ARTIFICIAL NEURAL NETWORK-BASED FAULT LOCATION IN EHV TRANSMISSION LINES

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ABSTRACT

This paper deals with the application of artificial neural networks (ANNs) to the fault detection and location in extra high voltage (EHV) transmission lines for high speed protection using one terminal line. The neural fault detector and locators have been trained with different sets of data available from a selected power network model and simulating different fault scenarios (fault types, fault locations, fault resistances and fault inception angles). A comparative study of the proposed fault locators has been carried out in order to determine which ANN fault locator structure leads to the best performance. The results show that the fault locator using current and voltage values is more accurate.

I. INTRODUCTION

Overhead transmission line are parts of the main components in an electric power system and, because transmission lines are exposed to the nature, the possibility of experiencing faults on transmission lines is generally higher than that on other main components. Line faults are the most common faults because lines are exposed to the elements and there are many causes of faults. Lines faults may be triggered by lightning strokes, trees may fall across lines, fog and salt spray on dirty insulators may cause the insulator strings to flash over, and ice and snow loading may cause insulator strings to fail mechanically. When a fault occurs on an electrical transmission line, it is very important to detect it and find its location in order to make necessary repairs and to restore power as soon as possible, the time needed to determine the fault point along the line will affect the quality of power delivery. Therefore, an accurate fault location on the line is an important requirement for a permanent fault. Pointing to a weak spot, it is also helpful for a transient fault, which may result from a marginally contaminated insulator, or a swaying or growing tree under the line.

Fault location for transmission lines has been subject of interest for many years. During the last decade a number of fault locating algorithms have been developed; including the steady-state phasor approach, the differential equation approach and the traveling-wave approach [1] as well as one-end [2] and two-end [3] algorithms. In the later category, synchronized [4] and non-synchronized [5] sampling techniques are used. However, two terminal data are not widely available. From the practical viewpoint, it is desirable for equipment to use only one-terminal data. The one-end algorithms, in turn, utilize different assumptions to replace the remote end measurements. Most of fault locators are only based on the local measurement. Currently the most widely used method of overhead line fault location is to determine the apparent reactance of the line during the time that fault current is flowing and to convert the ohmic result into distance based on the parameters of the line. It is widely recognized that this method is subject to errors when the fault resistance is high and the line is fed from both ends, and when parallel circuits exist over only part(s) of the length of the faulty line.

Many successful applications of artificial neural networks to power system have demonstrated including security assessment, load forecasting, control etc... Recent applications in protection have covered fault diagnostic for electric power system [6], transformer protection [7] and generator protection [8]. However, almost all these applications in protection merely use the ANN ability of classification, that is, ANNs only output 1 or 0.

In this paper, a single ended fault detector and three fault locators are proposed for on-line application using ANNs. A feed-forward neural network based on the back-propagation learning algorithm has been used to realize the fault detector and locator. The neural fault detector and fault locators have been trained and tested with a number of simulation cases by considering different fault conditions (fault types, fault locations fault resistances and fault inception angles) in a selected network model.

II. POWER SYSTEM UNDER CONSIDERATION

To evaluate the performance of the proposed neural network-based fault detector and locator, a 400 kV, 120 km transmission line extending between two sources as shown in Figure 1 is considered in this study. The transmission line is represented by distributed parameters and the frequency dependence of the line parameters is taken into account. The physical arrangement of the conductors is resumed in Figure 2 and the characteristics may be found in [9]. The input and output data used for training and testing the neural fault detector are generated from the S end of the sample power system model. A highly accurate transmission line simulation technique [10] was utilized to generate voltage and current waveforms for different fault types and conditions.

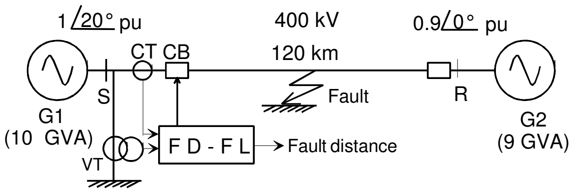

Figure 1. System under study, VT: Voltage Transformer, CT: Current Transformer, CB: Circuit-Breaker, FD: Fault Detector, FL: Fault Locator

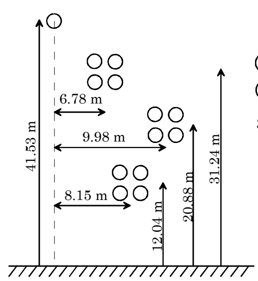

Figure 2. Transmission line configuration

III. PROPOSED FAULT DETECTOR AND LOCATOR BASED ON NEURAL NETWORKS

The first step is to detect the fault using instantaneous current and voltage values. In case a fault exists, the voltage and current signals are fed to one cycle DFT filters for extraction of the fundamental phasor magnitudes.

