Reason - A Technical Journal
ISSN 2277–1654
Volume - XIV • 2015

AN APPLICATION OF DWT AND RBFNN FOR FAULT LOCATION FOR SINGLE LINE TO GROUND FAULT ON HVAC TRANSMISSION LINE

B. Saha[1], B. Patel[2] and P. Bera[3]

Department of Electrical Engineering, Kalyani Government Engineering College,
Kalyani- 741235, India
Email: [1]binoykgec@gmail.com, [2]biks.ee@gmail.com, [3]parthabera1977@gmail.com

Paper received on: March 01, 2016, accepted after revision on: March 17, 2016

Abstract: This article demonstrates a technique for diagnosis of fault location on overhead transmission lines for single line to ground fault. The proposed method is based on discrete wavelet transform (DWT) and radial basis function neural network (RBFNN). A number of features have been extracted from faulty signal using DWT and are used for training of RBFNN for fault detection. It has been found that fault locator based on discrete wavelet transform and RBFNN neural network can accurately locate the fault with an average accuracy 2.31%. From the result it can be concluded that the proposed method for fault location estimation for a single line to ground fault (LG fault) is capable of giving results with acceptable accuracy.

Keywords: Discrete wavelet transform (DWT); Multi-resolution analysis (MRA); Radial basis function neural network; (RBFNN); Single line to ground fault (LG fault).

1. INTRODUCTION

Transmission line is an important part of electrical power system to transfer electrical power from generating station to load. Uninterrupted quality power supply depends on performance of transmission line. Relaying of transmission line is essential for this purpose which involves in fault detection, classification and estimation of fault location. This fault should be removed along with isolating the faulted section as quickly as possible to avoid cascade failure of alternators for a tidily interconnected system. The complexity of calculation increases in size of power system network for the conventional fault classification method and the calculation required the data for line parameters of the power system. Abdel-Akher et al. [1] have proposed a fault classification technique by modeling a sequence network of multiphase distribution system using symmetrical component. Soft computing techniques have shown better performances with respect to computation time and accuracy. The methods use reliable software like Electromagnetic Transient Program (EMTP), PSCAD and MATLAB for simulation of faults and apply signal processing tools like wavelet transform and S-transform for feature extraction. Chanda.et. al [2] have used peak absolute values of DWT coefficients obtained from the line voltages and currents to classify faults. High impedance faults are detected and classified using DWT coefficients of real time fault voltages [3]. Wavelet coefficient energy has been used by researchers for fault analysis [4, 5] and wavelet entropy has been used for detection and classification of faults [6-8]. Sedeghi.et.al. [9] have proposed high impedance fault detection based on wavelet transform and statistical pattern recognition. Artificial intelligence along with the signal processing tools has imparted interest towards fault analysis as it provides high accuracy. Neuro-Fuzzy Approach has been proposed for fault detection and estimation of location in the articles [10, 11]. Costa [12] has used support vector machine (SVM) technique for high frequency transient terminal protection technique. DWT features of fault signals were fed to the Back Propagation Neural Network (BPNN) to estimate the fault location, presented in [13, 14].

This paper presents a method to locate fault on transmission system based on combination of discrete wavelet transform and radial basis function neural network. RBFNN provides faster result than BPNN and is more accurate. The fault condition is simulated using Alternating Transient Program (ATP)/EMTP [15] and features of fault currents are extracted by using wavelet transform. Only positive and negative peak values of DWT coefficients are fed to radial basis function neural network for training process. The main objective of the present work is to locate and estimate single line to ground fault for different fault resistances.

2. WAVELET TRANSFORM

In the early 1980s, Wavelet transform (WT) was introduced and it has attracted much interest in the fields of speech and image processing. The potential benefits of applying wavelet transform for analysis of transient signals in power systems have been recognized in the recent years [16, 17]. Similar to Fourier transform, the wavelet transform decomposes a signal into its frequency components, except the later provides a non-uniform division of the frequency domain. The high frequency window is narrow providing high resolution where as low frequency window is wide with low resolution. This ability to tailor the frequency resolution can greatly facilitate the detection and characterization of the transient signals. The basic concept in wavelet transform is to select an appropriate wavelet function 'mother wavelet' and then perform analysis using shifted and dilated versions of this wavelet.

