iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 5 **Issue:** IX **Month of publication:** September 2017

DOI:

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

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

Dikendra Verma[1], Mrs. Varsha Sharma[2]
[1, 2] E.E.E Department, RSR-RCET, Bhilai, Chhattisgarh, INDIA

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.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

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.

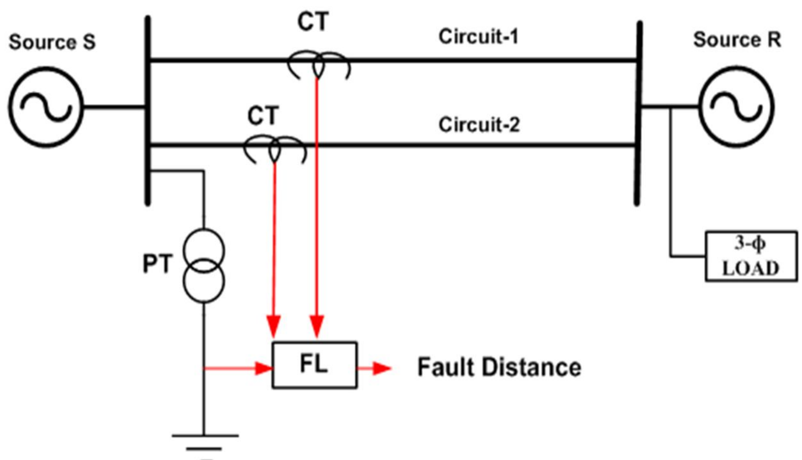


Figure 1: Single line diagram of power system model under study

Components	Parameters	
Transmission line	Length (km)	100
	Voltage (kV)	220
	Positive sequence impedance (Ω/km)	0.0181 + j0.292
	Zero sequence impedance (Ω/km)	0.2188 + j1.031
	Zero sequence mutual impedance (Ω/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:

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

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

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

Where θ_{max} and θ_{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).

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

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

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).

$$Y = [L_f] \tag{5}$$

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, $B_1 C_1G$, 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 Ω (for ground fault) & 0 Ω (for phase fault)
Fault Inception Angle (2)	0º & 90º

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 $9.94 * 10^{-06}$ in 282 epochs as shown in Fig. 3.

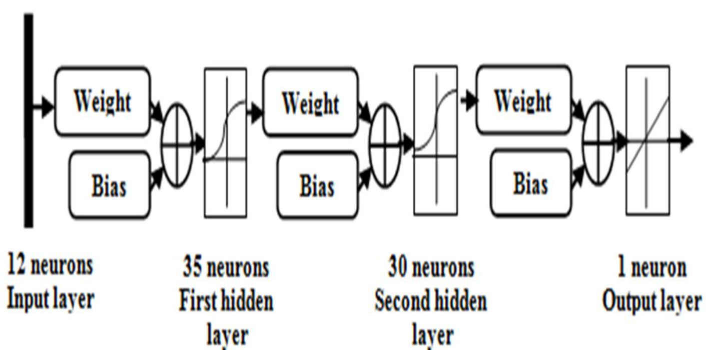


Figure 2: Architecture of ANN Based LG Fault Locato

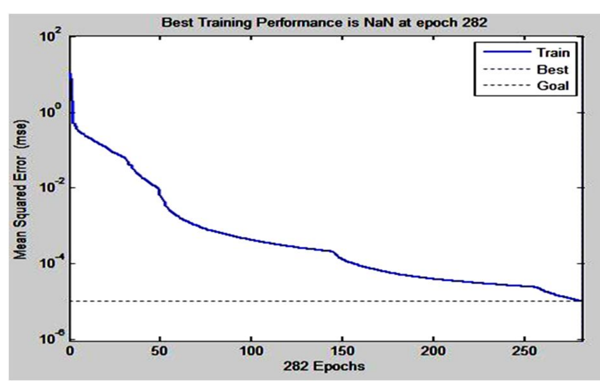
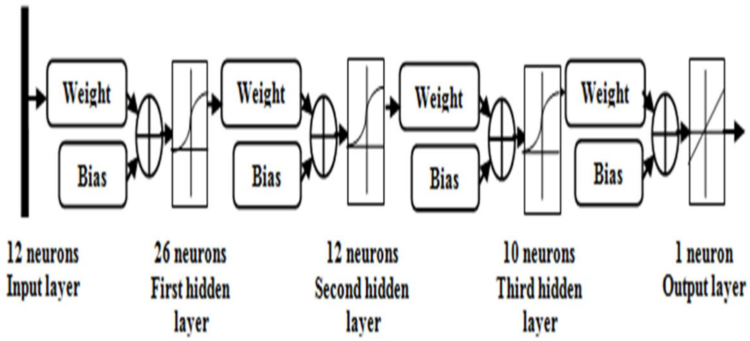


Figure 3: ANN training performance (MSE) for LG Fault Locator

2) Training for LLG Fault

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

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* 10^{-07} in 261 epochs as shown in Fig. 5.