The ANN fault detector (FD) proposed in this paper is designed to indicate the presence or absence of any fault type. The occurrence of the fault is determined by identifying the power system state directly from instantaneous current and voltage data using one terminal line. The fault locator (FL) is designed to indicate the distance of the fault in the transmission line.

The design process of the fault detector and fault locator goes through the following steps:

1) Preparation of suitable training data set that represents cases the ANN needs to learn.
2) Selection of a suitable ANN structure for a given application.
3) Training of the ANN.
4) Evaluation the trained ANN using test patterns until satisfied with its performance.

FAULT DETECTOR

Inputs and Outputs

In order to build up an ANN, the inputs and outputs of the neural network have to be defined for pattern recognition. Inputs to the network should provide a true representation of the situation under consideration. The phase current and voltage signals and the zero sequence current and voltage signals extracted from the simulation at the relay location (end S) are used as inputs to the ANN. The process of generating input patterns to the ANN is depicted in Figure 3.

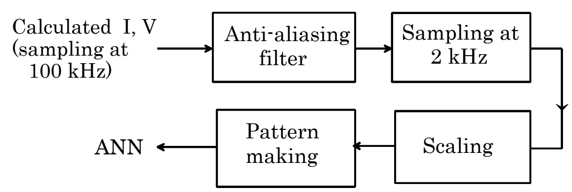

Figure 3. Process for generating input patterns to the ANN fault detector

The current and voltage signals are calculated as a string of samples corresponding to a 100 kHz sampling frequency. These signals are processed so as to simulate a 2 kHz sampling process (40 samples per 50 Hz cycle) using an anti-aliasing filter. This sampling rate is compatible with sampling rates presently used in digital relays. It should be mentioned that the input current and voltage samples have to be normalized in order to reach the ANN input level (±1). The phase and zero sequence signals are sampled at 2 kHz and used as input data to the ANN. The ANN output is indexed with either a value of “1” (presence of a fault) or “0” (non-faulty situation).

Structure and Training of the Neural Fault Detector

The fault detection task can be formulated as a pattern classification problem. A fully-connected multi layer (input, hidden and output) feed-forward neural network (FFNN) has been used to classify faulty/non-faulty data sets. The number of inputs to the network and the number of neurons in the input and hidden layers are decided empirically through extensive simulations. Various network configurations are trained and tested in order to establish an appropriate network with satisfactory performance. Performance criteria are fault tolerance, time response and generalization capabilities. The three layer FFNN is selected to implement the algorithm for single ended fault detection. Data strings of seven consecutive samples of the three phase and zero sequence voltage signals taken every 2 kHz are found to be appropriate inputs to the neural network. This represents a moving window with a length of 3 *ms*. In order to construct a good neural network system, it is vitally important to train and test it correctly. With supervised learning, ANN is trained with various input patterns corresponding to different types of fault (a-g, b-g, c-g, a-b-g, a-c-g, b-c-g, a-b, a-c, b-c, a-b-c and a-b-c-g, where a, b, and c are related to the phases and g refers to the ground) at various locations for different fault inception angles and fault resistances.

After a series of simulation training and testing it has been found that three-layer architecture leads to the best performance for the ANN-fault detector. The ANN consists of 56 input neurons for the three phase current and voltages (Ia, Ib, Ic, Va, Vb, Vc) and the zero sequence current and voltage (Io, Vo) input signals, 18 neurons in the hidden layer and one output neuron. A sigmoid transfer function was used and the error back-propagation method has been used for training [11]. The ANN structure of the fault detector is shown in Figure 4.