The continuous 1-dimension wavelet transform (CWT) of a signal x(t) is defined as [18] :

$$CWT\,(x, a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t)\, \psi^{*}_{a,b}\left(\frac{t-b}{a}\right) dt \quad (1)$$

where $\psi(t)$ is the mother wavelet and $\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\,\psi_{a,b}\left(\frac{t-b}{a}\right)$ is it's dilated and translated version. The constants a and b are called scale (dilation) and translation (times shift) parameters respectively. Selection of a mother wavelet is flexible if it satisfies the following condition.

$$\int_{-\infty}^{+\infty} \psi(t)\, dt = 0 \quad (2)$$

This implies that a wavelet is compactly supported in both the time domain and frequency domains. Instead of continuous dilation and translation, the mother wavelet may be dilate and translate discretely by selecting $a = a_0^m$ and $b = k a_0^m$, where a_0 and b_0 have fixed values with $a_0 > 1$, $b_0 > 0$ and *m*, *k* being positive integers. Then the discretized version of continuous wavelet known as Discrete Wavelet Transform (DWT) is represented by

$$\text{DWT}\,(x, m, n) = \frac{1}{\sqrt{a_0^m}} \sum_k x(k)\, \psi\left(\frac{n - k a_0^m}{a_0^m}\right) \quad (3)$$

The most frequently selected values of a_0 and b_0 are and $a_0 = 2$ and $b_0 = 1$ which is used in this paper and is given by

$$\text{DWT}\,(x, m, n) = \frac{1}{\sqrt{2^m}} \sum_k x(k)\, \psi\left(\frac{n - k2^m}{2^m}\right) \quad (4)$$

The actual implementation of DWT is done by multi-resolution analysis (MRA) [18]. In DWT, a time-scale representation of a digital signal is obtained using digital filtering techniques. Filters of different cut-off frequencies are used to analyze the signal at different scales. The signal is passed through a series of high pass and low pass filters to segregate high and low frequencies in the signal. Let x(n) be the discrete time signal with n numbers of samples. This signal is decomposed into $c_1(n)$ and $d_1(n)$ at scale 1, where $c_1(n)$ is the approximation version which is the high-scale, low-frequency component of the original signal and $d_1(n)$ is the detailed version containing low-scale, high-frequency components of the original signal as shown in Fig. 1. The approximation and detailed versions at scale 1 are given by

$$c_1(n)=\sum_{k=1}^{n+1} h[k-2n]\,x(k) \qquad (5)$$

$$d_1(n)=\sum_{k=1}^{n+1} h[k-2n]\,x(k) \qquad (6)$$

Here h(n) and g(n) are the associated filter coefficients that decompose x(n) to $c_1(n)$ and $d_1(n)$ respectively. The next higher scale (scale 2) decomposition will be on $c_1(n)$ which is decomposed to $c_2(n)$ and $d_2(n)$. The decomposition process can be iterated, with successive approximations being decomposed, so that one signal is broken down into many components of different resolutions.

This process of decomposition is known as Multi-Resolution Analysis (MRA) which provides a more efficient way of representing a signal at different resolution scales. As decompositions are done on higher scales, lower frequency components are filtered out progressively.

3. RADIAL BASIS FUNCTION NEURAL NETWORK

An RBF network is a feed-forward network consists of a single hidden layer and interconnected with an output layer. The units of hidden layer simultaneously receive the p–dimensional real valued input vector as shown in Fig. 2 [19]. And the input vector to the network is passed to the nodes hidden layer via unit connection weights. The hidden layer consists of a set of radial basis functions and calculates the Euclidean distance between the centre and the input vector and then the result is passed to the radial basis function.

