

# Fault Classification Accuracy Measurement for a Distribution System with Artificial Neural Network without using Signal Processing Technique

S.V.Khond, G. A.Dhomane



**Abstract:** Faults occurring on electrical distribution network are unpredictable and needs to be cleared at the earliest so as to reduce power outage time. Hence fault detection and their classification plays important role. In this research paper the fault classification accuracy was measured for an electrical power distribution network with artificial neural network without using any signal processing method. Although many digital signal processing methods are developed to enhance electrical fault classification accuracy, it is essential to measure it for comparison when no signal processing method is used. Fault classification was considered as a pattern recognition application of neural networks. Two layer feed forward back propagation neural network was used as classifier. IEEE 13 bus distribution feeder was simulated in MATLAB with Simulink for collecting the input data. The simulation results show that the faults can be classified satisfactorily. L-G, L-L and L-L-L faults were simulated for measuring the accuracy of fault classification.

**Keywords:** Electrical power distribution, Fault classification, artificial neural networks, signals processing technique.

## I. INTRODUCTION

Generally electricity consumers get supply from distribution systems. Due to component failure, lack of proper maintenance, over load and aging of components results in occurrence of faults resulting in power outages for the consumers. To reduce the power outages and enhance customer satisfaction, fast fault identification and classification is needed. This is achieved by removal of faulty section of the system from healthy one by implementing the properly designed protection systems. With accurate fault identification and classification methods implemented in the distribution systems an efficient, secured, effective and fast relaying operation can be provided [1-2].

A sudden change in the current or voltage values is a positive indication of fault occurrence on the network and it is used for to distinguishing the normal and the fault condition.

In conventional algorithms, the measurement of voltage and/or current is used to detect the fault condition. Use of artificial neural networks (ANN) as pattern recognition applications is reported by many researchers to identify and classify faults and also to design an effective protection system [3-7]. The conventional fault detection methods use parameters like change in fault resistance or source impedance, short circuit capability of distribution network using suitable filtering methods to measure magnitudes of current and voltage [12]. Back propagation, conjugate gradient and Marquardt algorithms etc are developed for such applications [8]. Other approaches based on static vector machine, deep learning, convolution neural networks, auto encoders, fuzzy inference systems, decision tree are used to classify and locate the electrical faults on distribution systems [9-11]. The digital signal processing methods are generally implemented on fault voltage or current signals for extracting features from sampled signals. These features are used as input to the classifier. Signal processing methods like discrete wavelet transform, Fourier transform, multiwavelet packet transform, S-transform (ST), Hyperbolic ST (HST), fast discrete orthonormal ST (FDOST) etc. are commonly used. [11]. As faults on the distribution system affects the transient stability of system, to maintain the transient stability, fast and correct measurements of fault current or voltage becomes essential. Use of artificial intelligence methods with suitable algorithms are used to classify and to identify the location of faults on power distribution systems [13-15].

Even if digital signals processing methods are used to improve the faults classification accuracy, it is essential to know it for comparing the results when no digital signal processing method is used.

In this research paper focus is to measure electrical fault classification without using any signal processing method. L-G, L-L and L-L-L faults were simulated on IEEE 13 bus test distribution feeder in MATLAB Simulink for classification and maximum value of fault current  $I_{max}$  was given as input to ANN.

This research paper is presented in five parts. First part covers introduction and discusses different approaches used for detection and classification of faults. Second part includes discussion on neural networks and details of training of it. The third part provides information about test distribution system under consideration and simulation details.

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The fourth part is result and the fifth part gives conclusion of the paper.

## II. ARTIFICIAL NEURAL NETWORK

ANN is a computational system inspired from working of biological neural networks like the working of human brains. ANN is used popularly where use of conventional computing finds limitations. It is a frame work of different machine learning algorithms which works together and can process complex input data. Due to its ability to reproduce, model the non linear processes and learn with experience, ANN are used effectively in pattern recognition, process control, speech recognition, gesture recognition, medical diagnosis, finance (automated trading systems) type applications. It can also work with the problems where the large volume of input information has to be processed [16].

