11418
A-B	1.97169	1.88669	0.00153	0
B-C	0.00211	1.97751	1.90139	0
C-A	1.91831	0.00123	2.01201	0
A-B-G	2.17137	2.09636	0.00202	0.06891
B-C-G	0.00282	2.16326	2.12461	0.06641
C-A-G	2.13819	0.00161	2.19403	0.06728
A-B-C	2.59921	2.56492	2.61268	0

Table II Generalized energy values of wavelet transform for ANN inputs

Type of fault	Phase A	Phase B	Phase C	Ground (G)
A-G	1	0.00102	0.00138	0.09053
B-G	0.00221	1	0.00132	0.09125
C-G	0.00187	0.00117	1	0.09337
A-B	0.92531	1	0.00111	0.00729
B-C	0.01519	1	0.95346	0.00132
C-A	0.95018	0.00062	1	0
A-B-G	1	0.9710	0.00091	0.03453
B-C-G	0.00134	1	0.97385	0.03381
C-A-G	0.97729	0.00072	1	0.03442
A-B-C	0.99921	0.99403	1	0

The system input for ANN is four normalized energy levels of phase A, B, C and G.

IV. Classification of fault by ANN

For the purpose of fault classification, 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 and the training data set size.

After study, the back-propagation algorithm has been decided 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 enhance 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.

A. ANN Regress Training for Fault Classification

In the first stage which is the classification of faulty phase, the network takes in four inputs at a time, which are the currents of all the three phases (scaled with respect to the pre-fault values). Hence the training set consisted with a set of four 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 a fault has been detected or not. After extensive simulations, it has been decided that the desired network two hidden layer with 18 neurons in the hidden layer are effective. 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.

Fig (6). shows the training process of the neural network with 4-12-6-1 configuration (4 neurons in the input layer, 2 hidden layers with 12 and 6 neurons in them respectively and 1 neuron in the output layer).

From the above training performance plots, it is to be noted that very satisfactory training performance has been achieved by the neural network with the 4-12-6-1 configuration (4 neurons in the input layer, 2 hidden layers with 12 and 6 neurons in them respectively and 1 neuron in the output layer). The overall MSE of the trained neural network is way below the value of 0.001 and is actually 1.55e+03 by the end of the training process. Hence this has been chosen as the ideal ANN for the purpose of fault classification.

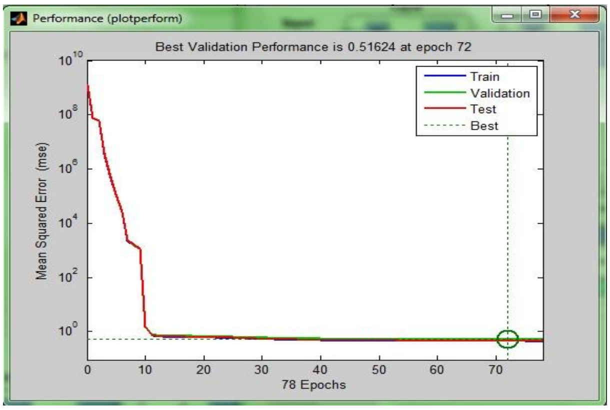


Fig.6: Mean-square error performance of the network (4-12-6-1).

B. *Testing The Fault Type By Neural Network*

Once the neural network has been trained, its performance has been tested by plotting the best linear regression that relates the targets to the outputs as shown in Fig 7.