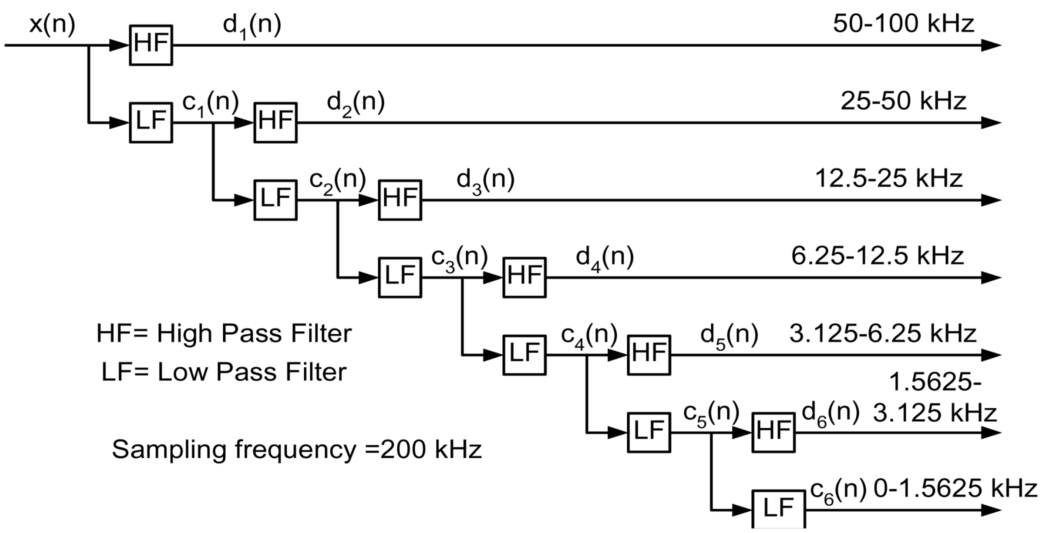

Fig. 1: Wavelet decomposition up to level 6

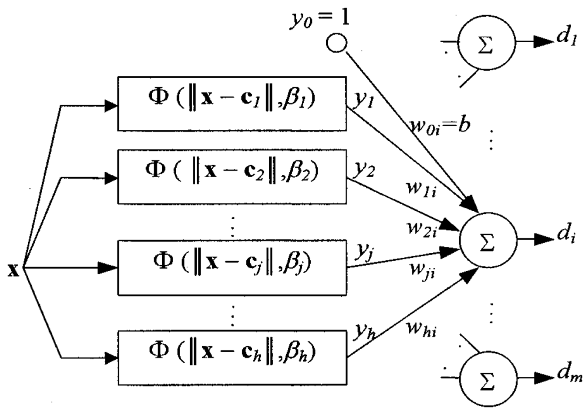

Fig. 2: Radial basis function neural network [19]

An RBF network is designed to perform a nonlinear mapping from the input space to the hidden space, followed by a linear mapping from the hidden space to the output space. The network represents a map from the p-dimensional input space to m-dimensional output space, written as according to [19] :

$$d_i = w_{oi} + \sum_{j=1}^{h} \omega_{ji} \left(\|x - c\|, \beta_j\right) \quad (7)$$

where, i = 1….m and j = 1,…..,h.

d_i is the i^{th} output.

$x \in R^P$ is the input vector.

ω_{0i} is the biasing term.

h is the number of hidden units.

ω_{ji} is the weight between the j^{th} hidden node and the i^{th} output node.

$c_j \in R^P$ is the centre of the j^{th} hidden node.

β_j is the real constant known as spread factor.

$\Phi(.)$ is the nonlinear function.

In this study, $\Phi(.)$ is chosen to be the Gaussian function, that is, for the jth hidden unit;

$$\Phi(z_j, \beta_j) = \exp(-z_j^2 / \beta_j^2)$$

where, $z_j = \|x - c_j\|$ 8

The RBF network is trained in the present work using new function 'NEWRB' in the neural network toolbox of the MATLAB software. Orthogonal least square algorithm has been implemented in the function 'NEWRB'.