Various computational models of the ANN like Feed forward, probabilistic NN, Radial Basis function (RBF), Time delay NN, Convolution NN, General Regression NN, Deep Learning NN, Auto encoder are developed over the years. Due to the ability of ANN to model the nonlinear processes and learn with experiences it can be used as a pattern recognition application in fault classification effectively. ANN can deliver accurate, fast and reliable outputs by setting proper training parameters like type of activation function used, choosing suitable number of hidden layers and neurons in the ANN, parameters of learning algorithm, and criterion for termination. After occurrence of the fault the current values increases significantly and it depends upon the type of fault. The fault current is minimum for L-G fault and is maximum for L-L-L fault condition. Using neural network, faults can be classified using the patterns generated in the post fault current values, obtained from the simulated model of the test feeder. The proposed neural network has the three inputs i.e. the maximum current  $I_{max}$  on each phases of distribution network during fault. With these three inputs the neural network is trained to classify inputs in seven types of faults (A-G, B-G, C-G, A-B, B-C, C-A, A-B-C) as output.

### A. Feed Forward neural network with back propagation algorithm (BPNN)

In these neural networks, information flows only in forward direction i.e., from the input to output layer through hidden layers if present. The output is fed back to the input so as to calculate changes in weight values. Initially the weights are chosen randomly and their values are updated after each iteration with new values. The process is repeated for all the input and output pairs used to train the network till the network convergences to predefined error value for given target values. Fig. 1 shows the back propagation process. Error is calculated after each iteration using different algorithms like mean square error, Cross-Entropy, and calculation of Jacobean and Hessian matrices [17].

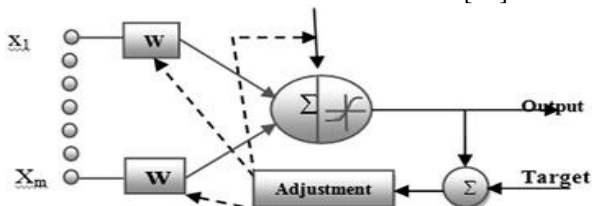


Fig.1 Back Propagation ANN Structure.

The BPNN algorithm can be represented as:

#### 1. Propagation in Forward direction

$$a_j = \sum_i^m w_{ji}^{(1)} * x_i(1)$$

$$z_j = f(a_j)$$

$$y_j = \sum_i^M w_{kj}^{(2)} * z_j$$

#### 2. Difference in Output

$$\delta_k = y_k - t_k$$

#### 3. Back propagation process in hidden layers

$$\delta_j = (1 - z_j^2) \sum_{k=1}^K w_{kj} * \delta_k$$

4. The error gradient between weights of second layer with respect to first layer is calculated.

5. Earlier weights are modified.

Where:  $a_j$ : weighted inputs sum.  $w_{ji}$ : weight associated with interconnection,  $x_i$ : input to neural network,  $z_j$ : input activation unit which sends connection for unit  $j$ ,  $\delta_k$ : error derivative at  $k^{\text{th}}$  neuron,  $y_i$ :  $i^{\text{th}}$  output,  $y_k$ : unit activation output for unit  $k$ ,  $t_k$ : corresponding input target and  $\delta_j$ : error derivative w.r.t. to  $a_j$ .

ANN learning rate is improved by choosing optimum weights after each iteration [18-19].

## III. MODELING OF TEST DISTRIBUTION NETWORK

Using MATLAB Simulink with Power Systems toolbox the IEEE 13 bus distribution system was simulated to obtain the maximum fault current  $I_{max}$  for developing a BPNN based pattern recognition problem for classifying faults. The IEEE 13 bus offers all common features present in real distribution networks such as:

- A  $\Delta$ -Y transformer and a Y-Y with voltage ratings 115/4.16 kV and 4.16/0.480 kV respectively.
- Separation of buses through medium distances with adequate loads connected to them.
- The interconnection of buses is through two underground cables and ten overhead lines sections.
- Unbalanced loads.
- Changes in phase configurations of interconnected buses.
- The supply from a generator and a voltage regulator.

Fig. 2 shows a screenshot of the IEEE 13 bus model build in MATLAB to obtain input data for training, validation and testing data sets for the ANN.

Using  $I_{max}$  the training patterns were obtained during fault condition at each bus. Entire distribution system was considered to obtain data by simulating faults at each bus.

