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# ANN Based Fault Location of Double Circuit Transmission Line Using Only One Terminal Data

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**Abstract:** *An accurate fault location algorithm based on application of artificial neural networks (ANN) for protection of double circuit transmission lines is presented in this research paper. The proposed method uses the magnitude and phase angle of current available at only the local end of line. This method is adaptive to the variation of fault resistance, fault inception angle and fault location. The Simulation results show that all types of phase-to-phase and phase-to-ground faults can be correctly located under varying system conditions. Large numbers of fault simulations using MATLAB/Simulink software has proved the accuracy and effectiveness of the proposed algorithm.*

**Keywords:** *Fault location (FL); Double circuit transmission line; artificial neural networks (ANN).*

## I. INTRODUCTION

Double circuit transmission lines increase the power transmission capability and reliability of the power system hence it is most widely used. However, the fault location of double circuit lines becomes more difficult and complex than a single circuit line due to the effect of mutual coupling among the circuits. When the fault location algorithm used for single lines is directly used for double circuit lines, which is often the case in practice, the fault location estimation accuracy can't be guaranteed because of the mutual coupling effect. Therefore a dedicated fault location algorithm has to be developed for the double circuit transmission lines.

Various fault location algorithms on double circuit transmission lines have been proposed [1-8]. A distributed parameter model-based fault location algorithm was proposed in [1] and it uses two-terminal voltages and currents and does not require the source impedance and fault resistance. Another researcher proposed a novel time-domain fault location algorithm that uses a differential component net by using two terminal currents [2]. Although two-terminal algorithms may present a better performance but single-terminal algorithms have advantages from the commercial viewpoint. This is mainly due to the additional complexity associated with two ends algorithms including communication and synchronization between both ends as well as the cost increases. Therefore, more researches focused on the application of the single end method so far. A practical fault location approach depending on modal transformation is using single end data of the double circuit transmission lines was proposed in [3]. A least error squares method for locating fault on coupled double-circuit HV transmission line are using one terminal data [4]. An accurate fault location algorithm on two-parallel transmission lines for both single phase-to-ground fault [5] and non-earth fault using one terminal data [6] were proposed by researchers. A new approach based on artificial neural networks using the fundamental components of the fault and pre-fault voltage and current magnitudes of the reference end also has been presented in [7]. More accurate fault location algorithm for double-circuit transmission systems that uses a current distribution factor in order to estimate the fault current using the voltage and current collected at only the local end of a single-circuit is proposed [8]. Faulty phase selection and distance location using neural network for single circuit transmission lines has been reported in [9]. Fault classification for double-circuit lines using self organization mapping feature neural network is presented in [10], however it does not locate the faults. The work presented in [11] deals with the compensation of fault resistance using ANN for determination of location of fault. A single line to ground fault location method employing wavelet fuzzy neural network in the distribution lines of an industrial system is proposed in [12], other types of fault have not been considered. An adaptive distance protection of double circuit line using zero sequence Thevenin equivalent impedance and compensation factor for mutual coupling is presented in [13]. The work presented in [14] deals with combined Wavelet and ANN approach for fault location in double circuit transmission lines. Negative-Sequence voltage magnitude has been used for Unsynchronized Fault Location for Double-Circuit Transmission Lines in [15]. This paper proposes an enhanced algorithm to determine the fault location on double-circuit transmission line for all possible types of shunt fault. The proposed algorithm uses the magnitude and phase angles of current signals of each phase of the two parallel lines at one end only. Its effectiveness has been tested on a double-circuit transmission system through various simulations using MATLAB. Simulation results of the proposed algorithm have shown its accuracy of the fault location in all cases considered.

## II. POWER SYSTEM NETWORK SIMULATION

The power system network studied is composed of 220KV, 50 Hz, 100km double-circuit transmission lines, connected to a source at each end, as shown in Fig. 1. All components of the power system network are modeled by the MATLAB ® Simulink & SimPowerSystem toolbox. The transmission line is simulated using distributed parameter line model. The Short circuit rating of the equivalent Thevenin sources on two sides of the line are considered to be 1.25 GVA with X/R ratio 10 and source to line impedance ratio is 0.5. The double circuit transmission line parameters are shown in Table-1.

