

Estimation of Fault Location Distance using One End Data

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ABSTRACT: This paper presents an accurate fault location technique for UHV transmission line using Artificial Neural Network and GA-ANFIS methods using one end data. Fault conditions are simulated using Matlab/simulink to obtain voltage and current signals. The proposed algorithm is tested for different locations, different inception angles and different types of faults. This paper deals with several types of faults, L-L-L, L-L-L-G, L-L-G and L-G. Simulation of the model was performed on SIMULINK by extracting initial inputs from SIMULINK to MATLAB. The performance of two systems are compared and analyzed. The result shows that GA-ANFIS approach gives correct fault location with better accuracy.

KEYWORDS : ANN, GA- ANFIS , Fault location, UHV Line , One end data.

I. INTRODUCTION

The power system is connected to large power plants and substations, once the fault occurs, it is need to find the fault location as soon as possible and recover the power supply. An accurate fault detection/location technique is an important in improving power system reliability including power relaying, analysis for line inspection, and routine maintenance. Fast and accurate fault location is a key task for the system restoration, reduction of outage times, and, hence, improving system reliability. Recognizing the importance of these factors for electric power utilities, a variety of fault-location algorithms has been developed in the past. Depending on the availability of the fault locator input data, these algorithms can be categorized into three groups: 1) one-terminal; 2) two-terminal; and 3) multi-terminal algorithms.

The usage of synchronized measurements of currents and voltages from all two terminals has been considered. Distributed parameter models of the line sections have been utilized by Aggarwal et al. [1]. This condition assures high accuracy of fault location, and the faulted line section is also reliably indicated.

The ANN and Wavelet based fault location scheme is also compared with ANFIS based fault location method. The Adaptive Network-Based Fuzzy Inference System (ANFIS) and discrete wavelet transform (DWT) have been proposed by Barakat et al.[2] to identify the fault location in high voltage transmission line. The fault location is identified using different fault inception angles and fault resistances. The demand and importance of developing fault location algorithms for three-terminal lines utilizing only two-end synchronized measurements of voltages and currents have been stated by Brahma et al. [3]. From a practical viewpoint, equipment should use only one-terminal data. The one-end algorithms, in turn, utilize different assumptions to replace the remote end measurements. Most of the fault locators are only based on local measurements.

Another fault location algorithm for LL only uses matrix inverse lemma for direct circuit analysis is proposed by Choi et al.[4]. The application of the matrix inverse lemma has greatly simplified derivation of the fault-location equation from phase circuit equations for the faulted system. A new technique was applied by Christos et al. [5] to find fault location for both transposed and un-transposed transmission lines. The line parameters were not required for this approach. SVM and Wavelet based technique was used by Ekici [6] to find the fault with investigation results on its characteristics of accuracy and robust location and classify the fault.

DWT is employed to extract the distinctive high-frequency components of the current and voltage signals. To reduce the learning data, wavelet entropy criterion is applied to wavelet detail coefficients. SVM are used for classifying the fault types and locating the ground faults. The negative sequence phase angle has been used by Fathabadi et al.[7]for fault

location estimation for only single line-to-ground fault (LLG). Other types of faults, such as LLG, line-to-line fault (LL) and triple line fault (LLL), multi-location faults and transforming faults are not considered in this work.

A fuzzy set technique was proposed by Ferrero et al.[8] to process the fault current symmetrical components in order to determine the nature of the fault. This method is quite effective in assessing whether a fault involving ground is a simple line to-ground fault or is a line-to-line fault (with ground involved), which is the most difficult situation to handle with the usual deterministic approach. The unsynchronized measurements has been used by Izykowski et al. [9] for estimating the distance to fault and the synchronization angle between measurements from different terminals of the line.

A simple fault location algorithm has been proposed by Hussain et al.[10] for multi-terminal 735 kV transmission line. The method is independent of fault resistance and source impedance.

A single ANN and GA-ANFIS Techniques are presented in this paper to find the accurate fault location for UHV transmission line. To illustrate the accuracy of the fault location, 1000 KV line with a distance of 360 km is considered. This system utilizes the voltage and current waveforms of the fault data from the one end only. This approach overcomes the difficulties associated with conventional algorithms. To tune the parameters of the FIS, adaptive network is trained based on with off-line data. The ANN and GA-ANFIS techniques are compared to find a fault location for UHV line. The system has been simulated using MATLAB.