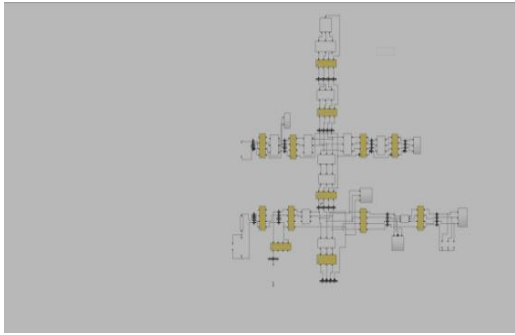


Fig. 2 IEEE 13 bus model screenshot

**A. Fault current measurement and pre-processing of data for ANN**

The fault condition was simulated during 0.04 -0.07 sec at 50 Hz frequency. Around 300 samples of fault current during fault condition was obtained. Samples were collected on each bus for L-G, L-L, and L-L-L type faults.

With extraction of features from sampled data the performance of ANN is improved as overall size of the input data is reduced and all important information in fault current signal is available and used effectively. For this purpose the maximum value of fault current signals during transients was obtained from samples.  $I_{max}$  was used to as input to the BPNN.

In Fig. 3 the voltage and current waveforms are shown for an A-B fault at bus 633 of the distribution test feeder. The changes in voltage and current are shown in first and second graph respectively before the occurrence of fault, during fault condition and when the fault duration over.

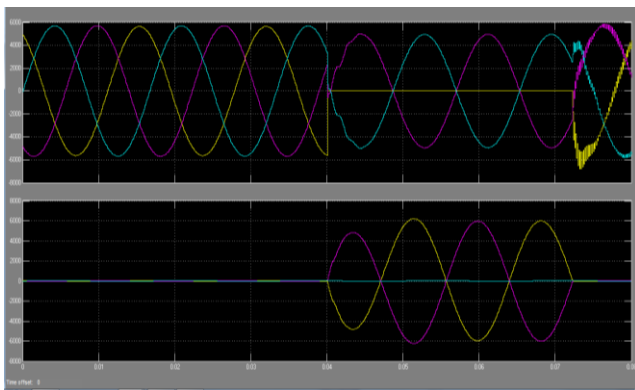


Fig. 3 Illustration of A-B fault at Bus 633.

**B. Training and testing of ANN**

Fig. 4 shows the ANN model developed using Neural Network tool box in MATLAB environment. The complete input data obtained from simulated model was divided in three parts. The training data, the validation data and the testing data. With the training data the ANN was trained to calculate the error gradient. The weights of ANN were updated till it converges to the predefined error value.

With the validation data, the error is monitored for entire validation data while training the ANN. It has only input values and does not have any output value. When error increases beyond a certain predefined value, the process of validation fails and further training of ANN is stopped. With the elements in test data set the overall performance of fully trained ANN was evaluated. If the performance of ANN is not

up to the expected level it has needs to be restructured by changing its parameters.

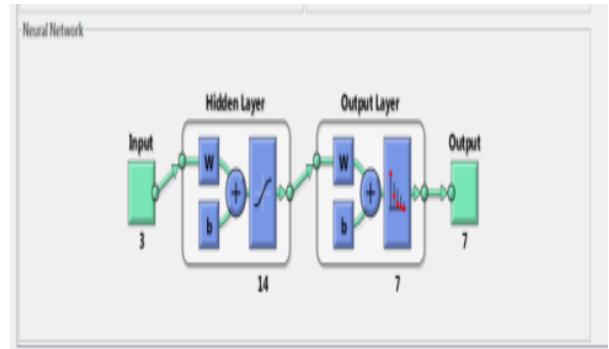


Fig. 4 BPNN model developed in Simulink.

**C. Classification of Faults**

The entire data set used for training of ANN had a total of 68 inputs and output patterns. Each combination of input-output pattern with three inputs and one output. The ANN under consideration has three inputs in the form of  $I_{max}$  for all fault types at each phase. The ANN has seven outputs such that every output shows one of the seven types of faults on the network. The output 0 indicates absence of fault and output 1 indicates presence of that fault e.g. when A-G fault was simulated on Phase A on any bus of network, the corresponding output was represented as 1 and the output for all other faults was represented as 0.

Feed forward back-propagation network model was analyzed by changing the number of neurons in hidden layer. The best performance was observed for ANN model with 1 hidden layer with 14 neurons and 07 neurons in the output layer. 70%, 15% and 15% of total input data was used for training, validation and testing respectively. The BPNN is expected to classify all seven types of faults on the network accurately.

Overall error measured in terms of cross entropy was observed to be 0.13514 for finally trained ANN. Fig.5 shows the overall error in terms of cross entropy. The similar nature of characteristics of testing and the validation curves in red and green colour indicates an efficient training of the ANN. Minimum value of cross entropy indicates efficient and effective classification of patterns as input to ANN while zero value indicates no error in classification at all.