4. SIMULATION OF AN HVAC SYSTEM USING EMTP

A 400kv three phase 50 Hz power system network is simulated using ATP/EMTP software and the diagram of the power system is shown in Fig. 3. The length of the transmission line is 150km. A three phase balanced load of rating two load of 350MVA, 0.97 lagging power factor (load1) and 150MVA, 0.9 lagging power factor (load2) are connected at the receiving end of the transmission line. A 3-phase transposed transmission line is modelled in EMTP using positive, negative and zero sequence component of transmission line resistance, inductance and capacitance. BCTRAN model of transformer is used in EMTP simulation. In the simulation, sampling time is taken as 10ns and time period of simulation in ATP has been taken as 0.1sec. LG fault with high impedance has been simulated in the present study. Fault has been initiated at 15 different locations starting from generating end each being 10km apart. For example, a fault current signal for LG fault at 40km distance for fault resistance 40 Ohm is shown in the Fig.4.

5. FEATURE EXTRACTION USING DWT

In this study, three fault currents at load end are used as the input signals for Multi-Resolution wavelet analysis. DWT with mother wavelet db7 is performed at different distances for different fault resistances. The plots of detailed coefficients at level 7 as shown in the Fig. 5 and Fig. 6 show sharp spikes corresponding to the fault initiation. According to DWT theory, these spikes indicate the highest frequency contained in the fault signals. These spikes have been observed to change appreciably with variations in fault types, fault locations, fault resistance and fault inception angle. The positive peak (W_{C1}) and negative peak (W_{C2}) values of DWT coefficients at different fault distances are shown in the Table 1 and Table 2.