II. PERFORMANCE EVALUATION OF POWER SYSTEM MODEL

To evaluate the performance of the proposed neural network based fault detector and locator, a 1000 kV, 360 km transmission line was considered in this study. The power system model simulated using MATLAB software is shown in Fig 1.

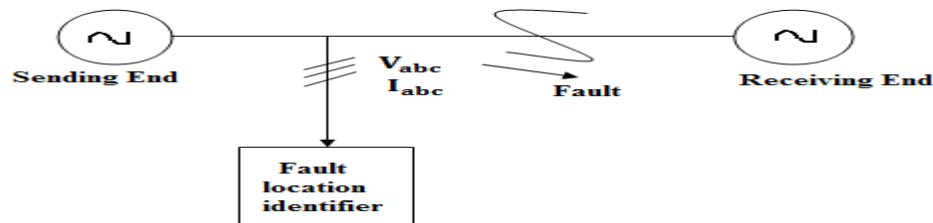


Fig.1 Power System Model for Fault Detection in ANN

The transmission line is represented by a distributed parameter of one line model. The proposed fault location algorithms require only the three phase voltages and currents samples at the sending end of the transmission line. A greater number of fault sample data were generated and considered for finding the fault locations, with different fault resistances, different fault inception angles.

The transmission line parameters are given below.

The parameters of power system model

- Line length = 360 km
- Line voltage = 1000 kV
- Frequency = 50 Hz
- Negative sequence impedance = $0.0225 + j0.01738$;
- Zero sequence impedance = $0.2188 + j 0.0032829$;
- Negative sequence capacitance = 6.794 nF/km;
- Zero sequence capacitance = 7.85551nF/km.

III. ARTIFICIAL NEURAL NETWORK

The neural network based technique was developed for a transmission line using fundamental components of three-phase voltages and currents.

3.1 Structure of ANN

The three layer feed-forward neural network was selected to implement the algorithm for the single ended fault location. The tanh function was used as the transfer function in the hidden layer. The linear function was used in the output layer. The desired inputs of ANN for the single-ended fault location, the voltage, and current phasors were used as input. Since they were complex values, they were split into real and imaginary parts. A real feed-forward neural network is used. The network must have the number of inputs and outputs to determine the right size and structure for the network. According to network architecture, transfer function and the learning algorithms, the ANN model was determined. The output value of the neuron in the output layers with the sigmoid activation function gives the impedance and resistance value. It should be mentioned that the final weights and biases were adjusted in the training phase using the training parameters. A standard type neuron was used. The linear output was obtained by making the sum of all the weighted inputs through its synaptic coefficients and which was applied to an activation function. The output was then connected to all inputs of the next layer.

3.2 Selection of Input and Output of Network

Hence, the network input chosen here are the magnitudes of the fundamental components (50 Hz) of three-phase voltage and three-phase current of the circuit. As the basic task of fault location is to determine the distance to the fault, fault distance location (L_f), in km about the total length of the line, is the only output provided by the fault location network. Thus, the input X and the output Y of the fault location network are given by:

$$X = V_a, V_b, V_c, I_a, I_b, I_c, \Phi_i \quad (1)$$

$$Y = L_f \quad (2)$$

3.3 Fault Patterns Generation and Processing

As the network is trained with suitable examples of the relevant phenomenon, the fundamental characteristics of the problem can be learnt by a network. The fault location was estimated by the fault locator on the transmission line. While the number of hidden layers and neurons in the layer were chosen, its attribute should be maintained well for generalization. This is the major issue while designing the architecture of ANN based on a heuristic approach.

The ANN architecture includes the number of inputs and the number of neurons in hidden layers which are determined by testing with various network configurations. After several trials with modification of the ANN architecture, a three-layer neural network has been used to obtain the best performance with seven inputs, one output, and the optimal number of neurons in the hidden layer. The architecture of a single ANN-based fault locator is 7-10-1.

3.4 Training Data

A large number of training data were generated for different ANNs based on fault location using MATLAB software. The various fault conditions were considered as prescribed in such as different fault locations L_f (100,150,200,250 km), different fault inception angles ($0^\circ, 90^\circ, 120^\circ, 200^\circ$) and various fault ($R_f = 30\Omega, 50\Omega, 60\Omega, 100\Omega$). The 224 ground fault cases and 128 line fault cases were simulated for analysis.