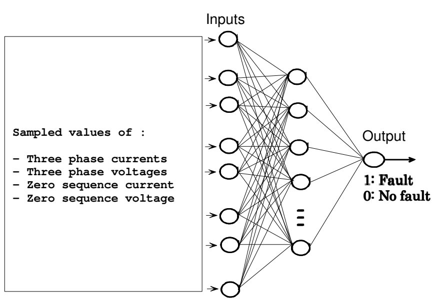

Figure 4. Structure for ANN fault detector

Tests and Results

After training, the neural fault detector (FD) was tested with 90 new fault conditions for each type of fault. These conditions included different fault locations, different inception angles (0, 30, 60 and 90 degrees) and different fault resistances (0, 5, 40, 80 and 100 Ω).

Figures 5 to 9 show the phase and zero sequence voltage waveforms and the response of the proposed ANN-fault detector for some examples.

The results of Figure 5 are obtained for a single phase to ground fault (b-g) located at 117 km with a fault resistance of 5 Ω and an inception angle of 30° which corresponds to the occurrence of the fault at time 27 ms.

In Figure 6 are shown the results for a double phase to ground fault (a-c-g) located at 10 km with a fault resistance of 40 Ω and an inception angle of 90° which corresponds to the occurrence of the fault at time 30.5 ms.

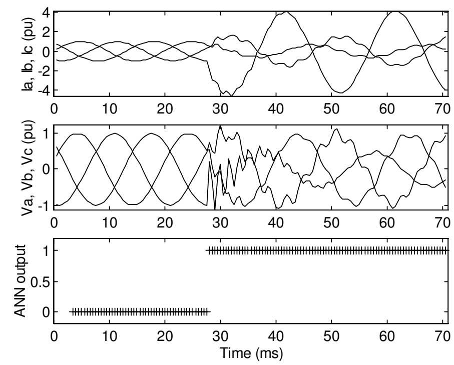

Figure 5. Current and voltage waveforms and ANN output for b-g fault at 117 km from S with a fault resistance of 5 Ω and an inception angle of 30°

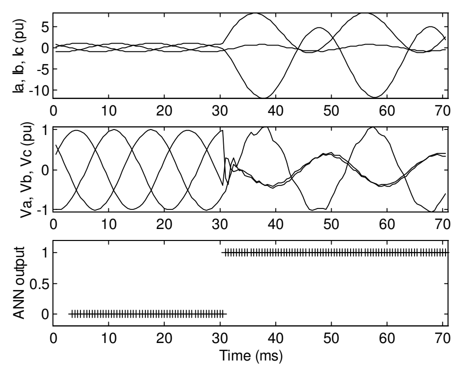

Figure 6. Current and voltage waveforms and ANN output for a-c-g fault at 10 km from S with a fault resistance of 40 Ω and an inception angle of 90°

The voltage waveforms and the ANN output shown in Figure 7 are related to a double phase fault (b-c) located at 50 km without fault resistance and with an inception angle of 60° which corresponds to a fault at 29 ms.

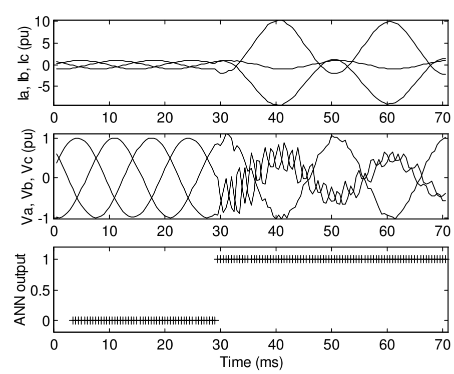

Figure 7. Current and voltage waveforms and ANN output for b-c fault at 50 km from S with and inception angle of 60°

In Figure 8 are shown the results for a three-phase to ground fault (a-b-c-g) located at 10 km with a fault resistance of 80 Ω and an inception angle of 90° which corresponds to the occurrence of the fault at time 30.5 ms.

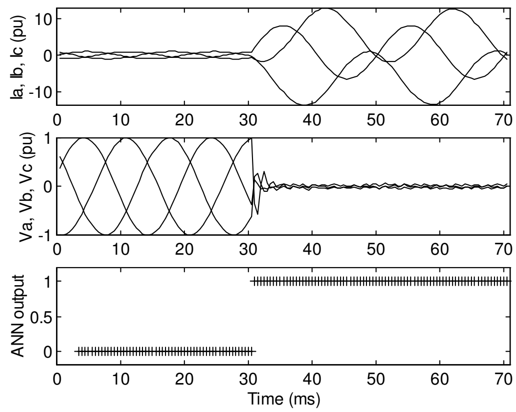

Figure 8. Current and voltage waveforms and ANN output for a-b-c-g fault at 10 km from S with a fault resistance of 80 Ω and an inception angle of 90°