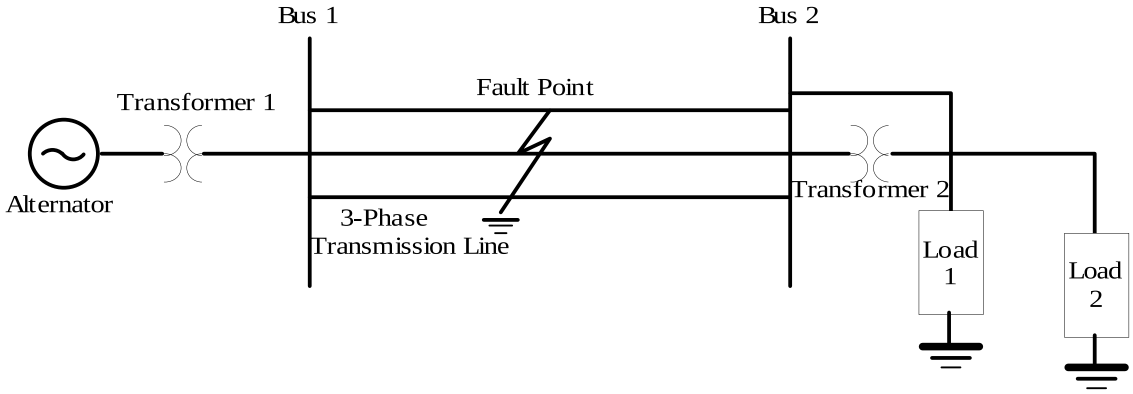

Fig. 3: 400kV, 150km length transmission line model

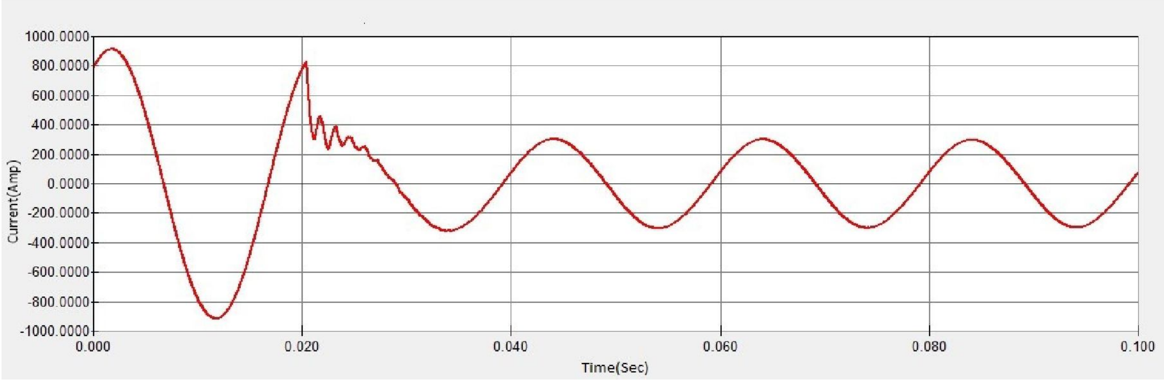

Fig. 4: Current (I_a) vs Time for LG fault at phase A at 40 km distance

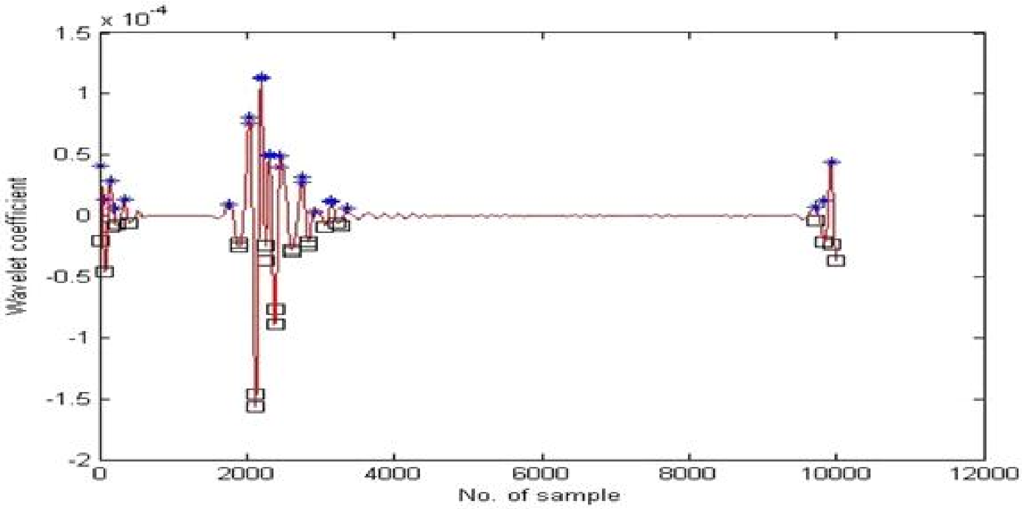

Fig. 5: Wavelet coefficient vs number of samples for LG fault at 40km for 40 Ohm fault resistance