3.5 Training Process of Single ANN

Once the network input and output are selected, the final determination of the ANN architecture requires the relevant transfer functions in the hidden and output layers to be established. The activation function of the hidden layer is a hyperbolic tangent sigmoid function. Neurons with a sigmoid function produce real-valued outputs that give the ANN ability to construct complicated decision boundaries in an n-dimensional feature space. It is important because the smoothness of the generalization function produced by the neurons, and hence its classification ability, is directly dependent on the nature of the decision boundaries.

Saturating linear transfer function is used in the output layer as an output should be 0 or 1 based on the fault type which occurs on the system. The single ANN based fault detector & classifier are trained using Levenberg–Marquardt training algorithm as it gives the fastest convergence as compared with other algorithms. To decide the number of neurons in the hidden layer, there is currently no mathematical theory. The simulated model of Neural Network performance structure to locate the fault distance is shown in Fig. 2.

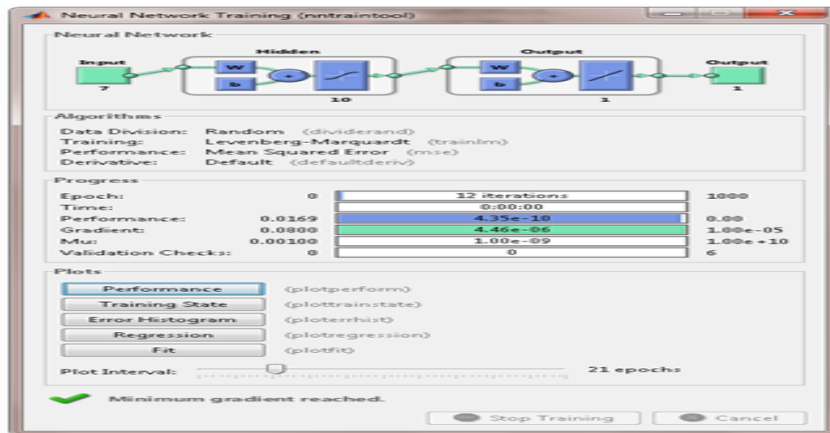


Fig.2 Simulated ANN Performance Structure for Fault Detection

In ANN, 12 iterations are used for fault location with 1000 epochs. The mean square error is 4.35×10^{-10} . The reality is that structured trial and error must be used. If too few hidden neurons are used, the network will be unable to model complex data, resulting in a poor fit. If too many hidden neurons are used, then training will become excessively long and the network may overfit. The structured trial and error process were used to determine the number of hidden neurons. When a fault occurs in phase C to ground, the fault current under various fault condition are shown in Fig. 3.

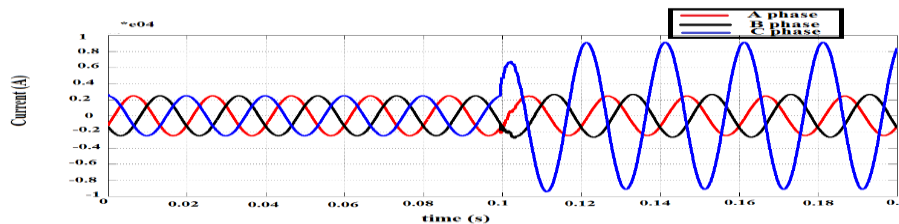


Fig. 3. Fault Current (LG fault)

IV. IMPLEMENTATION OF GA

The MATLAB software was used to implement the GA for training the ANFIS. Each chromosome in the GA consisted of 46 genes which represent all the ANFIS parameters. These genes included 3 genes for the input scaling factor, 1 gene for output scaling factor, 42 genes for the premise parameters of the ANFIS structure. The Universe Of Discourse (UOD) for each input variable was selected to be from -6 to 6. Four real coded GA operators were used in this work. These operators include the hybrid selection, the elitism, the crossover, and the mutation operator, which is a combination of the roulette wheel and the deterministic selection. The procedure of the real coded GA adapted to train the ANFIS to find the fault location is

Step 1: Initialize the crossover probability (P), the mutation probability (P), the population size, and the maximum number of generations.

Step 2: Generate randomly the initial population of chromosomes within certain limits. Each of these chromosomes represents the entire premise and consequent parameters along with the input and output scaling factors for ANFIS controller (red graph in a GA- ANFIS graph).