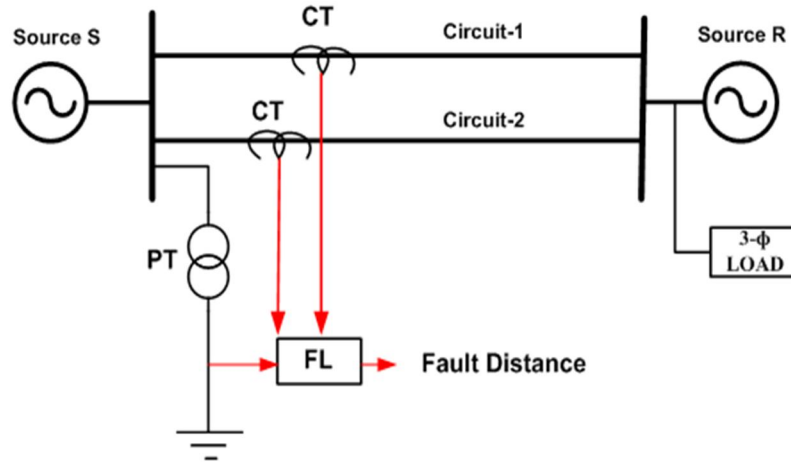


Figure 1: Single line diagram of power system model under study

Components	Parameters	
Transmission line	Length (km)	100
	Voltage (kV)	220
	Positive sequence impedance ( $\Omega/\text{km}$ )	$0.0181 + j0.292$
	Zero sequence impedance ( $\Omega/\text{km}$ )	$0.2188 + j1.031$
	Zero sequence mutual impedance ( $\Omega/\text{km}$ )	$0.20052 + j0.6535$
	Positive sequence capacitance (nF/km)	12.571
	Zero sequence capacitance (nF/km)	7.8555
	Zero sequence mutual capacitance (nF/km)	-2.0444

Table 1: Double circuit transmission line parameters

## III. ANN BASED FAULT DISTANCE LOCATOR

The basic procedure used to implement a neural network for the fault detection and classification algorithm in double circuit transmission line is described below.

### A. Selecting the right architecture

The main factor in determining the right size and structure for the neural network is the number of inputs and outputs that it must have. To enable the method to be implemented in both fault detection and classification, the magnitude and phase angles of each current signals recorded at the relay location are extracted by using discrete Fourier transform and the difference between maximum phase angle and minimum phase angle for each current signals are calculated as given below:

$$\theta_{\max} = \max\{\theta(1), \theta(2), \dots, \theta(m)\} \quad (1)$$

$$\theta_{\min} = \min\{\theta(1), \theta(2), \dots, \theta(m)\} \quad (2)$$

$$\Delta\Phi = \Phi_{\max} - \Phi_{\min} \quad (3)$$

Where  $\theta_{\max}$  and  $\theta_{\min}$  are the maximum and minimum phase angle out of  $m$  samples for current signals of the corresponding phases. Hence the neural network inputs chosen here are the magnitude and changes in the phase angles of six currents measured at the relay location. Thus the network inputs for fault locator are total twelve as given in (4).

$$X = [\Delta\Phi_{A1}, \Delta\Phi_{B1}, \Delta\Phi_{C1}, \Delta\Phi_{A2}, \Delta\Phi_{B2}, \Delta\Phi_{C2}, I_{A1}, I_{B1}, I_{C1}, I_{A2}, I_{B2}, I_{C2}] \quad (4)$$

As the basic task of fault location is to determine the distance to the fault. Therefore fault distance in km with regard to the total length of the line, should be the only output provided by the fault location network. Thus the output Y for the fault location network is given as in (5).

$$Y = [L_f] \quad (5)$$

### B. Training Dataset Generation

Training dataset of ANN consist of input and corresponding target dataset. To get the input the power system model is simulated at different location, inception angle and resistance in MATLAB. Table 2 gives the various combinations of fault types and parameters for input pattern generation.