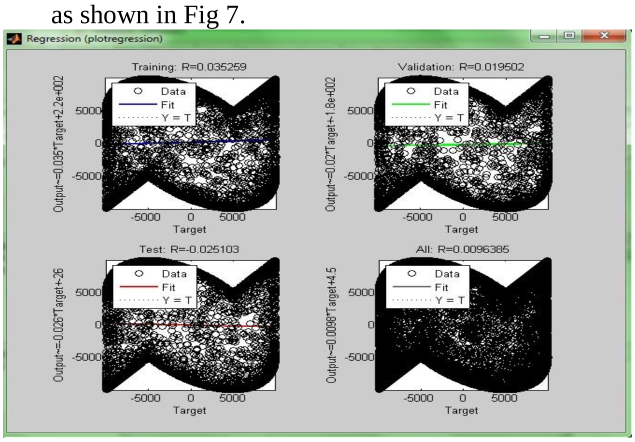


Fig.7: Regression fit of the outputs vs. targets for the Faulty Network (4-12-6-1)

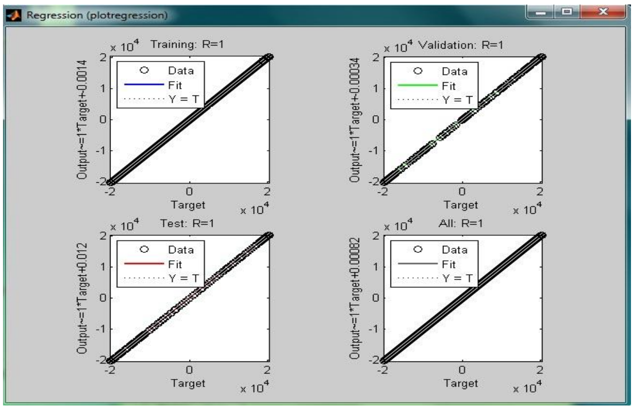


Fig.8: Regression fit of the outputs vs. targets for the Healthy Network (4-12-6-1)

The second step in the testing process is to create a separate set of data called the test data to analyze the performance of the trained neural network.

After the test data has been fed into the neural network and the results obtained, it was noted that the efficiency of the neural network in terms of its ability to detect the occurrence of a fault is more than 90 percent. Hence the neural network can, with utmost accuracy, differentiate a normal situation from a faulty situation on a transmission line.

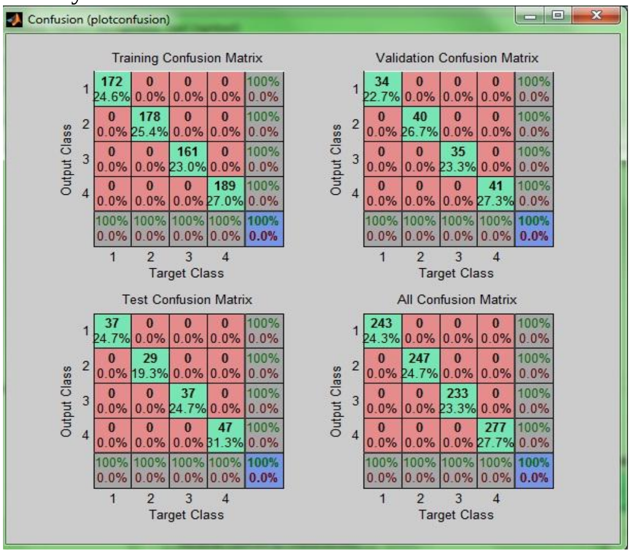


Fig.9: Confusion Matrices for Training, Testing and Validation Phases

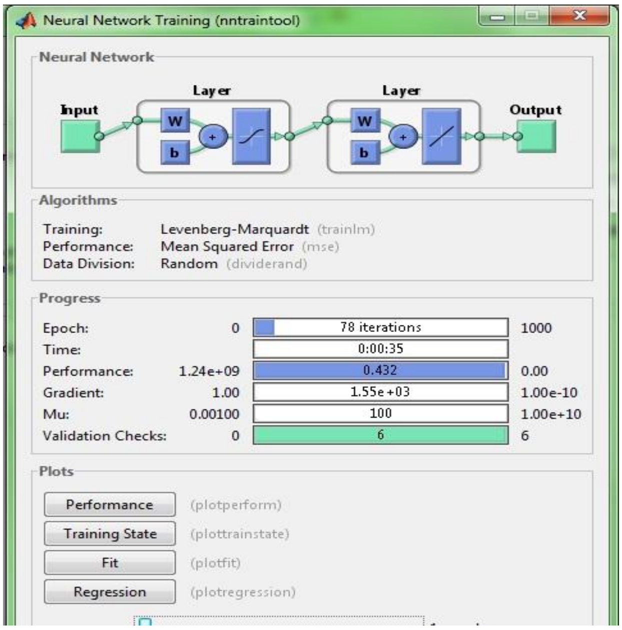


Fig.10: Overview of the ANN (4-12-6-1) chosen for fault classification.

