Most Suited Mother Wavelet For Localization Of Transmission Line Faults

Sushma Verma

Abstract: This paper is a modest approach to determine the most suited mother wavelet for localization of transmission line faults. Discrete wavelet transform (DWT) and artificial neural network (ANN) based algorithm has been developed for this purpose. Extensive simulation studies were carried out in ATP for various types of fault conditions, locations and fault resistances. DWT analysis of the sending end current signals was done using 'daubechies' wavelets. Five wavelets: 'db1', 'db2', 'db3', 'db4' & 'db5' were selected associated with different centre frequency and period. The statistical features extracted from the DWT coefficients of the sending end current signals were used to train the ANN for identifying the fault locations. The results shows that the 'db3' mother wavelet is best suited for localization of transmission line faults, because of its short period and more number of vanishing moments.

Keywords: Transmission line, Fault localization, Discrete Wavelet Transform (DWT), Mother wavelet, Wavelet function, Artificial Neural Network (ANN), Alternate Transient Program (ATP).

1 INTRODUCTION

The increased demand in electricity has raised the issue of better power quality and reliability. The need of time is accurate and efficient operation of transmission lines. Overhead transmission lines are most vulnerable to faults than any other power system components. Protecting transmission line is one of the important tasks to safeguard the electric power systems. Faults on transmission lines needs to be detected, classified and located as fast as possible. Power system transmission line fault detection, localization and classification are of utmost importance to ensure quality performance of the power system. The increasing complexity of power system requires fast fault detection and localization, making transient important phenomena. Wavelet transform is better suited for the analysis of transient signals than widely used FFT or DFT techniques [1]. Due to this reason wavelet analysis has received great attention in the power community in the last few years. Several papers have been presented proposing the use of wavelets for signal analysis [1], data compression [2], analysis of power quality problem [3,4], power quality assessment [5], transient analysis and fault classification [6-8]. Very less work has been done for localization of overhead transmission line faults [9-12]. The potential benefits of applying wavelet transforms in combination with soft computing techniques like Artificial Neural Networks (ANNs) have already been recognized by various researchers [11-20]. However, the present investigation aims to study the impact and to determine the most suited mother wavelet for localization of the transmission line faults.

2 WAVELET ANALYSIS

A wavelet is a waveform of effectively limited duration that has an average value of zero. Comparing wavelets with sine waves, which are the basis of Fourier analysis, it can be appreciated that sinusoids are smooth and predictable; wavelets tend to be irregular and asymmetric. Therefore, the procedure of wavelet analysis may run like this – a wavelet prototype function, called an analyzing wavelet or mother wavelet is adopted and then temporal analysis is performed with a contracted, high frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low frequency version of the same wavelet . Thus the original signal or function can be represented in terms of a wavelet expansion, using coefficients in a linear combination of the wavelet functions. Data operations can be performed using just the corresponding wavelet coefficients. There are two wavelet transforms known as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). DWT results are associated with frequency bands following a dyadic scale fixed by the sampling frequency and the number of decomposition levels previously selected.

3 SELECTION OF MOTHER WAVELET

Wavelet transform involves correlating the signal being analyzed and a prototype wavelet function. Thus, the choice of the wavelet function may influence the performance of fault localization system [21]. Every wavelet is associated with a particular center frequency and a bandwidth determined by its period [22]. The center frequency f_c and the bandwidth f_b of the wavelet are the tuning parameters [23]. The transmission line faults are fast decaying in nature having short duration. The analysis of such a signal requires a mother wavelet with a short period [24]. '*daubechies*' series mother wavelet are suited for detecting transients associated with fault events as the associated transforms are fast, stable and accurate[18]. They are ideally suited for detecting fast decaying and oscillating type of signals [25].

TABLE 1

Comparison of centre frequency of different wavelets used.