Parameters	Set Value
Type of Faults (4)	$A_1G, B_1G, C_1G, A_2G, B_2G, C_2G, A_1B_1G, B_1C_1G, A_1C_1G, A_2B_2G, B_2C_2G, A_2C_2G, A_1B_1, B_1C_1, A_1C_1, A_2B_2, B_2C_2, A_2C_2, A_1B_1C_1, A_2B_2C_2$
Fault Location (11)	1, 4, 8, 13, 20, 35, 48, 59, 73, 87, 99
Fault Resistance (4)	1,60,120,180 $\Omega$ (for ground fault) & 0 $\Omega$ (for phase fault)
Fault Inception Angle (2)	0° & 90°

Table 2: Training Data Pattern Generation

### C. Training of Fault Locator

The network for fault locator is trained using “Levenberg Marquard Algorithm”. The goal achieved is shown as the minimum number of root mean square error meets after a significant number of iteration. The number of hidden layer neurons and transfer function is chosen based on the “trial and error” method.

#### 1) Training for LG Fault

Here two hidden layer of 35 and 30 neuron in first and second hidden layers respectively and ‘logsig’ transfer function is used for both hidden layer and ‘purelin’ transfer function is used for output layer that gives the best performance as shown in Fig. 2. The network of fault locator is multi layered feed forward ANN with 12 neurons in the input layer, 35 neuron in first hidden layer, 30 neuron in second hidden layer and 1 neuron in output layer (12-35-30-1) is capable of minimizing the mean square errors (MSE) to a goal of  $9.94 \times 10^{-6}$  in 282 epochs as shown in Fig. 3.

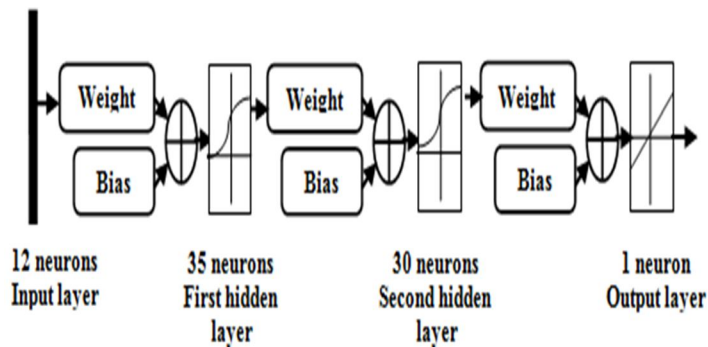


Figure 2: Architecture of ANN Based LG Fault Locator

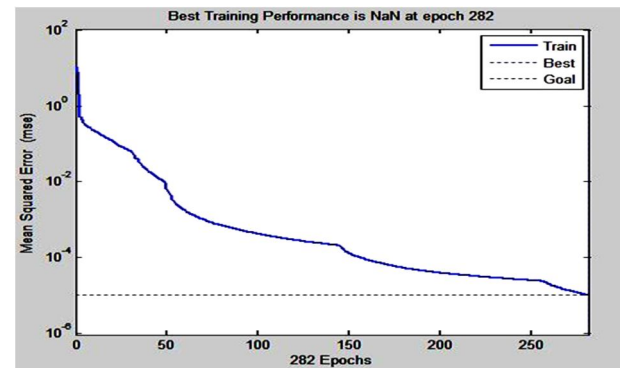


Figure 3: ANN training performance (MSE) for LG Fault

#### 2) Training for LLG Fault



Here three hidden layer of 26, 12 and 10 neuron in first, second and third hidden layers respectively and 'logsig' transfer function is used for both hidden layer and 'purelin' transfer function is used for output layer that gives the best performance as shown in Fig. 4. The network of fault locator is multi layered feed forward ANN with 12 neurons in the input layer, 26 neuron in first hidden layer, 12 neuron in second hidden layer, 10 neuron in third hidden layer and 1 neuron in output layer (12-26-12-10-1) is capable of minimizing the mean square errors (MSE) to a goal of  $9.85 \times 10^{-07}$  in 261 epochs as shown in Fig. 5.