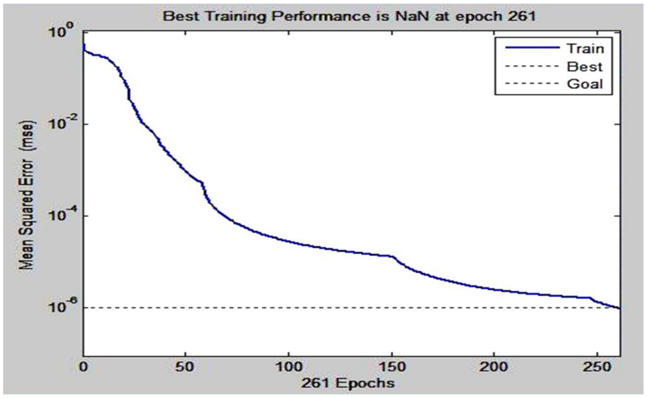
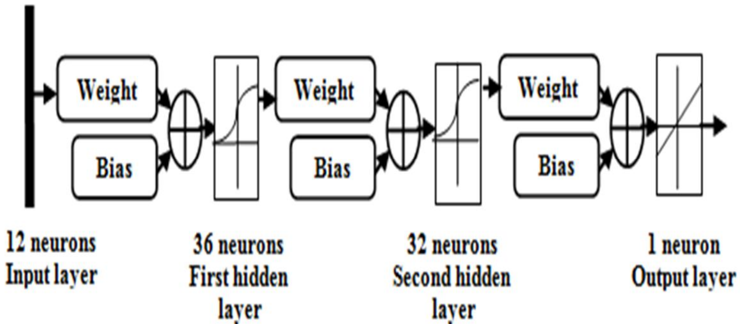


Figure 4: Architecture of ANN Based LLG Fault Locator

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

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* 10^{-12} in 124 epochs as shown in Fig. 7.



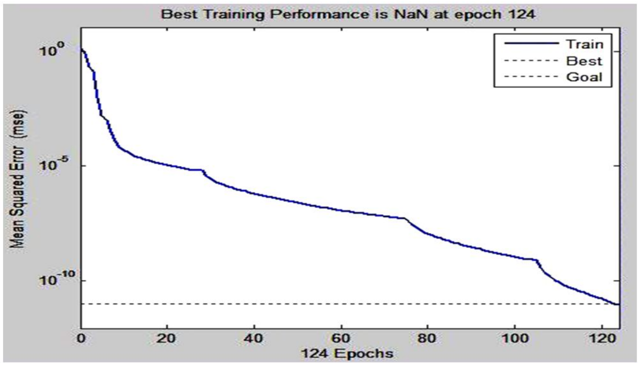


Figure 6: Architecture of ANN Based LL Fault Locator

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* 10^{-13} in 5 epochs as shown in Fig. 9.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue IX, September 2017- Available at www.ijraset.com

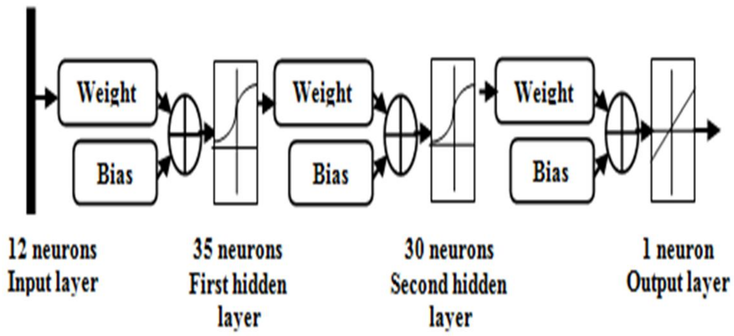


Figure 8: Architecture of ANN Based LLL Fault Locator

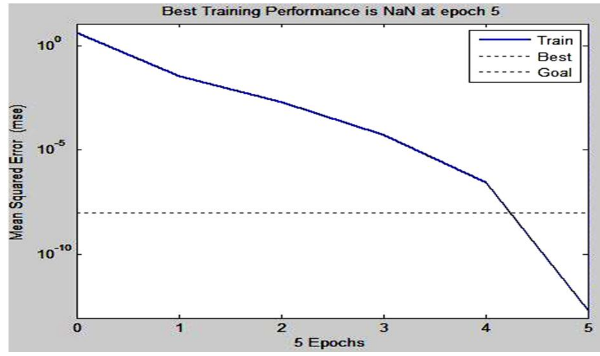


Figure 9: ANN training performance (MSE) for LLL Fault Locator

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).