Mother wavelet	Centre Frequency	No of vanishing moments	Period
db1	0.9961	1	1.0039
db2	0.66667	2	1.5
db3	0.8	3	1.25
db4	0.7143	4	1.4
db5	0.66667	5	1.5

It is reported in [26] that 'db4' is used as the mother wavelet for classification of transmission line faults as it closely matches the signal to be processed. In the literature it has been found that '*daubecheis'* mother wavelet is having good capability to capture time of transient occurrence and extraction of frequency features during power system fault and disturbance [27]. The work done in the paper [27] demonstrates the use of 'db1' as a mother wavelet with DWT for classification of different types of transmission line faults using sending end line current signals for three phases. 'db3' is employed to classify and locate faults on transmission systems in [28]. The transient fault signals are analyzed with three level decomposition of discrete wavelet transform in [28]. Another important aspect for selection of mother wavelet is that to get improved frequency resolution a wavelet function represented by more number of vanishing moments should be selected, since the frequency can be determined via more points. '*daubechies*' orthogonal wavelets are represented by even index numbers only [1]. The index number refers to the number of coefficients. Each wavelet has a number of zero moments or vanishing moments equal to half the number of coefficients. The vanishing moment limits the wavelet's ability to extract information from a signal. '*db3*' and '*db4*' mother wavelets seem to be suited for localization of transmission line faults because of their short period and higher number of vanishing moments. Other three wavelets 'db1', 'db2'& 'db5' are considered for comparison purpose.

4 PROPOSED METHOD

The schematic representation of the proposed work is shown in the Fig. 1.

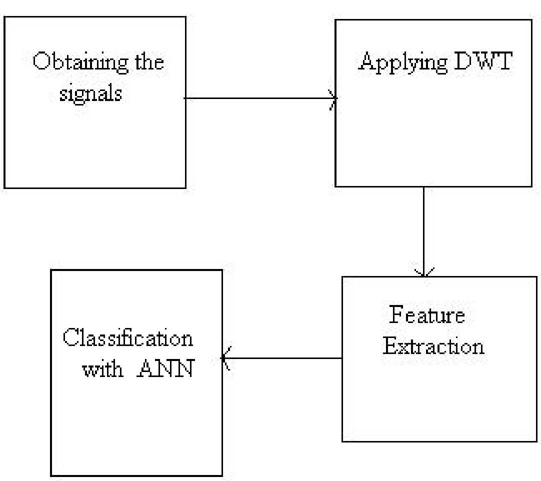

Fig. 1. *Block diagram of the proposed scheme.*

5 SYSTEM SIMULATIONS AND FEATURES EXTRACTION

In this study a power system network consisting of two three phase voltage sources are used. The length of the transmission line is 80 km as presented in Fig. 2(a) along with the Alternate Transient Program (ATP) model in Fig. 2(b).

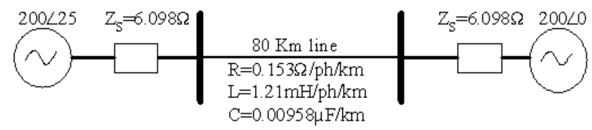

Fig. 2(a). *Single Line Diagram of the System [29].*

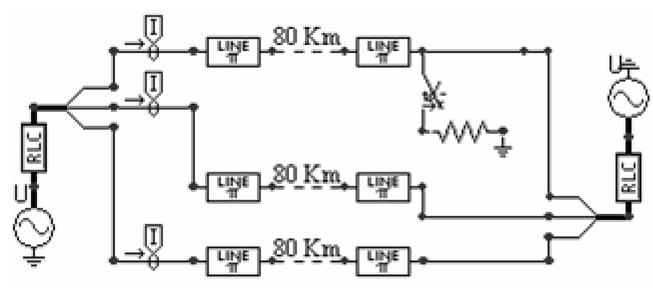

Fig. 2(b). *ATP Model of the System under Study [29].*

Extensive simulations were carried out using ATP, with different fault locations- 10km, 15 km, 20 km, 25 km, 40 km , 45 km, 50 km, 55 km, 60 km, 65 km, 70 km, 75 km & 80 km for single line to ground fault (LG) and double line to ground fault (LLG) for different fault resistances-10Ω, 15Ω, 20Ω, 25Ω, 30Ω, 40Ω, 45Ω , 50Ω, 55Ω, 65 Ω ,70Ω , 75Ω & 100Ω. Fault current signals for three phases from sending end were captured using ATP simulation environment. The current wave forms were generated at a sampling frequency of 12KHZ as shown in Fig. 3 below.