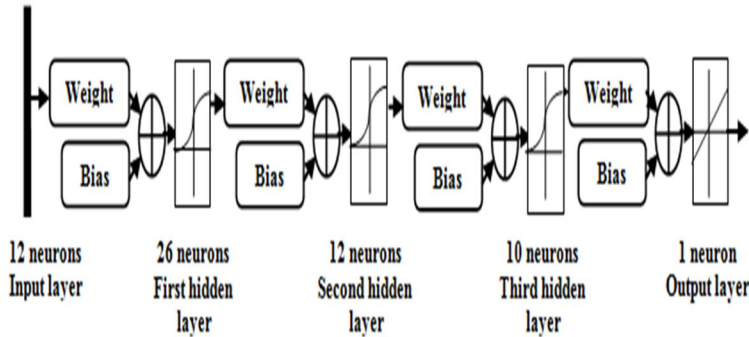


Figure 4: Architecture of ANN Based LLG Fault Locator

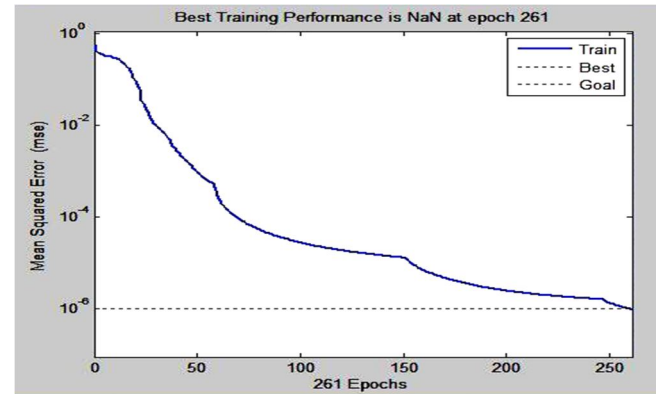


Figure 5: ANN training performance (MSE) for LLG Fault

### 3) Training for LL Fault

Here two hidden layer of 36 and 32 neuron in first and second hidden layers respectively and 'logsig' transfer function is used for both hidden layer and 'purelin' transfer function is used for output layer that gives the best performance as shown in Fig. 6. The network of fault locator is multi layered feed forward ANN with 12 neurons in the input layer, 36 neuron in first hidden layer, 32 neuron in second hidden layer and 1 neuron in output layer (12-36-32-1) is capable of minimizing the mean square errors (MSE) to a goal of  $9.19 \times 10^{-12}$  in 124 epochs as shown in Fig. 7.

