A Novel Approach For Fault Analysis In Electrical Transmissions Line Using Neural Network In Matlab

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Abstract- *This Paper focuses on detecting and classifying the faults on electric power transmission lines. Fault detection, fault classification and fault location have been achieved by using artificial neural networks. Feedforward networks have been employed along with backpropagation algorithm for each of the three phases in the Fault location process. Analysis on neural networks with varying number of hidden layers and neurons per hidden layer has been provided to validate the choice of the neural networks in each step. Simulation results have been provided to demonstrate that artificial neural network based methods are efficient in locating faults on transmission lines and achieve satisfactory performances.*

Keywords- Artificial Neural Networks, Feedforward networks, Backpropagation Algorithm, Levenberg-Marquardt algorithm.

I. INTRODUCTION

One of the most important factors that hinder the continuous supply of electricity and power is a fault in the power system [2]. Any abnormal flow of current in a power system's components is called a fault in the power system. These faults cannot be completely avoided since a portion of these faults also occur due to natural reasons which are way beyond the control of mankind. Hence, it is very important to have a well coordinated protection system that detects any kind of abnormal flow of current in the power system, identifies the type of fault and then accurately locates the position of the fault in the power system. The 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. Hence some of the important challenges for the incessant supply of power are detection, classification and location of faults [3]. Faults can be of various types namely Transient, persistent, symmetric or asymmetric faults and the fault detection process for each of these faults is distinctly unique in the sense, there is no one universal fault location technique for all these kinds of faults.

From quite a few years, intelligent based methods are being used in the process of fault detection and location. Three major artificial intelligence based techniques that have been widely used in the power and automation industry are [6]:

1 Expert System Techniques
2 Artificial Neural Networks
3 Fuzzy Logic Systems

Among these available techniques, Artificial Neural Networks (ANN) have been used extensively in this thesis for fault location on electric power transmission lines. These ANN based methods do not require a knowledge base for the location of faults unlike the other artificial intelligence based methods [7]

II. ARTIFICIAL NEURAL NETWORK

INTRODUCTION

An Artificial Neural Network (ANN) can be described as a set of elementary neurons that are usually connected in biologically inspired architectures and organized in several layers [9]. The structure of a feed-forward ANN, also called as the perceptron. There are Ni numbers of neurons in each ith layer and the inputs to these neurons are connected to the previous layer neurons. The input layer is fed with the excitation signals. Simply put, an elementary neuron is like a processor that produces an output by performing a simple non-linear operation on its inputs. A weight is attached to each and every neuron and training an ANN is the process of adjusting different weights tailored to the training set. An Artificial Neural Network learns to produce a response based on the inputs given by adjusting the node weights. Hence we need a set of data referred to as the training data set, which is used to train the neural network.

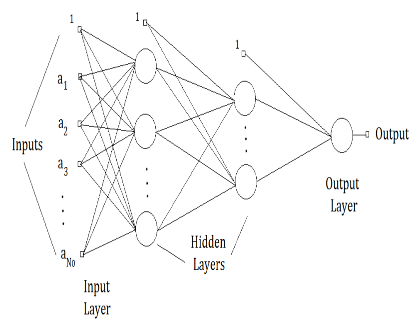

Fig 1 A basic two-layer architecture of a feed-forward ANN.

In Fig 1, a1, a2 … aN0 is the set of inputs to the ANN. Due to their outstanding pattern recognition abilities ANNs are used for several purposes in a wide variety of fields including signal processing, computers and decision making. Some important notes on artificial neural networks are:

- The output provided by the neural network corresponds to the concerned decision which might be the type of fault, existence of a fault or the location of a fault.
- The most important factor that affects the functionality of the ANN is the training pattern that is employed for the same.
- Pre-processing and post-processing techniques may be employed as well to enhance the learning process and reduce the training time of the ANN.

III. MODEL OF A NEURON

Any basic neuron model as shown in Fig 2 can be described by a function that calculates the output as a function of N0 inputs to it.