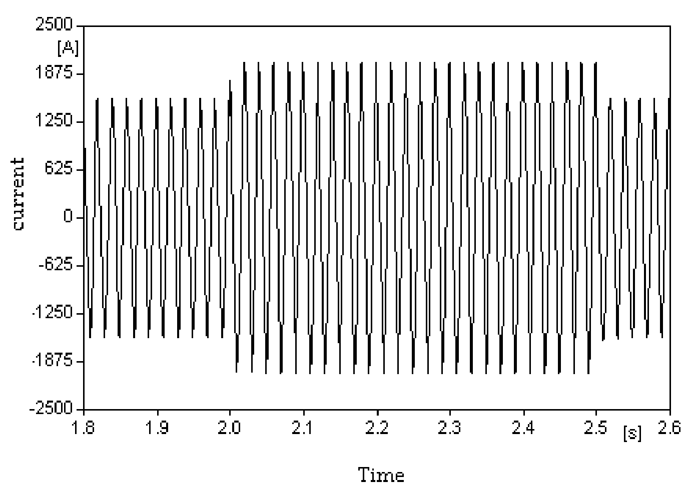

Fig. 3. *Phase 'A' current for single line to ground fault at 60 km with fault resistance of 100Ω as recorded on sending end.*

To identify the best suited mother wavelet a good feature extractor is also required. In this work, to illustrate the performance of different wavelets, DWT has been used as a signal processing tool. It provides enough information and offers high reduction in computational time [15]. The raw data of the fault transient signals were imported in the MATLAB workspace and DWT coefficients at sixth level were computed for 'db1', 'db2', 'db3', 'db4' and 'db5' mother wavelets. In all the simulations the step length of the moving window was set to 7.3 ms at a supply frequency of 50HZ. Finally the R.M.S, Mean, Max, Min values of the sixth level DWT coefficients were computed for all mother wavelets. These features thus obtained were used as attributes to train the Artificial Neural Network (ANN). A typical six level decomposition plot of DWT for 'db3' mother wavelet is shown in Fig. 4.

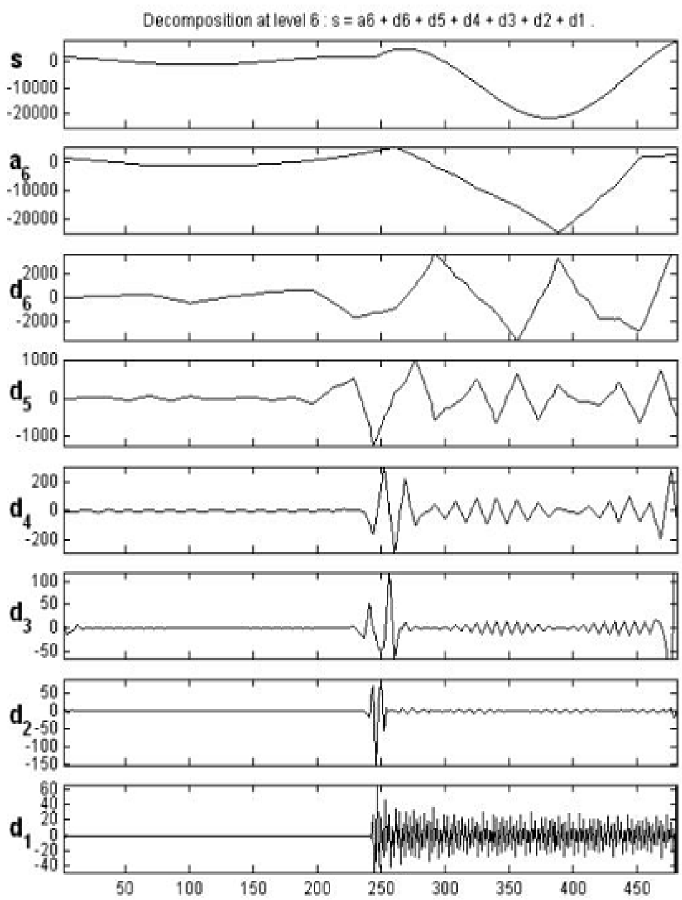

Fig. 4. *Six level DWT decomposition of phase 'A' current for LLG-ab at a distance of 10km with fault resistance of 30Ω.*