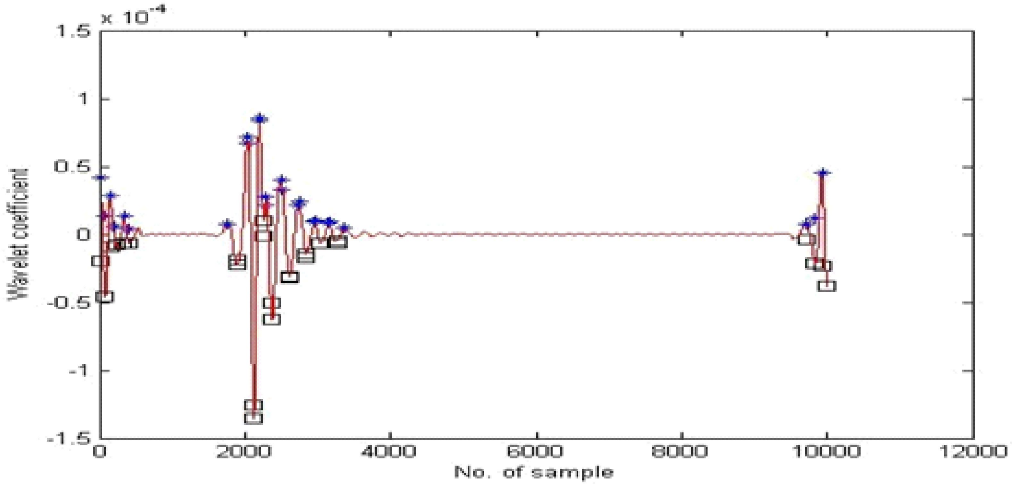

Fig. 6: Wavelet coefficient vs no of samples for LG fault at 40km for 100 Ohm fault resistance

Table 1: DWT coefficients of phase currents for single line to ground fault at phase A with fault impedance value of 40 Ohm

Distance (Km)	For phase A current (I_a)		For phase B current (I_b)		For phase C current (I_c)	
	W_{C1}	W_{C2}	W_{C1}	W_{C2}	W_{C1}	W_{C2}
10	0.00043394	-0.00069282	$8.8961X10^{-5}$	-0.00015217	$9.3051X10^{-5}$	-0.00016317
20	0.00049556	-0.00066993	0.00010177	-0.00016072	0.00010388	-0.00017138
30	0.00052431	-0.00061251	0.0001159	-0.00016011	0.00011657	-0.00017034
40	0.00046976	-0.00050689	0.00011309	-0.00014648	0.00011338	-0.00015629
50	0.00032098	-0.00035516	$8.1619X10^{-5}$	-0.00011521	$8.2422X10^{-5}$	-0.00012462
60	0.00032989	-0.00020108	$5.5686X10^{-5}$	$-7.3145X10^{-5}$	$6.4193X10^{-5}$	$-8.1983X10^{-5}$
70	0.00035184	-0.00019566	$6.9835X10^{-5}$	$-4.7624X10^{-5}$	$8.1073X10^{-5}$	$-5.1713X10^{-5}$
80	0.00035654	-0.00019902	$7.8037X10^{-5}$	$-5.4792X10^{-5}$	$8.537X10^{-5}$	$-6.5567X10^{-5}$
90	0.0003348	-0.00018547	$8.1556X10^{-5}$	$-7.9234X10^{-5}$	$8.8811X10^{-5}$	$-9.1205X10^{-5}$
100	0.00031258	-0.00017971	$7.9857X10^{-5}$	$-5.1107X10^{-5}$	$8.7046X10^{-5}$	$-6.1945X10^{-5}$
110	0.00029894	-0.00017574	$7.8165X10^{-5}$	$-4.9665X10^{-5}$	$8.5344X10^{-5}$	$-4.9708X10^{-5}$
120	0.00029397	-0.00016893	$7.7404X10^{-5}$	$-5.2485X10^{-5}$	$8.4581X10^{-5}$	$-5.1248X10^{-5}$
130	0.00029197	-0.00015928	$7.7065X10^{-5}$	$-5.6289X10^{-5}$	$8.428X10^{-5}$	$-6.8295X10^{-5}$
140	0.00029445	-0.0001584	$7.7091X10^{-5}$	$-7.5102X10^{-5}$	$8.4224X10^{-5}$	$-8.9408X10^{-5}$

6. FAULT LOCATION ESTIMATION USING RBFN

The DWT coefficients given in Table 1 and Table 2 are used for fault location estimation using RBFNN. The positive and negative peak values of DWT coefficients with respect to fault location are used as the input features to the RBFNN and output is distance. After training the neural network, 5 numbers of testing (predicting) patterns are generated each for fault resistance of 40 Ohm and 100 Ohm at distances different from those used for training and a satisfactory performance is realized as given in the Table 3 with an average error of 2.31%.

Table 2: DWT coefficients of phase currents for single line to ground fault at phase A with fault impedance value of 100 Ohm.