The results demonstrate the ability of the fault detector to produce the correct response in all simulation tests. 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 (either very close to unity or zero) under fault conditions. This clearly confirms the effectiveness of the proposed fault detector. It should be mentioned that the technique described herein is based on a time domain moving window approach as discussed previously. The results show that in the fault cases presented, there is a very rapid transition in the ANN outputs as the windows move from the pre-fault to the fault states. The results reveal that the network is able to generalize the situation from the provided patterns and accurately indicates the presence or the absence of the fault.

Performance

The performance characteristics of an ANN fault detector are:

1. The stability of ANN output values in the normal steady-state and under fault conditions.
2. The minimal time error t_e of fault detection which is the difference between the desired fault detection time value t_d and the actual fault detection time value $t_a : t_e = t_a - t_d$.
3. Generalization capabilities.

A good ANN fault detector is obtained when the time error of fault detection is minimal, the ANN output values are stable in the normal conditions (i.e. 0) and under fault conditions (i.e. 1) and capable of providing fast and accurate fault detection under a variety of fault situations.

The only means of verifying the performance of a trained neural network is to perform extensive testing. After training, the neural fault detector is then extensively tested using independent data sets consisting of fault scenarios never used previously in training. As mentioned before, the fault detector performances are evaluated in terms of the time error t_e of fault. The best performances are obtained when the time error t_e is minimal.

The testing patterns corresponding to 90 new fault conditions for each fault type (11 types of fault) which represent 990 fault cases and the no-fault case are used to asses the performance of the fault detector.

Table 1 gives the percentage of fault cases versus time error of fault detection t_e of the FD for single phase to ground, double phase to ground, double phase, triple phase, triple phase to ground fault type and all faults, respectively.

Table 1. Fault cases versus fault detection time error of FD for different fault types

t_e [ms]	Number of fault cases (%)					
	Fault type					
	a-g b-g c-g	a-b-g b-c-g c-a-g	a-b b-c c-a	a-b-c	a-b-c-g	All faults
0.5	100	100	98.33	100	100	99.54
1.0	0.00	0.00	01.66	0.00	0.00	0.45

It can be seen that the maximal time error t_e of fault detection is 1 ms. A number of 99.54% of fault cases are detected with a time error of 0.5 ms and a number of 0.45% of tested cases are detected with a time error of 1 ms. All faults (100%) are detected with a time error less than 1 ms which represent very good performance.

FAULT LOCATOR

Inputs and Outputs

The ANN relay is supposed to locate faults in transmission lines, having the magnitudes of the voltage and/or current phasors corresponding to the post-fault fundamental frequency as inputs. In order to obtain the magnitudes of such waves, the Discrete Fourier Transform (DFT) filter was utilized. So the three voltage (|Va|, |Vb|, |Vc|) and/or current (|Ia|, |Ib|, |Ic|) magnitudes seen at the busbar S are utilized as the inputs of the neural network. Normally, the interesting outputs are the fault distance. As mentioned, the magnitudes of the phasors are the input quantities to the proposed ANN. In fact, for practical applications, the FFT (Fast Fourier Transform) should be employed. The FFT is a fast algorithm used for efficient implementation of the DFT. It should be mentioned that the input variables have to be normalized in order to reach the ANN input level (±1). Due to the necessity of different scaling for voltages and currents, the normalized current must be divided by an additional factor. Figure 9 shows the schematic diagram for the fault locator (FL). The voltage and current signals are taken from the transmission line, passed through low pass (anti-aliasing) filter. A DFT filter is used to extract the amplitude of the fundamental signal.

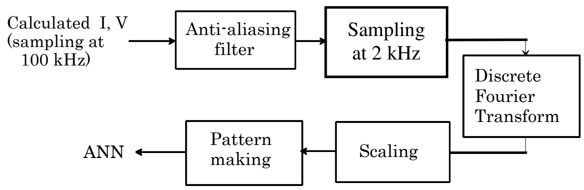

Figure 9. Process for generating input patterns to the ANN fault locator

Architecture and Learning Rule

We present three fault locators. The first (FL1) uses only current values, the second (FL2) uses only voltage values and the third (FL3) uses both current and voltage values. The three layer feed-forward neural network is selected to implement the algorithm for the single ended fault location. The transfer functions of the hidden and the output layer neurons are respectively the sigmoid function and the linear function. Concerning the ANN architecture, parameters such as the number of inputs to the network, as well as the neurons in the input and hidden layers were decided empirically. This process involved experimentation with various network configurations.