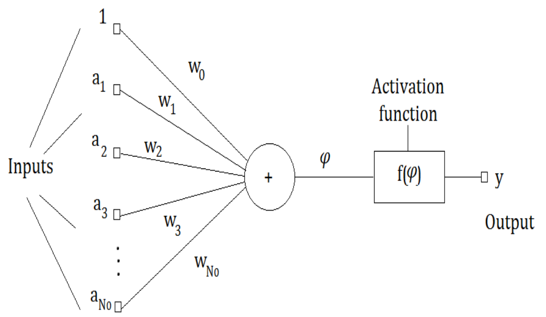

Fig 2 Typical model of a neuron

The output of the neuron is given by

$$\mathbf{y = f(\varphi) = (\textstyle\sum_{i=0}^{n0} Wi.ai\,)}$$
(1)

(3.1)

Where: w0a0 is the threshold value (polarization), f(φ) is the neuron activation function,

φ is the summation output signal and y is the neuron output.

$$\mathbf{\varphi = WT.A} \qquad (2)$$

$$Where\ \boldsymbol{W} == [\boldsymbol{W0}\ \boldsymbol{W1} \ldots\ldots\ldots.\boldsymbol{Wk0}],$$

$$\boldsymbol{A} = [\boldsymbol{a0}\ \boldsymbol{a1} \ldots\ldots\ldots\ldots\ldots\ldots \boldsymbol{aN0}]\boldsymbol{T} \qquad (3)$$

FAULT LOCATION IN POWER TRANSMISSION LINES USING NEURAL NETWORKS

Artificial neural networks have been used for the protection of power transmission lines. The excellent pattern recognition and classification abilities of neural networks have been cleverly utilized in this thesis to address the issue of transmission line fault location. , a complete neural-network based approach has been outlined in detail for the location of faults on transmission lines in a power system. To achieve the same, the original problem has been dealt with in three different stages namely fault detection, fault classification and fault location.

MODELLING THE POWER TRANSMISSION LINE SYSTEM

A 735 kV transmission line system has been used using ANNs. Fig 3 shows a one-line diagram of the system. The system consists of two generators of 500 kV each located on either ends of the transmission line along with a three phase fault simulator used to simulate faults at various positions on the transmission line. The line has been modelled using distributed parameters so that it more accurately describes a very long transmission line.

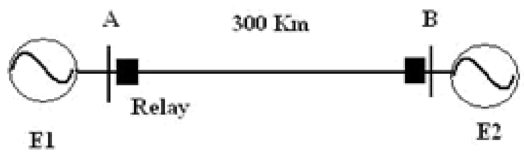

Figure 3 One-line diagram of the studied system.

This power system was simulated using the SimPowerSystems toolbox in Simulink by The MathWorks. A snapshot of the model used for obtaining the training and test data sets is shown in Fig 4 The three phase V-I measurement block is used to measure the voltage and current samples at the terminal A. The transmission line (line 1 and line 2 together) is 300 km long and the three-phase fault simulator is used to simulate various types of faults at varying locations along the transmission line with different fault resistances.

The values of the three-phase voltages and currents are measured and modified accordingly and are ultimately fed into the neural network as inputs. The SimPowerSystems toolbox has been used to generate the entire set of training data for the neural network in both fault and non-fault cases.

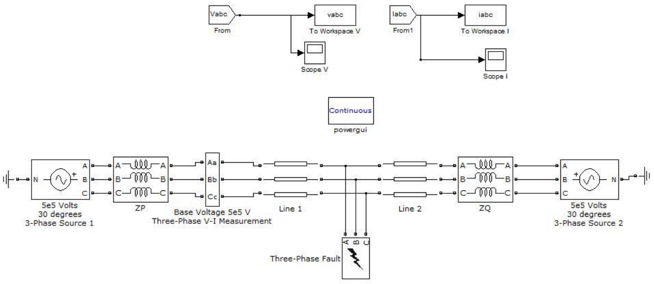

Figure 4 Snapshot of the studied model in Sim Power Systems.