6 LOCALIZATION OF FAULTS USING ANN

An Artificial Neural Network (ANN) is a set of highly interconnected simple nonlinear processing elements called neurons, where each connection has an associated weight. A neural network can achieve desired input output mapping with a specified set of weights stored in the connections between neurons and can be trained to do a particular job by adjusting the weights on each connection [3]. ANNs have been extensively used in different power system applications [11-20]. In this work localization of faults are done by using ANN. A two layer feed forward neural network has been trained by back propagation algorithm as shown in Fig. 5 below...

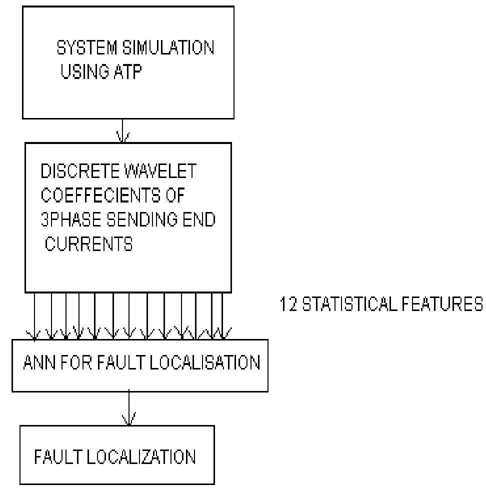

Fig. 5. *Block diagram of the ANN based fault localization.*

The ANN has been used to localize the transmission line faults. The developed ANN has twelve input neurons namely RMS, Mean, Max, Min values of DWT coefficients of 3-phase sending end currents, two hidden layers with twenty two and twenty four neurons respectively, and one output neuron. The activation functions at the hidden layers and output layer in the network have been tan-sigmoid, log-sigmoid and purelin respectively. The architecture of neural network used is shown in Fig 6 below.

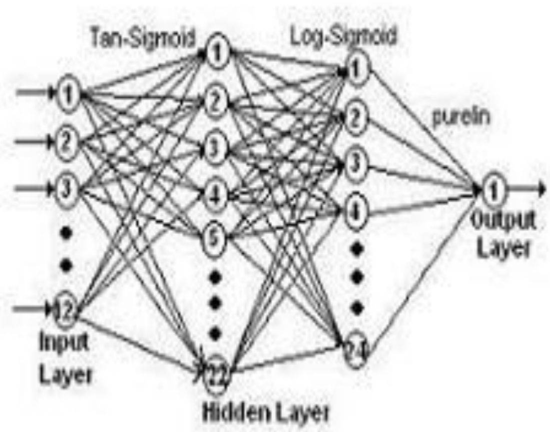

Fig. 6. *Architecture of neural network.*

7 RESULTS AND ANALYSIS

Extensive simulations were carried out using ATP as mentioned in section 5. Total no of 79 data points are taken after applying signal processing for single line to ground (LG) and double line to ground (LLG) faults at different locations with different fault resistances. Among them 49 data points are used for training and 30 data points are used for testing purpose. The accuracy of the training and testing results for various mother wavelets for localization of faults are tabulated in Table 2-Table 5.