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

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 = 0-99.5KM), fault resistances (R_f = 0-179Ω) and fault inception angles (Φi = 0-360°). 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 Φi (deg)	Actual Fault Location L_f (in km)	ANN Output (in km)	% Error
A_1G	1	0	2	2.1531	0.1531
B_1G	50	60	25	24.0704	0.0704
C_1G	70	150	34	34.8064	0.8064
A2G	100	210	56	56.9943	0.9943
B_2G	150	300	80	79.7075	0.7075
C_2G	179	360	99	99.2460	0.2460
A_1B_1G	1	0	2	2.1928	0.1928
A_1C_1G	50	60	25	25.6647	0.6647
B_1C_1G	80	150	34	34.9517	0.9517
A_2B_2G	100	210	56	56.5763	0.5763
B_2C_2G	150	300	80	80.0120	0.0120
A_2C_2G	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 Φi (deg)	Actual Fault Location L_f (in km)	ANN Output (in km)	% Error
A_1B_1	0.01	0	3	2.9963	0.9963
A_1C_1	0.01	30	20	19.9486	0.9486
B_1C_1	0.01	60	35	35.0988	0.0988
A_2B_2	0.01	90	48	48.0000	0.0000
A_2C_2	0.01	120	64	64.0364	0.0364
B_2C_2	0.01	180	72	71.9896	0.9896
$A_1B_1C_1$	0.01	300	85	84.9163	0.9163
$A_2B_2C_2$	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 Ω), fault locations L_f (0-99.5 km) and fault inception angles Φi (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

I would like to sincerely thank Mrs. Varsha Sharma, Assistant Professor (Dept. of E.E.E.) who provided expertise that greatly assisted the research work.

REFERENCES

[1] T. Takagi, Y. Yamakoshi, J. Baba, K. Uemura and T. Sakaguchi, “A new algorithm of an accurate fault location for EHV/UHV transmission lines. Part I: Fourier transform method”, IEEE Trans. Power Appar. Syst. PAS-100, 3, (1981), pp. 1316-1322.

[2] T. Takagi, Y. Yamakoshi, J. Baba, K. Uemura and T. Sakaguchi, “A new algorithm of an accurate fault location for EHV/UHV transmission lines. Part II: Laplace transform method”, IEEE Trans. Power Appar. Syst. 101, 3, (1982), pp. 564-573.

[3] S. A. Soliman, M. H. Abdel-Rahman, E. Al-Attar and M. E. El-Hawary, “An algorithm for estimating fault location in an unbalanced three-phase power system”, International Journal of Electrical Power and Energy Systems, Vol. 24, 7, Oct. 2002, pp 515-520.

[4] B. Liana, M. M. A. Salamaa and A. Y. Chikhanib, “A time domain differential equation approach using distributed parameter line model for transmission line fault location algorithm”, Electric Power Systems Research, Vol. 46, Issue 1, July 1998, pp 1-10.

[5] Gopalakrishnan, M. Kezunovic, S.M.McKenna, D.M. Hamai, “Fault location using the distributed parameter transmission line model”, IEEE Transactions on Power Delivery, Vol. 15, Issue 4, Oct. 2000 pp - 1169-1174.

[6] M. Kizilcay, P. La Seta, D. Menniti, M. Igel, “A new fault location approach for overhead HV lines with line equations”, IEEE Power Tech Conference Proceedings 2003, Bologna, 23-26 June 2003, Vol. 3, pages: 7.

[7] G. B. Ancell, N. C. Pahalawaththa, “Maximum likelihood estimation of fault location on transmission lines using traveling waves,” IEEE Trans. Power Delivery, Vol.9, pp.680-689, Apr. 1994.

[8] M.M. Tawfik, M.M. Morcos, “A novel approach for fault location on transmission lines”, IEEE Power Eng. Rev. 18, Nov. 1998, pp. 58U˝ 60.

[9] Anamika Jain, V.S. Kale and A.S. Thoke, “Application of artificial neural networks to transmission line faulty phase selection and fault distance location”, Proceedings of the IASTED International conference “Energy and Power System”, Chiang Mai, Thailand, Mar. 29-31, 2006, paper No. 526-803, pp. 262-267.

[10] R.K. Aggarwal, Q.Y. Xuan, A.T. Johns, R.W. Dunn, “Fault classification for double-circuits using self-organization mapping neural network”, Proc. 32nd Universities Power Engineering Conf., 1 September 1997.

[11] S.A. Khaparde, N. Warke and S.H. Agarwal, “An adaptive approach in distance protection using an artificial neural network”, Electric Power Systems Research, vol. 37, Issue 1, April 1996, pp. 39-46.

[12] Fan Chunju, K.K. Li, W.L. Chan, Yu Weiyong and Zhang Zhaoning, “Application of wavelet fuzzy neural network in locating single line to ground fault (SLG) in distribution lines”, International Journal of Electrical Power & Energy Systems, vol. 29, Issue 6, July 2007, pp. 497-50.

[13] A.G. Jongepier and L. Van Der Sluis, "Adaptive distance protection of double circuit lines using artificial neural networks", IEEE Transactions on Power Delivery, vol. 12, No.1, January 1997, pp. 97- 105.
[14] A. Yadav, A. Swetapadma, "A single ended directional fault section identifier and fault locator for double circuit transmission lines using combined wavelet and ANN approach", Int. Journal of Electric Power and Energy Systems, vol. 69, pp. 27-33, July 2015.
[15] Behnam Mahamedi, Jian Guo Zhu, "Unsynchronized Fault Location Based on the Negative-Sequence Voltage Magnitude for Double-Circuit Transmission Lines". IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 29, NO. 4, AUGUST 2014.