Faults can be classified broadly into four different categories namely:

- line to ground faults
- line to line faults
- double-line to ground faults
- three-phase faults

There have been 1100 different fault cases simulated for the purpose of fault detection, 1100 different fault cases simulated for fault classification and varying number of fault cases (based on the type of fault) for the purpose of fault location.

IV. EXPERIMRENTAL RESULTS

FAULT DETECTION:- For the purpose of fault detection, 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 employed and the training data set size.

TRAINING THE FAULT DETECTION NEURAL NETWORK:-

In the first stage which is the fault detection phase, the network takes in six inputs at a time, which are the voltages and currents for all the three phases (scaled with respect to the pre-fault values) for ten different faults and also one for no-fault case. Hence the training set consisted of about 1100 input output sets (100 for each of the ten faults and 100 for the no fault case) with a set of six 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 or not a fault has been detected.

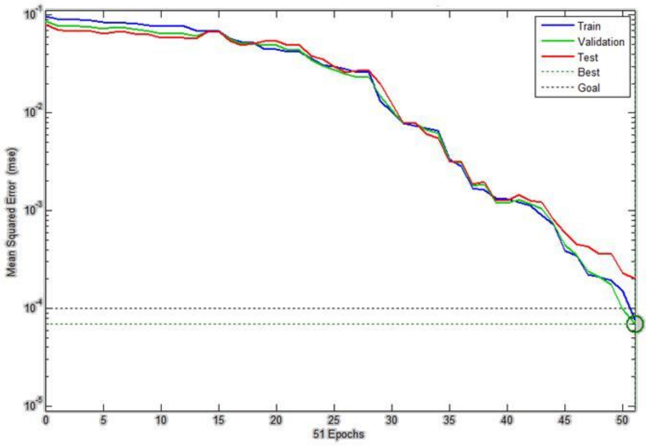

Figure 5Mean-square error performance of the network (6-10-5-3-1).

A neural network with 6-10-5-3-1 configuration (6 neurons in the input layer, 3 hidden layers with 10, 5 and 3 neurons in them respectively and one 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 6-10-5-3-1 configuration (6 neurons in the input layer, 3 hidden layers with 10, 5 and 3 neurons in them respectively and one neuron in the output layer). The overall MSE of the trained neural network is way below the value of 0.0001 and is actually 6.9776 e-5 by the end of the training process. Hence this has been chosen as the ideal ANN for the purpose of fault detection.

TESTING THE FAULT DETECTION NEURAL NETWORK

Once the neural network has been trained, its performance has been tested by three different factors. The first of these is by plotting the best linear regression that relates the targets to the outputs as shown in Fig 6.

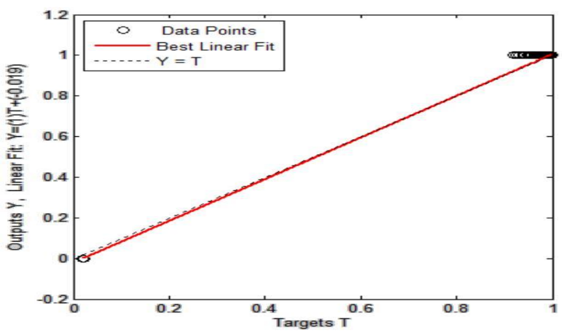

Figure 6 Regression fit of the outputs vs. targets for the network (6-10-8-1).

FAULT CLASSIFICATION

Once a fault has been detected on the power line, the next step is to identify the type of fault. This section presents an analysis on the fault classification phase using neural networks. A review of the different neural networks that were analyzed is provided which is followed by the chosen network

TRAINING THE FAULT CLASSIFIER NEURAL NETWORK:- The designed network takes in sets of six inputs (the three phase voltage and current values scaled with respect to their corresponding pre-fault values). The neural network has four outputs, each of them corresponding to the fault condition of each of the three phases and one output for the ground line. Hence the outputs are either a 0 or 1 denoting the absence or presence of a fault on the corresponding line (A, B, C or G where A, B and C denote the three phases of the transmission line and G denotes the ground). Hence the various possible permutations can represent each of the various faults

Hence the training set consisted of about 1100 input output sets (100 for each of the ten faults and 100 for the no fault case) with a set of six inputs and one output in each input-output pair.