Distance (Km)	For phase A current (I_a)		For phase B current (I_b)		For phase C current (I_c)	
	W_{C1}	W_{C2}	W_{C1}	W_{C2}	W_{C1}	W_{C2}
10	0.0003405	-0.00056098	$7.4167X10^{-5}$	-0.0001286	$7.7684X10^{-5}$	-0.0001381
20	0.00037352	-0.00054654	$7.9149X10^{-5}$	-0.00013566	$8.1422X10^{-5}$	-0.00014505
30	0.00038653	-0.00050763	$8.6476X10^{-5}$	-0.00013541	$8.7875X10^{-5}$	-0.00014468
40	0.00035539	-0.000438	$8.4186X10^{-5}$	-0.00012624	$8.5271X10^{-5}$	-0.00013533
50	0.00027623	-0.00034248	$6.7402X10^{-5}$	-0.00010639	$6.915X10^{-5}$	-0.00011526
60	0.00027361	-0.00024432	$5.0677X10^{-5}$	$-8.0373X10^{-5}$	$5.7161X10^{-5}$	$-8.8849X10^{-5}$
70	0.00028733	-0.00018877	$5.7215X10^{-5}$	$-5.8511X10^{-5}$	$6.3825X10^{-5}$	$-6.6447X10^{-5}$
80	0.00029264	-0.00018887	$6.5194X10^{-5}$	$-4.7324X10^{-5}$	$7.1689X10^{-5}$	$-5.8114X10^{-5}$
90	0.00028312	-0.00020017	$6.9201X10^{-5}$	$-6.376X10^{-5}$	$7.5617X10^{-5}$	$-7.4694X10^{-5}$
100	0.00026954	-0.00019857	$6.935X10^{-5}$	$-5.2448X10^{-5}$	$7.5734X10^{-5}$	$-6.2959X10^{-5}$
110	0.00025927	-0.00018806	$6.8578X10^{-5}$	$-3.8649X10^{-5}$	$7.4941X10^{-5}$	$-4.6211X10^{-5}$
120	0.00025445	-0.00017365	$6.8111X10^{-5}$	$-4.0807X10^{-5}$	$7.443X10^{-5}$	$-4.6211X10^{-5}$
130	0.00025195	-0.00015592	$6.7687X10^{-5}$	$-4.6202X10^{-5}$	$7.5909X10^{-5}$	$-5.7607X10^{-5}$
140	0.00025189	-0.00013914	$6.7369X10^{-5}$	$-6.0184X10^{-5}$	$7.3541X10^{-5}$	$-7.2451X10^{-5}$

Table 3: Results of fault location estimation from RBFNN

Fault Category	Fault Resistance (Ohm)	Target Value (km)	Predicted Value (km)	Percent Error
AG	40	17	16.1	-5.29
		35	34.43	-1.62
		105	107.01	+1.91
		127	125.82	-0.92
		132	130.25	-1.32
	100	17	16.51	-2.88
		35	34.34	-1.88
		105	99.00	-5.71
		127	125.01	-1.56
		132	131.96	-0.03

7. CONCLUSION

In this present work features have been extracted from current signals using discrete wavelet transform for a single line to ground fault occurring in a power system. A number of features are used for fault detection and these are positive maximum value of wavelet coefficient and negative maximum value of wavelet coefficient. The radial basis function neural network is trained for fault occurring at different equidistance location and the RBFNN based fault locator has been rigorously tested by simulating fault condition with different values of fault location and resistance. It has been found that fault locator based on discrete wavelet transform and RBFNN neural network can accurately locate the fault with an average accuracy 2.31%. From the result it can be concluded that the proposed method for fault location estimation for a single line to ground fault is capable of giving results with acceptable accuracy and valid for fault resistance variation too.

REFERENCES

[1] Abdel-Akher, M. and Mohamed N.K., Fault analysis of multiphase distribution systems using symmetrical components, IEEE Trans. Power Deliv., Vol. 25, No. 4, pp. 2931–2939, 2010.

[2] Chanda, D., Kishore, N.K. and Sinha, A.K., Application of wavelet multi resolution analysis for identification and classification of faults on transmission lines, Electr. Power Syst. Res., Vol. 73, pp. 323–333, 2005.