TABLE 2

Comparison of fault location training accuracy results for 'db2' & 'db3' mother wavelet

MOTHER WAVELET IS DB2				**MOTHER WAVELET IS DB3**			
DESIRED OUTPUT (KM)	NETWORK OUTPUT (KM)	FAULT RESISTANCE Ω	TRAIN ERROR (KM)	DESIRED OUTPUT (KM)	NETWORK OUTPUT (KM)	FAULT RESISTANCE Ω	TRAIN ERROR (KM)
10	10.191828	70	0.19182	10	9.937534	10	0.062466
20	19.653322	100	0.346678	20	20.078845	10	0.078845
40	39.524761	40	0.475239	40	40.060362	10	0.060362
50	49.665647	100	0.334353	50	50.751074	100	0.751074
60	60.394574	40	0.394574	60	59.250527	100	0.749473
70	69.364295	40	0.635705	70	70.921473	40	0.921473
80	80.117212	10	0.117212	80	79.552907	100	0.447093

TABLE 3

Comparison of fault location testing accuracy results for 'db2' & 'db3' mother wavelet

MOTHER WAVELET IS DB2				**MOTHER WAVELET IS DB3**			
DESIRED OUTPUT (KM)	NETWORK OUTPUT (KM)	FAULT RESISTANCE Ω	TEST ERROR (KM)	DESIRED OUTPUT (KM)	NETWORK OUTPUT (KM)	FAULT RESISTANCE Ω	TEST ERROR (KM)
15	15.3896	75	0.3896	15	15.26509	75	0.265088
25	25.40207	45	0.402074	25	23.64243	15	1.357573
45	46.33991	45	1.339912	45	42.9949	15	2.005097
55	55.38443	75	0.38443	55	54.54088	25	0.459125
65	60.44966	25	4.550338	65	65.18186	25	0.181863
75	72.0592	35	2.940801	75	75.43432	35	0.434321

TABLE 4

Comparison of fault location training accuracy results for 'db4' & 'db5' mother wavelet.

MOTHER WAVELET IS DB4				**MOTHER WAVELET IS DB5**			
DESIRED OUTPUT (KM)	NETWORK OUTPUT (KM)	FAULT RESISTANCE Ω	TRAIN ERROR (KM)	DESIRED OUTPUT (KM)	NETWORK OUTPUT (KM)	FAULT RESISTANCE Ω	TRAIN ERROR (KM)
10	9.983799	70	0.016201	10	9.9558810	70	0.044119
20	20.11452	10	0.114516	20	18.951285	10	1.048715
40	40.61307	40	0.613068	40	43.874158	50	3.874158
50	48.80003	100	1.199973	50	49.437612	40	0.562388
60	60.42532	20	0.425315	60	60.088659	20	0.088659
70	70.06529	20	0.065294	70	69.589603	20	0.410397

TABLE 5

Comparison of fault location testing accuracy results for 'db4' & 'db5' mother wavelet.

MOTHER WAVELET IS DB4				**MOTHER WAVELET IS DB5**			
DESIRED OUTPUT (KM)	NETWORK OUTPUT (KM)	FAULT RESISTANCE Ω	TEST ERROR (KM)	DESIRED OUTPUT (KM)	NETWORK OUTPUT (KM)	FAULT RESISTANCE Ω	TEST ERROR (KM)
15	14.67064	15	0.32936	15	13.857718	15	1.14228
25	25.78352	15	0.783517	25	28.687033	75	3.68703
45	44.07506	45	0.92494	45	47.237706	15	2.23771
55	53.22175	45	1.778247	55	51.405862	15	3.59414
65	63.97152	45	1.028478	65	67.583849	35	2.58385
75	74.52535	15	0.474651	75	76.992926	25	1.99293

TABLE 6

Averaged localization results for different wavelets used

WAVELET NAME	DB1	DB2	DB3	DB4	DB5
AVERAGE ERRC IN KM	0.472!	0.569	0.2588	0.29{	0.5592

8 CONCLUSION

In the present era of open access and deregulated electricity market reliable supply of power is very important. So fast and accurate localization and identification of fault is of prime concern. Localization of transmission line faults using wavelets have been tried by few researchers [9,10,28]. But no one has clearly mentioned the accuracy. It is already discussed that the selection of mother wavelet plays a very crucial role for accurate localization of faults. So the present work is a systematic and logical approach to find the most suited mother wavelet for this purpose. To analyze the fast decaying fault signal high centered frequency i.e. wavelets having short period is suitable. From this point of view 'db1' should give the best result. As 'db1' has only one vanishing moment, its frequency resolution is poor. 'db3' has optimized period and vanishing moments which match with the transmission line fault current signals. The performances of different mother wavelets, as presented in the Table VI are same as theoretical prediction. *The results obtained from the proposed method are comparable (TableVII) with previous work even with a lower sampling frequency and only using sending end currents.*