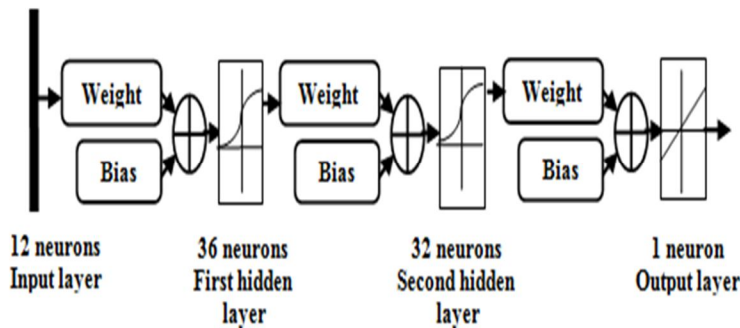


Figure 6: Architecture of ANN Based LL Fault Locator

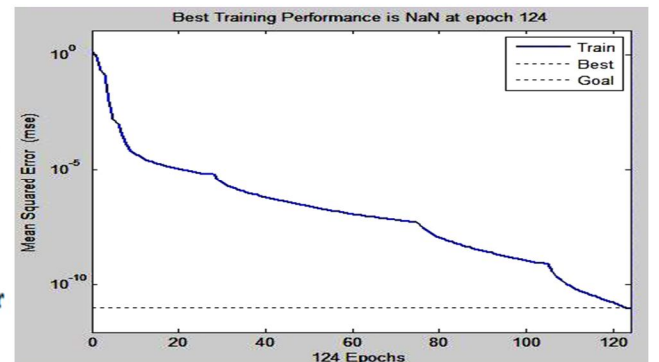


Figure 7: ANN training performance (MSE) for LL Fault Locator

### 4) Training for LLL Fault

Here two hidden layer of 35 and 30 neuron in first and second hidden layers respectively and 'logsig' transfer function is used for both hidden layer and 'purelin' transfer function is used for output layer that gives the best performance as shown in Fig. 8. The network of fault locator is multi layered feed forward ANN with 12 neurons in the input layer, 35 neuron in first hidden layer, 30 neuron in second hidden layer and 1 neuron in output layer (12-35-30-1) is capable of minimizing the mean square errors (MSE) to a goal of  $2.03 \times 10^{-13}$  in 5 epochs as shown in Fig. 9.

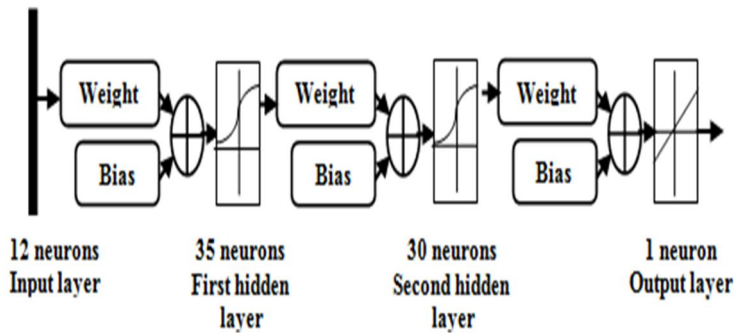


Figure 8: Architecture of ANN Based LLL Fault Locator

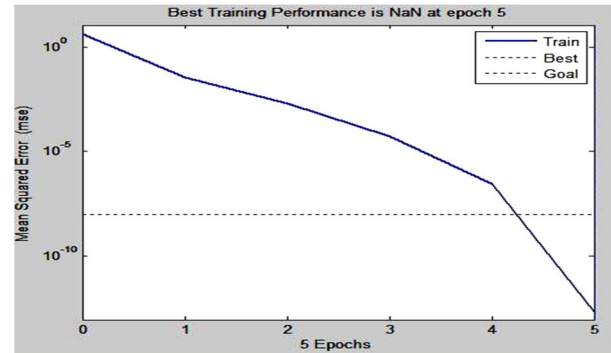


Figure 9: ANN training performance (MSE) for LLL Fault Locator

#### IV. TEST RESULTS OF ANN BASED FAULT LOCATOR

After training the networks of all phase to phase and phase to ground faults, we need to test the trained network to check networks are properly trained or not. Test dataset is generated at different fault parameter which is not used during training pattern generation. At various locations all types of phase faults and ground faults were tested to find out the maximum deviation of the estimated distance  $L_f$  measured from the relay location and the actual fault location  $L_a$ . The estimated error is expressed as a percentage of total line length as given in equation (6).

$$\% \text{ Error} = \frac{\text{Actual Location} - \text{Estimated location}}{\text{Total line length}} \times 100 \quad (6)$$