Fig.(8) Presents a snapshot of the trained ANN with the 4–12–6–1 configuration and it is to be noted that the number of iterations required for the training process were 78. It can be seen that the mean square error in fault classification achieved by the end of the training process was 1.55e+03 and that the number of validation check 6 by the end of the training process.

The structure of the chosen neural network for fault classification is shown in Fig. (11). It is to be noted that there are 4 neurons in the input layer, 2 hidden layers with 12 and 6 neurons in them respectively and 1 neuron in the output layer.

Table III: Fault code for ANN output

Type of Fault	Network Outputs			
	A	B	C	G
A-G Fault	1	0	0	1
B-G Fault	0	1	0	1
C-G Fault	0	0	1	1
A-B Fault	1	1	0	0
B-C Fault	0	1	1	0
C-A Fault	1	0	1	0
A-B-G Fault	1	1	0	1
B-C-G Fault	0	1	1	1
C-A-G Fault	1	0	1	1
A-B-C Fault	1	1	1	0

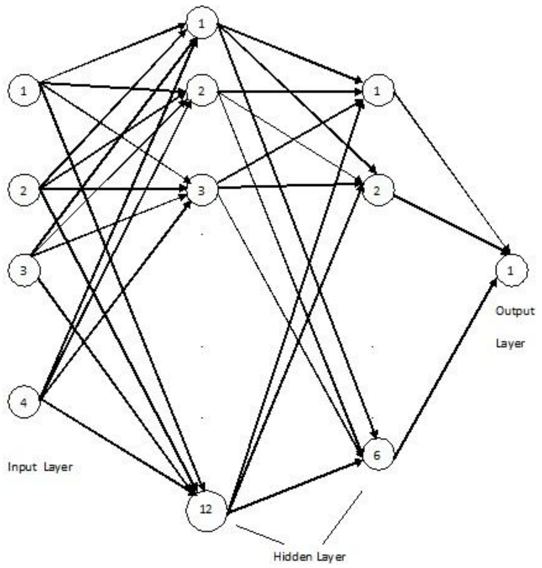


Fig.11: Chosen ANN for Fault classification (4–12–6–1).

V. Conclusion

In case of fault, current is an important parameter to deal with distribution power system because it directly affects the load connected to the system and it may be harmful for electronic and electrical equipments. This paper has proposed the usage of ANN as an alternative method for the identification and classification of faults in electrical distribution lines. The methods employs make the use of line currents (scaled with respect to their pre-fault values) as inputs to the artificial neural network. Various possible kinds of faults namely single line-ground, line-line, double line-ground and three phase faults have been taken into consideration in this work and ANN have been proposed for these faults.
Only three line currents data with ground current is needed as inputs to the ANN for training the ANN which reduces the complexity the ANN.

To simulate the entire distribution power system model and to obtain the training data set, MATLAB 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. The accuracy of the proposed method is satisfactory and is able to classify all ten types of faults accurately.

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AUTHOR□S DETAILS

Rajveer Singh received the B.Tech.from Jamia Millia Islamia and M.Tech. from NSIT (D.U.) New Delhi, and Ph.D. pursuing in Electrical Engineering from JMI, New Delhi, India. He is currently working as Assistant Professor in the Department of Electrical Engineering, Jamia Millia Islamia, New Delhi-110025. His research interests include distribution power system, renewable energy, transmission line fault.