[3] Doaa, K.I., El Sayed, T.E., Essam, M.A.Z. and Saber, M.S., Real time evaluation of DWT-based high impedance fault detection in EHV transmission, Electric Power Systems Research, Vol. 80, pp. 907–914, 2010.

[4] Costa, F.B., Fault-induced transient detection based on real time analysis of the wavelet coefficient energy, IEEE Trans. Power Deliv., Vol. 29, No. 1, pp. 140–153, 2014.

[5] Silva, K.M., Souza, B.A. and Brito, N.S. D., Fault Detection and Classification in Transmission Lines Based on Wavelet Transform and ANN, IEEE Transactions On Power Delivery, Vol. 21, No. 4, pp. 2058-2063, 2006.

[6] Safty, S.El and El-Zonkoly, A., Applying wavelet entropy principle in fault classification, Electrical Power and Energy Systems, Vol. 31, pp. 604-607, 2009.

[7] He, Z., Fu, L., Lin, S. and Bo, Z., Fault Detection and Classification in EHV Transmission Line Based on Wavelet Singular Entropy, IEEE Transactions on Power Delivery, Vol. 25, No. 4, 2010.

[8] El-Zonkoly, A.M. and Desouki, H., Wavelet Entropy Based Algorithm for Fault Detection and Classification in FACTS Compensated Transmission Line, Energy and Power Engineering, Vol. 3, pp. 34-42, 2011.

[9] Sedighi, A.-R., Haghifam, M.-R., Malik, O.P. and Ghassemian, M.-H., High impedance fault detection based on wavelet transform and statistical pattern recognition, IEEE Trans. Power Deliver, Vol. 20, No. 4, pp. 2414–2421, 2005.

[10] Reddy, M.J., and Mohanta, D.K., A wavelet-fuzzy combined approach for classification and location of transmission line faults, Int. J. Electr. Power, Vol. 29, pp. 669–678, 2007.

[11] Nguyen, T. and Liao, Y., Transmission line fault type classification based on novel features and neuro-fuzzy system, Electr. Power Compon. Syst., Vol. 38, No. 6, pp 695–709, 2010.

[12] Costa, F.B., High-frequency transients-based protection of multi terminal transmission lines using the SVM technique, IEEE Transaction On Power Delivery, Vol. 28, No. 1, pp. 188–196, 2013.

[13] Bhowmik P.S., Purkait P., Bhattacharya K., A novel wavelet transform aided neural network based transmission line fault analysis method, Electrical Power and Energy Systems, Vol. 31, pp. 213-219, 2009

[14] Ngaopitakkul A., Bunjongjit S. An application of a discrete wavelet transform and a back-propagation neural network algorithm for fault diagnosis on single-circuit transmission line, International Journal of Systems Science, Vol. 44, No. 9, pp. 1745–1761, 2013,

[15] Dommel, H.W., Electromagnetic transients program reference manual, EMTP Theory Book, 1986.

[16] Robertson, D.C., Camps, O.I., Mayer, J.S. and Gish, W.B., Wavelet and electromagnetic powers system transients, IEEE Trans. Power Delivery, Vol. 11, No. 2, pp. 1050-1058, 1996.

[17] Chaari, O., Meunier, M. and Brouaye, F., Wavelets: A new tool for the resonant grounded power distribution systems relaying, IEEE Trans. on Power Delivery, Vol. 11, No. 3, pp. 1301-1308, 1996.

[18] Mallat, S.G., A theory for multi resolution signal decomposition: The wavelet representation, IEEE Trans. Pattern Anal. Mach. Intelligence, Vol.11, No. 7, pp. 674-693, 1989.

[19] Segal, R., Kothari, M.L. and Madnani, S., Radial Basis Function (RBF) Network Adaptive Power System Stabilizer, IEEE Transactions on Energy Conversion, Vol. 15, No. 2, pp. 722–727, 2000