The neural fault locator architectures are resumed in Table 2. The error back propagation algorithm has been used throughout. The ANN structure of the FL3 is shown in Figure 10.

Table 2. Architectures of the neural fault locators

Fault locator	Input variable	Number of neurons		
		Input layer	Hidden layer	Output layer
FL1	I	3	18	1
FL2	V	3	18	1
FL3	I, V	6	20	1

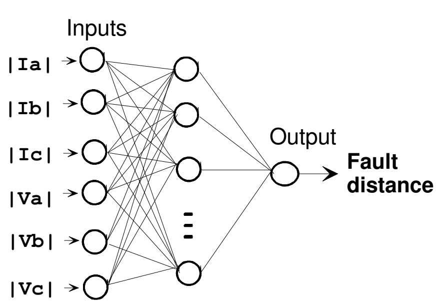

Figure 10. ANN architecture of the fault locator FL3

Performance

In the following, only the results for single phase to ground faults are presented. The fault resistance is assumed to be less than 30 Ω. To get good general performance, for the single ended fault location, the fault locators are tested with a set of independent test patterns to cover wide system and fault conditions e.g. fault inception angle, fault location and fault resistance. Table 3 gives some examples for the test results. The first column is the desired outputs and the right three columns are the actual outputs of the ANNs corresponding to the three proposed fault locators FL1, FL2 and FL3; respectively.

Table 3. Test results for fault location

Desired location (km)	Actual location (km)		
	FL1	FL2	FL3
08.00	07.9519	08.0151	07.6660
13.00	13.0510	13.0400	12.7839
18.00	17.8848	17.9388	17.9528
23.00	22.8658	23.0389	23.1537
31.00	30.7401	30.7508	30.9293
42.00	42.1383	41.9349	41.9101
48.00	48.1432	47.9267	47.8919
58.00	57.7599	58.0352	57.8454
61.00	60.9604	61.2677	61.1975
72.00	71.8332	72.0497	72.1174
78.00	78.2810	77.9490	78.2182
83.00	82.8993	82.5490	82.7222
90.00	90.1776	90.0444	90.0219
95.00	94.9842	94.9412	94.8803
100.00	100.202	99.9474	100.004
105.00	105.073	105.270	105.177
110.00	110.015	110.568	110.306
115.00	114.795	114.429	114.804

The error in fault location is defined as:

$$\text{Error} = |\text{ actual location - desired location }| \text{ (km)} \quad (1)$$

Figures 11 to 13 give the error (in km) in the estimation of the fault location for FL1, FL2 and FL3; respectively.

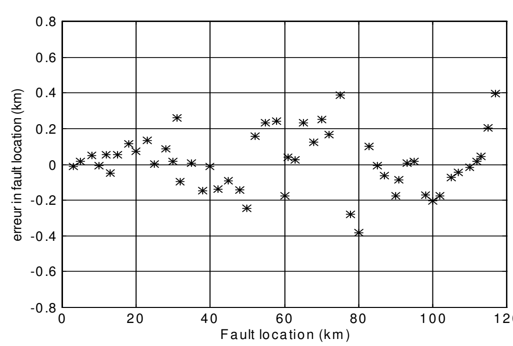

Figure 11. Test results of FL1.

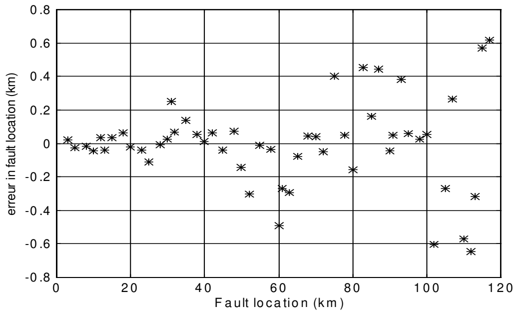

Figure 12. Test results of FL2.