After training, the ANN based Fault detector and Fault classifier was then extensively tested using independent data sets consisting of fault scenarios which were never used previously in the training process. For different faults cases of the test data set, fault type, fault location, fault resistance and fault inception angle were changed to investigate the effects of these factors on the performance of the proposed protection algorithm. The network was tested and performance was validated by presenting all types of fault cases with varying fault locations ( $L_f = 0-99.5\text{KM}$ ), fault resistances ( $R_f = 0-179\Omega$ ) and fault inception angles ( $\Phi_i = 0-360^\circ$ ). The test results of ANN based Fault Locator for ground faults and for phase faults are given in Table 3 and 4. It is clear from the table that the estimated location is approximately same as actual fault location for both phase faults and ground faults and the ANN output is immune to the changes in varying system parameters. The maximum and minimum percentage errors of the test result for ground faults are 0.9943% and 0.0120% respectively. The maximum and minimum percentage errors of the test result for phase faults are 0.9963% and 0.00% respectively.

Fault Type	Fault Resistance $R_f$ (ohm)	Fault Inception angle $\Phi_i$ (deg)	Actual Fault Location $L_f$ (in km)	ANN Output (in km)	% Error
A <sub>1</sub> G	1	0	2	2.1531	0.1531
B <sub>1</sub> G	50	60	25	24.0704	0.0704
C <sub>1</sub> G	70	150	34	34.8064	0.8064
A <sub>2</sub> G	100	210	56	56.9943	0.9943
B <sub>2</sub> G	150	300	80	79.7075	0.7075
C <sub>2</sub> G	179	360	99	99.2460	0.2460
A <sub>1</sub> B <sub>1</sub> G	1	0	2	2.1928	0.1928
A <sub>1</sub> C <sub>1</sub> G	50	60	25	25.6647	0.6647
B <sub>1</sub> C <sub>1</sub> G	80	150	34	34.9517	0.9517
A <sub>2</sub> B <sub>2</sub> G	100	210	56	56.5763	0.5763
B <sub>2</sub> C <sub>2</sub> G	150	300	80	80.0120	0.0120
A <sub>2</sub> C <sub>2</sub> G	179	360	99	99.2491	0.2491

Table 3: Test results of ANN based Fault Locator for Ground Faults

Fault Type	Fault Resistance $R_f$ (ohm)	Fault Inception angle $\Phi_i$ (deg)	Actual Fault Location $L_f$ (in km)	ANN Output (in km)	% Error
A <sub>1</sub> B <sub>1</sub>	0.01	0	3	2.9963	0.9963
A <sub>1</sub> C <sub>1</sub>	0.01	30	20	19.9486	0.9486
B <sub>1</sub> C <sub>1</sub>	0.01	60	35	35.0988	0.0988
A <sub>2</sub> B <sub>2</sub>	0.01	90	48	48.0000	0.0000
A <sub>2</sub> C <sub>2</sub>	0.01	120	64	64.0364	0.0364
B <sub>2</sub> C <sub>2</sub>	0.01	180	72	71.9896	0.9896
A <sub>1</sub> B <sub>1</sub> C <sub>1</sub>	0.01	300	85	84.9163	0.9163
A <sub>2</sub> B <sub>2</sub> C <sub>2</sub>	0.01	360	99.5	100.2526	0.7526

Table 4: Test results of ANN based Fault Locator for Phase Faults

## V. CONCLUSIONS

This paper presents new approaches for the ANN based fault location in double circuit transmission line using only one terminal data, which can be used in the digital protection of the double circuit power transmission system. These approaches are based on magnitude and changes in the phase angle of current signals of each phase of both the circuits which is given as input to the artificial neural network for fault location task. The protection scheme effectively eliminates the effect of varying fault resistance, fault location and fault inception angle. The performance of the proposed protection scheme has been investigated by a number of offline tests considering all possible types of faults with varying fault resistance  $R_f$  (0-179  $\Omega$ ), fault locations  $L_f$  (0-99.5 km) and fault inception angles  $\Phi_i$  (0-360°). Test results show that the fault location algorithm proposed can be used to very support a new generation of protection relay systems at high speed. These advantages make the proposed techniques extremely suitable for online and supervised location of faults with high fidelity in large-scale power systems.

## VI. ACKNOWLEDGMENT

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