Fig 7 shows the training performance plot of the neural network 6-35-4 (6 neurons in the input layer, 1 hidden layer with 35 neurons in it and four neurons in the output layer). It can be seen that the best validation performance in terms of the Mean Square Error (MSE) by the end of the training process in this case is 0.00359.

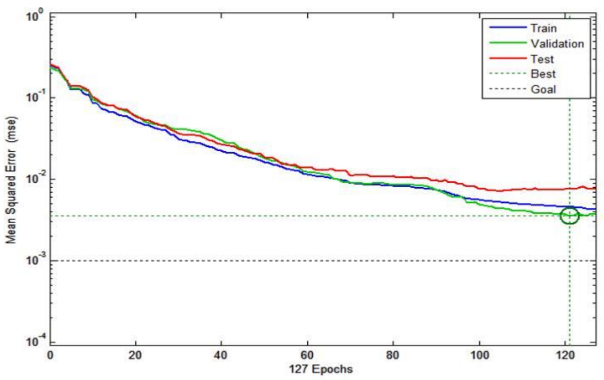

Figure 7 Mean-square error performance of the network with configuration (6-35-4).

From the above training performance plots, it is to be noted that satisfactory training performance has been achieved by the neural network with the 6-35-4 configuration (6 neurons in the input layer, 35 neurons in the hidden layer and one neuron in the output layer). The overall MSE of the trained neural network is 0.0035986 and it can be seen from Fig 7 that the testing and the validation curves have similar characteristics which is an indication of efficient training. Hence this has been chosen as the ideal ANN for the purpose of fault classification.

TESTING THE FAULT CLASSIFIER NEURAL NETWORK

Once the neural network has been trained, its performance has been tested by taking three different factors into consideration. The first of these is by plotting the best linear regression that relates the targets to the outputs as shown in Fig 8. The correlation coefficient in this case was found to be 0.98108 which indicates satisfactory correlation between the targets and the outputs. The dotted line in the figure indicates the ideal regression fit and the red solid line indicates the actual fit of the neural network. It can be seen that both these lines track each other very closely which is an indication of very good performance by the neural network.

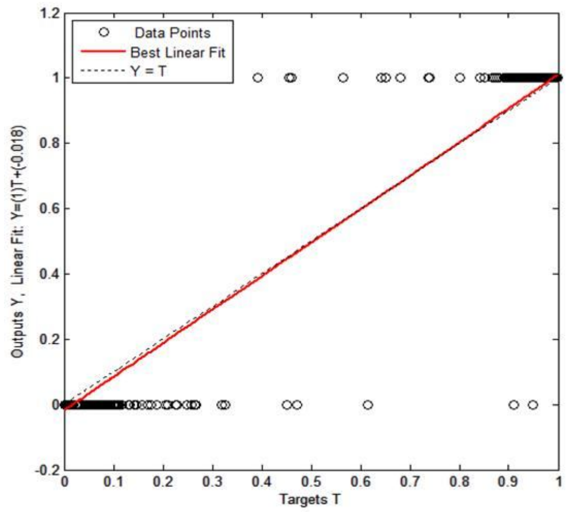

Figure 8 Regression plot of network with configuration (6-35-4).

V. CONCLUSIONS

This paper has studied the usage of neural networks as an alternative method for the detection, classification and location of faults on transmission lines. All the neural networks investigated in this paper belong to the back-propagation neural network architecture. A fault location scheme for the transmission line system, right from the detection of faults on the line to the fault location stage has been devised successfully by using artificial neural networks.

The simulation results obtained prove that satisfactory performance has been achieved by all of the proposed neural networks in general. To simulate the entire power transmission line model and to obtain the training data set, MATLAB R2010a has been used along with the SimPowerSystems toolbox in Simulink. In order to train and analyze the performance of the neural networks, the Artificial Neural Networks Toolbox has been used extensively.

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