Step 3: Evaluate the objective function for each chromosome in the population using the Integral Square of Errors (ISE) criterion, which is given by the Equation 3,

$$\text{Fitness} = \frac{1}{\varepsilon + \text{objectivefunction}} \quad (3)$$

Step 4: Arrange all the chromosomes in the current population (that is, the first one is the fittest) in descending order. Then, apply the elitism strategy described before.

Step 5: Select two individuals from the current population utilizing the hybrid selection method, and then apply the real-coded crossover and mutation operators described previously to generate two new chromosomes.

Step 6: Place the resulting two chromosomes in the new population.

Step 7: Repeat Step 5 until all the chromosomes in the new population are generated, that is, until the new population size is equivalent to the initial (old) population size.

Step 8: Replace the initial (old) population with the new population.

Step 9: Stop if the maximum number of generations is reached, and the first chromosome in the last generation is the optimal controller found by the GA, otherwise increase the generation counter by one and go to step 3.

4.1 Fault Location Using ANFIS

Symmetrical and unsymmetrical faults with different inception angles, different locations, and different fault resistances were simulated to evaluate the performance of the proposed fault location algorithm. Different fault types at various locations in each section of the system under study with different inception angles and fault resistances were used for training and testing the ANFIS for faulty section determination

The training data used to train the ANFIS of the fault location unit were taken : i) Fault distance (L_f) ii) All type of faults (i.e. single phase to ground, phase to phase, double phase to ground and three-phase fault iii) Inception angle (Φ_i) iv) Fault resistances (R_f) . There are 444 training data. The input data to the ANFIS of the locating unit were the impedances of the three phases (magnitude and phase i.e. six inputs) after dividing them by their no-fault values. The output data from the ANFIS was the normalized fault distance value.

4.2 Testing Data

The impedance of the transmission line is based on its distance. When a fault occurs at any point, the line impedance gets vary on line distance variation which impacts on the current. ANFIS controller receives current value continuously from the source file. It has trained rules to detect normal current and abnormal current. Various numbers of rules in ANFIS controller is framed to find the distance/resistance as per the current value.

4.3 Training process of ANFIS

In this step, the suitable data are collected as input data to ANFIS. An appropriate network is established by training the various network configurations with satisfactory performances. The fault is detected by training the ANFIS where the fault position is. The trained ANFIS is evaluated using test patterns until getting a satisfactory performance. When Network is trained, an acceptable output should be given by ANFIS for unseen data. An acceptable range of network error and output of test pattern are reached, and then the fuzzy rules and the functions of membership are adjusted well. These steps are done in off-line. The parameters of ANFIS were adjusted via training (similar as for neural network schemes). The structure of an ANFIS is developed with six inputs and one output.

The ANFIS has the following design parameters:

- Type-Sugeno,
- Triangular functions,
- Two linguistic terms for each input membership function,
- 16 linear terms for output membership functions,
- 16 rules (resulting from a number of inputs and membership function terms),
- Fuzzy operators: product (and), maximum (or), product (implication), maximum (aggregation), average weight (defuzzification).

Sixteen rules are used to assign a detector in ANFIS. The rules are given below as:

1. If (I_a is in 1mf1) and (I_b is in 2mf1) and (V_a is in 3mf1) and (V_b is in 4mf1) then (Output is out1mf1) (1)
2. If (I_a is in 1mf1) and (I_b is in 2mf1) and (V_a is in 3mf1) and (V_b is in 4mf2) then (Output is out 1mf2) (1)
- .
- .
- .
16. If (I_a is in 1mf1) and (I_b is in 2mf2.) and (V_a is in 3mf1) and (V_b is in 4mf1) then (Output is out 1mf16) (1)

Three values for fault impedance, four values for fault angle and five fault types are considered in this analysis. Thus, a total combination of $5 \times 4 \times 3 = 60$ has been chosen for fault simulation studies. For each of these combinations, all five types of short-circuit faults can be applied at any point on the transmission line. Hence, in aggregate, different fault simulation studies are possible. The performance of the proposed scheme was trained for all of these $11 \times 60 = 660$ training cases.