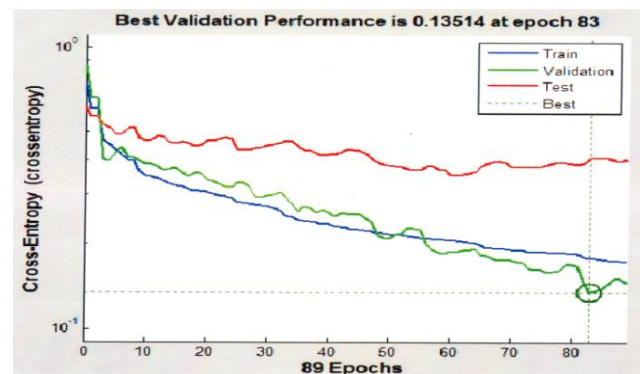


Fig. 5 Performance Cross-Entropy of neural network

The performance of ANN was measured by two methods, firstly with the receiver operating characteristics (ROC) of ANN. ROC represents true positive classification rate plotted against false positive classification rate in terms of percentage for all the output classes. Fig. 6 shows training, validation, test and all ROC plots. The lines in plot closer to the left and top corner indicate satisfactory classification.

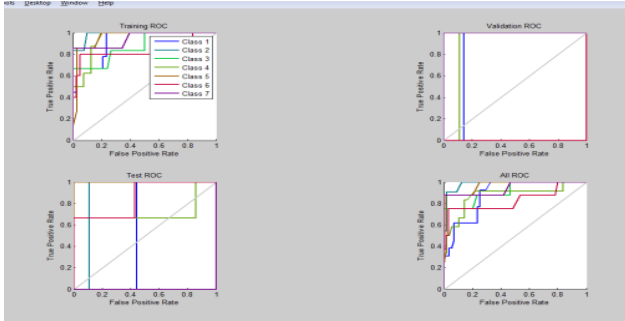


Fig. 6 ROC of the ANN.

Secondly, from the all confusion matrixes. All confusion matrixes indicate the ability and efficiency of the finally trained ANN in classifying all types of the fault as output. The output is represented in the form of four confusion matrixes. Training confusion, validation confusion, test confusion and all confusion matrixes. The lower right blue squares represent overall classification accuracy.

As seen from Fig.7, the all confusion matrixes of ANN indicates 77.9 % accuracy to classify amongst all seven types of faults simulated on a test distribution system.

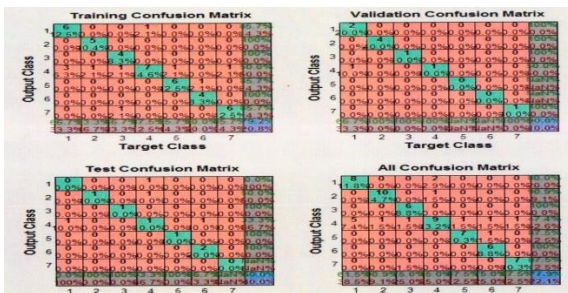


Fig. 7 Training, Validation, Testing, All Confusion matrix

IV. RESULT

The results for measurement of fault classification accuracy without using any signal processing method are shown in tabulated form as follows:

Table- I: Fault classification measurement

Sr No	Input to ANN	Cross Entropy (Error)	All Confusion Matrixes (Classification Accuracy)
1	$I_{max}$	0.13514	77.9 %

Thus, with  $I_{max}$  i.e. maximum value of fault current given as inputs to the BPNN as the pattern recognition application of ANN, the error in terms of cross entropy was 0.1351 and the overall classification accuracy of BPNN was 77.9%. Without applying any signal processing method, the proposed neural network has delivered the satisfactory performance.

V. CONCLUSION

From the above discussion, it can be concluded that, if sufficient training data is given to a back propagation neural network, it delivers good result. Sufficient training data was obtained with extensive simulations on test distribution feeder. Therefore the back propagation network was chosen in this research work. Structure of neural network and learning algorithm changes performance of an ANN significantly. With out applying any signal processing method on the input data the BPNN was able to classify the L-G, L-L, L-L-L faults with accuracy of 77.9% which is satisfactorily high.

Suitable protection schemes can be designed and implemented for the distribution systems to isolate the faulty portion from the healthy portion to reduce the power outage time based on the ANN used as classifier.

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