TABLE 7

Comparison of the work with the previous work done.

Reference & year	AIM	Signal used	Mother wavelet	Method used	Sampling Frequency	Fault type	Features	Accuracy
[9], 2013	FAULT LOCATION	Model current I_M = Ia - 2Ib +2Ic	db1	DWT & spectral energy analysis	200 KHz	LG, LLG, LLL,LL	Spectral energy analysis of two frequency bands of detail 1 & detail 5 for 5 level decomposition of model current	Not mentioned
[10], 2013		Three phase fault currents	db5	DWT level 3 & MRA	-	LG, LLG, LLLG,LL	Absolute value of fault levels for each phase	Not mentioned
[28], 2008		Line voltage signals	db3	DWT level 3	--	LG,LL	Max & min of level 3 DWT detailed coefficients	Not mentioned directly
Present work		Sending end line currents Ia, Ib, Ic	db3	DWT level 6	12KHZ	LG,LLG	RMS,MEAN,MAX, MIN of 6TH level DWT coefficients	Average error < 0.2588 km

ACKNOWLEDGMENT

The author wish to thank Mr.Ashish kumar for his cooperation.

REFERENCES

[1] I.Daubechies, "Ten lectures on wavelets," Society for industrial and applied mathematics, Philadelphia, PA, 1992.

[2] T.B.Littler &D.J Morrow, "Wavelets for the analysis and compression of power system disturbances," IEEE Transactions on power delivery, vol4, pp358-64, apr1999

[3] Zwee-Lee Giang, "Wavelet based neural network for power disturbance recognition and classification," IEEE Transactions on power delivery, vol19, pp1560-68, oct2004.

[4] P. Pillay & A. Bhattacharjee, "Application of wavelets to model short term power system disturbances," IEEE Transactions on power systems, vol1, pp2031-37, nov1996.

[5] S. Santoso, E.J Powers & P.Hofmann, "Power quality assessment via wavelet transform Analysis,"IEEE Transactions on power deliverys , vol11,issue 2,, pp3387-97, 1981

[6] O.A.S.Youssef, "Fault classification based on wavelet transforms," Transmission and Distribution Conference and Exposition, 2001 IEEE/PES

[7] M.Y Chow, S.O Yee &L.S Taylor, "Recognizing animal-caused faults in power distribution Systems using ANN," IEEE Transactions on power delivery, vol. 8, pp1268-74, 1993.

[8] Robertson DC, Camps OI, Mayer JS, "Wavelet and electromagnetic power system transients," IEEE Transactions on power delivery, vol11, issue2, pp1050-58, 1996.

[9] Reena Sharma, Aziz Ahmad, Shailendra Kr. Saroj, "Protection of Transmission Lines using Discrete Wavelet Transform", International Journal of Innovative Technology and Exploring Engineering

(IJITEE) ISSN: 2278-3075, Volume-3, Issue-1, June 2013 .

[10] MukeshThakre, Suresh Kumar Gawre & Mrityunjay Kumar Mishra, "Distribution System faults Classification And Location Based On Wavelet Transform", International Journal on Advanced Computer Theory and Engineering (IJACTE) ISSN (Print) : 2319 – 2526, Volume-2, Issue-4, 2013.