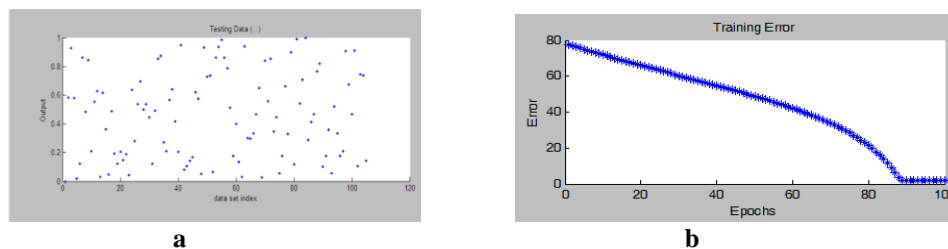
4.4 ANFIS learning algorithm

A forward pass and backward pass are the two modes of learning which are employed in ANFIS. In a forward pass, the current premise parameters are used to optimize rule consequent parameters with a least square estimation based on output error. The premise parameters are altered by using gradient-based learning in a backward pass. This process of learning is known as hybrid learning. The learning process in the backward pass is similar to the back-propagation in neural networks. The Sugeno model is a FIS which was developed by Takagi–Sugeno–Kang. The membership functions are adjusted by the ANFIS from the input-output data, using the least-squares method for linear systems and the back-propagation descent method for nonlinear systems. The design process of the ANFIS fault detector goes through the generation of suitable training data.

1. Generation of suitable training data.

The limit of input parameters should be determined precisely to use the ANFIS for fault detection. The output indicates where the fault occurred. The training/testing data are generated using simulation. The computer program simulates fault for different fault conditions. i.e. A-G, CA-G, A-B-C-G and A-B-C fault).

Some of the /testing data of ANFIS are shown in Fig. 4.a. Fig.4.b. shows the training error of ANFIS for fault distance



**Fig. 4. a. Testing data of ANFIS for fault location
b. Training error of ANFIS for fault location**

On the other hand, the performance of the proposed scheme has been checked for different cases. The total combination of test cases was $660 \times 60 = 39600$. However, as it is not feasible to include in the thesis all of the numerical results corresponding to these 39600 test cases due to space limitations, the output values (which indicate the fault type) obtained from the ANFIS results for a few representative test cases. It is evident from the results obtained in the analysis that there is a small floatation in the ANFIS output. From the results given, it is observed that the proposed fault location technique

is capable of determining the fault type accurately in all cases with accuracy. Fig. 5 shows the testing and training data of GA-ANFIS for fault distance

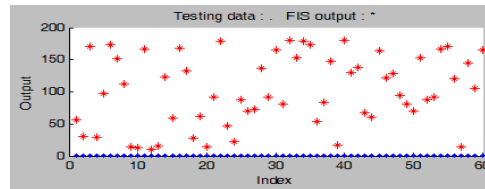


Fig.5 Testing Data of GA- ANFIS

4.5 Testing Data for ANFIS

ANFIS controller receives current value continuously from the source file. It has trained rules to detect normal current and abnormal current. Various numbers of rules in ANFIS controller is framed to find the distance/resistance as per present current value. It again tunes the result with the GA testing, training data to produce an accurate result. The different current samples are given to GA and trained. The optimum current from GA is taken as testing data for ANFIS.

4.6 Process of GA-ANFIS

The impedance of the transmission line is based on its distance. When a fault occurs at any point of the line, the impedance will change. The variation of impedance impacts on the current. The different current values are given to GA to obtain the optimum value (error). From every iteration, the optimum value is obtained. The output scaling factor (minimum error) is obtained from GA which is testing data i.e. input for ANFIS. The ANFIS is tuned by using the GA output to get accurate fault distance.

V. SIMULATION RESULTS AND ANALYSIS

Once the training procedure is done completely, the networks are tested using simulated fault patterns. The fault distance is calculated for different types of faults at different inception angles using ANN and GA-ANFIS. Some of the test results of the proposed algorithm have been obtained for different faults with different power system conditions. The error percentage was calculated from the actual distance and calculated distance.

The fault distance error is also calculated using following equation and the result is given in Tables

$$\% \text{ Error} = \frac{\text{Actual fault distance} - \text{ANN output}}{\text{Total length of the line}} \times 100 \quad (5)$$

The fault distance error is also calculated at different fault conditions, different inception angle and at a different location and the result is given in Tables 1 and 2.