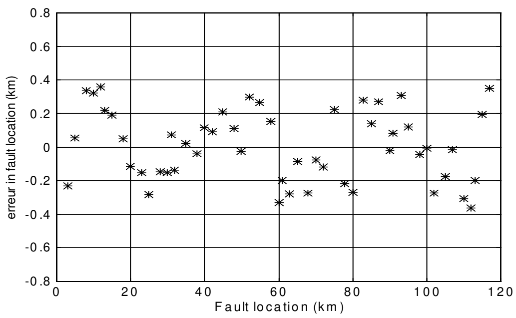

Figure 13. Test results of FL3.

The criterion for evaluating the performance of the fault locators is defined as:

$$\text{Error}\,(\%) = \frac{|\,\text{actual location - desired location}\,|}{\text{length of the line}} \times 100 \qquad (2)$$

The minimum, the maximum and the average percentage errors of the fault locators are listed in Table 4.

Table 4. Results of the fault locators

	Error of fault location					
	FL1		FL2		FL3	
	(km)	(%)	(km)	(%)	(km)	(%)
Min	0.0038	0.0031	0.0074	0.0062	0.0048	0.0040
Max	0.3977	0.3314	0.6432	0.5360	0.3647	0.3039
Aver.	0.1215	0.1013	0.1743	0.1452	0.1803	0.1503

It can be seen that the FL3 (uses current and voltage phasor magnitudes) is the best fault locator. The minimum error is 4.8m (0.004%) and the maximum error is 364.7m (0.3039%).

IV. CONCLUSION

An efficient neural network-based fault detector for very fast EHV transmission lines protection and three neural network-based fault locators have been proposed in this paper. The results demonstrated the ability of the ANNs to generalize the situation from the provided patterns and accurately indicate the presence and the location of the fault using one terminal data. The neural fault detector use only instantaneous current and voltage values, while the neural fault locator uses the magnitudes of the voltage and/or current phasors. Test results presented demonstrate the effectiveness and the accurateness of fault detection under a variety of faulty situations including fault type, fault locations, fault inception angles and fault resistances. The use of currents and voltages phasor magnitudes gives the best fault locator.

V. REFERENCES

1. B. Lian and M.M.A. Salama, "An overview of digital fault location algorithms for power transmission lines using transient waveforms", Electric Power System Research, 29 (1994), pp.17-25.
2. Q. Zhang, Y. Zhang, W. Song and Y. Yu, "Transmission line fault location for phase-to-earth fault using one-terminal data", IEE Proc. Transm. Distrib., Vol. 146, No 2, March 1999, pp. 121-124
3. L. B. Sheng and S. Elangovan, "A fault location algorithm for transmission lines", Electric Machines and Power Systems, 26 (1998), pp. 991-1005.
4. M. Kezunovic and J. Mrkic' "An accurate fault location algorithm using synchronized sampling", Electric Power System Research, 29, 1994, pp. 161-169.
5. D. Novosel, D.G. Hart, E. Udren and J. Garitty, "Un-synchronized two-terminal fault location estimation", IEEE Trans. on Power Delivery, Vol. 11, No. 1, January 1996, pp. 130-138.
6. E. A. Mohamed and N. D. Rao, "Artificial neural network based fault diagnostic system for electric power distribution feeders", Electric Power System Research, 35, 1995, pp. 1-10.
7. M. R. Zaman and M. A. Rahman, "Experimental testing of Artificial neural network based protection of power transformer ", IEEE Trans. on Power Delivery, Vol. 13, No. 2, April 1998, pp. 510-515.
8. A. I. Megahed and O. P Malik, "An Artificial neural network based digital differential protection scheme for synchronous generator stator winding protection", IEEE Trans. on Power Delivery, Vol. 14, No. 1, January 1999, pp. 130-138.
9. W. D. Humpage, K. P. Wong and T. T. Nguyen, "Network Equivalents in Power System Electromagnetic Transient Analysis", Electric Power Systems Research, No 5, 1982, pp 231-243.
10. A.T. Johns, R.K. Aggarwal, "Digital simulation of faulted e.h.v. transmission lines with particular reference to very high speed protection", IEE Proceedings on Generation, Transmission and Distribution, Vol. 123, No. 4, April 1976, pp 353-359.
11. D. V. Coury and D. C. Jorge, "Artificial Neural Network Approach to Distance Protection of Transmission Lines", IEEE Transactions on Power Delivery, Vol. 13, No. 1, January 1998, pp. 102-108.