[11] Ngu Eng Eng, *Krishnathevar Rama;"*Single-Ended Traveling Wave Based Fault Location on Two Terminal Transmission Lines",IEEE2009

[12] Tahar Boothbay, "Fault Location In EHV Transmission Lines Using Artificial Neural Networks", International Journal of Applied Mathematics and Computer Science, Vol. 14, 2004

[13] M.E.Baran,J.Kim, "A classifier for Distribution Feeder Overcurrent Analysis," IEEE Transactions on power delivery, vol21,No1, pp456-462, Jan2006.

[14] S.Santoso, W.M.Grady, E.J.Powers, J.Lamoree and S.C.Bhatt, "Characterization of Distribution Power Quality Events with Fourier and Wavelet Transforms, ", " IEEE Transactions on power delivery, vol15,No1, pp247-254, Jan-2000.

[15] A.Mgouda, ,M.M.A Salama, M.R Sultan and A.Y.Chikhani, "Power Quality Detection and Classification using Wavelet –Multiresolution Signal Decomposition," IEEE Transactions on power delivery, vol14,No4, pp1469-76, oct1999.

[16] D. V. Coury D. C. Jorge, "Artificial Neural Network Approach to Distance Protection of transmission lines," IEEE Transactions on power delivery, vol13,No1, pp102-108, Jan 1998.

[17] Wael R. Anis Ibrahim and Medhat M. Morcos, "Artificial Intelligence and Advanced Mathematical Tools for Power Quality Applications: A Survey", IEEE Transactions on power delivery, vol. 17, No. 2,pp668-673 April 2002.

[18] A.W.Galli and O.M.Nielse "CAP tuorial:Wavelet analysis for power system transients," IEEE Comput .Appl.Power, vol12,no1,pp16-16,Jan 1999.

[19] S. Santoso, E.J Powers , W.M.Grady & Antony C. Parsons, " Power Quality Disturbance Waveform Recognition Using Wavelet-Based Neural Classifier—Part 1: IEEE Transactions on power delivery, vol15No1, pp222-228, Jan-2000

[20] P. Konar, P. Chattopadhyay, "Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs),"Applied Soft Computing, 11 (2011), pp. 4203–4211.

[21] S. Mezghani, L. Sabri, M. El Mansori, H. Zahouani, "An the optimal choice of wavelet function for multi-scale honed surface characterization,"13th International Conference on Metrology and Properties of Engineering Surfaces (2011) pp1-7.

[22] N. D. Kelley, R. Osgood, J. Bialasiewicz, A. Jakubowski, "Using Time-Frequency and Wavelet Analysis to Assess Turbulence/Rotor Interactions," Proceedings of 19thAmerican Society of Mechanical Engineers (ASME) Wind Energy Symposium, 2000,pp130–149.

[23] R..J..Merry, Wavelet theory and applications- A Literature study, Eindhoven University of technology,(2005),Available online:http://alexandria.tue.nl/repository/books/612762.pdf

[24] Prochazka, J. Uhlir, P. J. W. Payner, N. G. Kingsbury, Signal Analysis and Prediction (Applied and Numerical Harmonic Analysis), Birkhäuser boston (1998).

[25] P.L Mao and R.K.Aggarwal, "A novel approach to the classification of the transient phenomena in power transformers using combined wavelet transform and neural network," IEEE Transactions on power delivery, vol16,No4,pp654-660,oct 2001.

[26] M.Singh, B.K.Panigrahi and R.P Maheshwari, "Transmission Line Fault Detection and Classification," Proceedings of ICETECT 2011,pp 15-21.

[27] J.Upendra, C.P Gupta and G.K Singh, "Discrete Wavelet Transform and Probablistic Neural Network Based Algorithm for Classification of Fault on Transmission system", IEEE Transactions on power delivery , 2008.

[28] P.S Bhowmick, P.Purkait and K.Bhattacharya, "A Novel Wavelet Transform And Neural network Based Transmission Line Fault Analysis Method", Developments in Power System Protection, 2008. DPSP 2008. IET 9th International Conference, 2008, pp477-483.

[29] S.Verma, P. Konar and Dr.P.Chattopadhyay, "A Wavelet Based Fult Localisation in Transmission Network",IEEE conference 28-30 dec,2011.