Table 1. Results of Proposed Techniques for Fault Distance at 100 km

Fault Type	Actual Distance (km)	Inception Angle (°)	Fault Distance (km)		Percentage Error	
			ANN	GA-ANFIS	ANN	GA-ANFIS
Single phase to ground(LG)	100	90	101.75	100.3	-0.4861	-0.0833
		120	101.7	100.36	-0.4722	-0.1000
Two phase to ground fault (LLG)	100	90	101.75	100.5	-0.4861	-0.1389
		120	101.7	100.4	-0.4722	-0.1111
Three phase to ground (LLL)	100	90	101.75	100.3	-0.4861	-0.0833
		120	101.7	100.3	-0.4722	-0.0833
Two phase short	100	90	101.7	100.5	-0.4722	-0.1389

circuit (LL)		120	101.7	100.4	-0.4722	-0.1111
Three phase short circuit(LLL)	100	90	101.7	100.3	-0.4722	-0.0833
		120	101.7	100.3	-0.4722	-0.0833

Table 2. Results of Proposed Techniques for Fault Distance at 150 km

Fault Type	Actual Distance (km)	Inception Angle (°)	Fault Distance (km)		Percentage Error	
			ANN	GA-ANFIS	ANN	GA-ANFIS
Single phase to ground(LG)	150	0	151.75	150.3	-0.4861	- 0.0833
		90	151.75	150.6	-0.4861	- 0.1667
Two phase to ground fault(LLG)	150	0	151.8	150.4	-0.5000	- 0.1111
		90	151.8	150.3	-0.5000	- 0.0833
Three phase to ground(LLL)	150	0	151.85	150.5	-0.5139	- 0.1389
		90	151.7	150.3	-0.4722	- 0.0833
Two phase short circuit (LL)	150	0	151.8	150.4	-0.5000	- 0.1111
		90	151.8	150.5	-0.5000	- 0.1389
Three phase short circuit (LLL)	150	0	151.7	150.5	-0.4722	- 0.1389
		90	151.5	150.4	-0.4167	- 0.1111

It is clear from test results shown above that, the faults are correctly detected, and located accurately using GA-ANFIS. The maximum error percentage in the ANN is -0.4861 GA-ANFIS technique is -0.1389 % at 100 km. At 150 km, the maximum error percentage in the ANN is -0.5 % and in GA-ANFIS maximum error percentage is -0.1667%. From the result, it is proved that the GA-ANFIS technique gives the accurate fault distance compared to ANN.

The performance of the ANN and GA-ANFIS controllers for the condition of 100 km at 90° fault inception angle is presented in Fig. 6.a and for 150 km at 120°. Fault inception angle is presented in Fig.6.b.

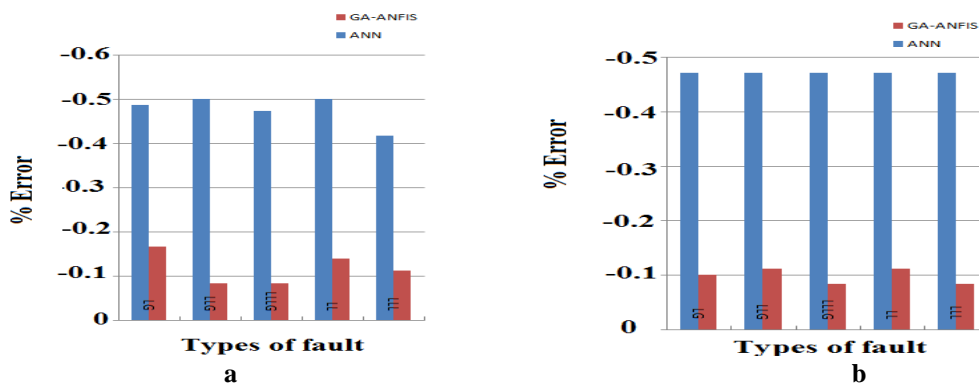


Fig. 6. Performance Analysis of Proposed Techniques for Fault Distance Error (a) for 100 km at 90° Inception Angle (b) at 150 km at 120° Inception Angle

VI. CONCLUSION

In this paper, a new efficient fault location algorithm for over-head transmission lines is presented which can locate asymmetrical and three-phase symmetrical fault distance. The algorithm is based on forming an optimization problem utilizing voltages and currents from the sending end. The performance of the algorithm was evaluated for various faults on 1000 kV transmission lines using ANN and GA-ANFIS techniques. ANN modules and GA-ANFIS modules for fault

detection according to the type of faults (LG, LL, LLG, and LLL and LLLG) have been developed and tested under different resistance, inception angle at different distance for different fault types. The test result of both techniques is compared. The comparison of the test results of ANN and GA-ANFIS approach shows that the GA-ANFIS approach is more accurate. The GA-ANFIS fault detection test results are very encouraging and confirm the suitability of the technique for protection of transmission line.

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