International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463
Vol. 2 Issue 11, November-2013, pp: (97-104), Available online at: www.erpublications.com

HVDC Transmission Line Fault Location Using Wavelet Feeded Neural Network Bank

Jebu John Mathew[1], Anish Francis[2]
[1]Saintgits College of Engg., Kottayam, Kerala, India
[2]Asst. Engineer, KSEB, Lower Periyar, Kerala, India

Abstract: This paper presents fault location in an HVDC transmission link. The fault location is done by using Radial basis neural networks. We present a new approach which uses a neural network bank for fault location. Each network is trained for locating a particular zone .The fault signal is processed in frequency domain using wavelets and an appropriate feature of the fault is selected. This is passed to a neural network bank. The outputs of each network are compared for accurate prediction of the fault zone. The proposed method is simulated using MATLAB neural network toolbox and Simulink package.

Keywords: Fault location, Radial Basis Network, Haar Wavelets.

I. NOMENCLATURE

HVDC	High voltage Direct Current
FFT	Fast Fourier Transform
SVM	Support vector machines
ANN	Artificial Neural Network
CPU	Central processing unit
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
AI	Artificial Intelligence
RBNN	Radial Basis Neural Network
DG	Distributed Generation
BPNN	Backpropagation Neural Network
AC	Alternating current

II. LITERATURE REVIEW

HVDC transmission line links are one of the major elements in power system. This lines holds much importance due to the lowest loss of transmission between grids. The HVDC transmission line also holds relevance due to the advent of DC Microgrids, in which DC supply is the power to consumer sites. Fault location is the major issue in HVDC system, due to large distance of transmission from source site to destination. Our Present work focuses on Fault location in HVDC links.

Numerous works were done related with different techniques for fault location in HVDC link [1-7]. Majority of the works were done, using travelling wave techniques.

In [1], Morphological application was developed, in [2], [4] travelling wave technique with wavelet analysis were employed. We closely referred [7] in which wavelets technique, used for a combination of different types of transmission lines (over head and underwater).

The majority of the recent works in fault location employs frequency domain techniques like FFT and wavelets. The time frequency localization of wavelets makes it a powerful signal processing tool unlike Fourier analysis. For doing a work in fault location, the type of wavelet (CWT or DWT), mother wavelets etc has to be studied. In [8], [9], [10] and [20] CWT techniques are employed. Authors of [9], [13] and [16] used DWT for fault location .The advantages of different wavelets, development of customized wavelets were discussed in [15-18]. In [22], author's uses fast Fourier transforms for fault location. We choose DWT for its various advantages over CWT based on the above reviews.

The core requirement of fault location technique is accuracy. Normal reactance based relay systems are not accurate when long distance transmission lines are considered. The recent state of the art fault location systems couple above signal processing technique with artificial intelligence. Major AI tools are SVM (support vector machines) and ANN (Artificial neural network).We closely followed the work and pattern of authors of [14, 21, 23] in which they employs wavelet assisted neural network for fault location. In [14],the authors describes a substation end fault location center with a CPU. We are following a similar system architecture in the present work. In [15] wavelet multi resolution analysis coupled with ANN is described.SVM based wavelets for fault location is described in [19].In [24] wavelet entropy is used along with neural network for fault location. Rest of the literature review related with RBNN will be discussed in section III.

In the light of the above literature review, and during the progress of work, we found that most of the present works, neglects feature selection of wavelets. This is more important when the input to the neural network is wavelet signal. In the present work the wavelet portion is preprocessed via feature selection technique. Adequate feature selection improves memory utilization, and fast execution of the fault location algorithm. This is not only applicable to wavelet domain but also in Neural network domain, the popular feed forward Back propagation algorithm require much time compared to radial basis neural network in creation of the network object.

In the following section, we describe a brief architecture of ANN employed (Section III). In section IV the wavelets used in the present work will be described. In section V we will describe the work methodology. This is the major section in which we describe the work flow, HVDC system architecture, and results. In section VI we conclude with a summary of major contributions from this work and observations.

III. NEURAL NETWORK ARCHITECTURE

The fault location tool in the present work is radial basis neural network. We have followed references [25-31] for modeling our system. Fault diagnosis of HVDC with pre-classifier is discussed in [25]. We closely followed the use of RBNN from [25-27]. Comparison of BPNN and RBNN is discussed in [27] which motivated us for using RBNN in the present work. The RBNN has less execution time, fastest creation of network object etc. We followed the creation of network with training parameters, in [28]. The concept of zoning in the present work, is similar to the approach in [28]. Other works referred have different application background [31] but the way the neural network configured is same [28-31].

RBNN is based on supervised learning. The network consists of input layer, hidden layer and output layer. The input layer feeds the input data, to the hidden layer. In the present work, the input data is the processed wavelet sample from HVDC system which will be discussed in next section. The hidden layer works by neurons loaded with radial basis activation function. The output layer is powered with neurons of linear activation function. The architecture of RBNN shown in Fig 1 [27].

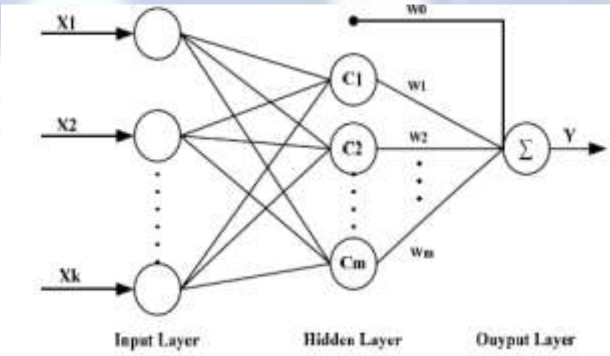

Fig. 1: Structure of Radial Basis Neural network

The network inputs k input nodes and m hidden neurons.For a Kdimension wavelet data W' the network computes the scalar value Z .

$$Z = f(w') = w_0 + \sum_{i=1}^{m}(w_i \emptyset(D_I) \qquad (1)$$

Where w_0 is the weight bias, w_i is the weight parameterD_I is the Radial basis function. The radial basis function for input$t$ is e^{-t^2} .The plot of the radial basis function is Gaussian double sided bell curve. In the present work the network iteratively creates radial basis network one neuron at a time. Neurons are added to the network until the sum-squared error falls beneath an error goal or a maximum number of neurons have been reached.
The above network is created by using neural network tool box in MATLAB.

IV. DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform is the solution for shortcomings for fourier transform which was the first signal processing tool in frequency domain.The DWT has time-frequency localization which makes it the best candidate for applications like fault location.The purpose of wavelet in the present work is as the pre-processing tool for fault voltages,prior feeding the neural network system described in section III.
The DWT of the fault voltage V for K samples can be represented [9] as

$$DWT(V) = \frac{\sum_k V(k)\varphi\left(\frac{(a-b)}{a}\right)}{\sqrt{a}} \qquad (2)$$

In the above equation the function φ represent the mother wavelet and variables a and b are translation and dilation parameters. In the present work we have used $haar$ wavelet as the mother wavelet .This was selected after testing different mother wavelets and choosing appropriate one. The $Haar$ [32-33] basis function is defined as

$$\varphi(x) = \begin{cases} 1 & 0 \le x < \frac{1}{2} \\ -1 & \frac{1}{2} \le x < 1 \\ 0 & otherwise \end{cases} \qquad (3)$$

The output of the above equation (2) is fed to the neural network system described in section III.

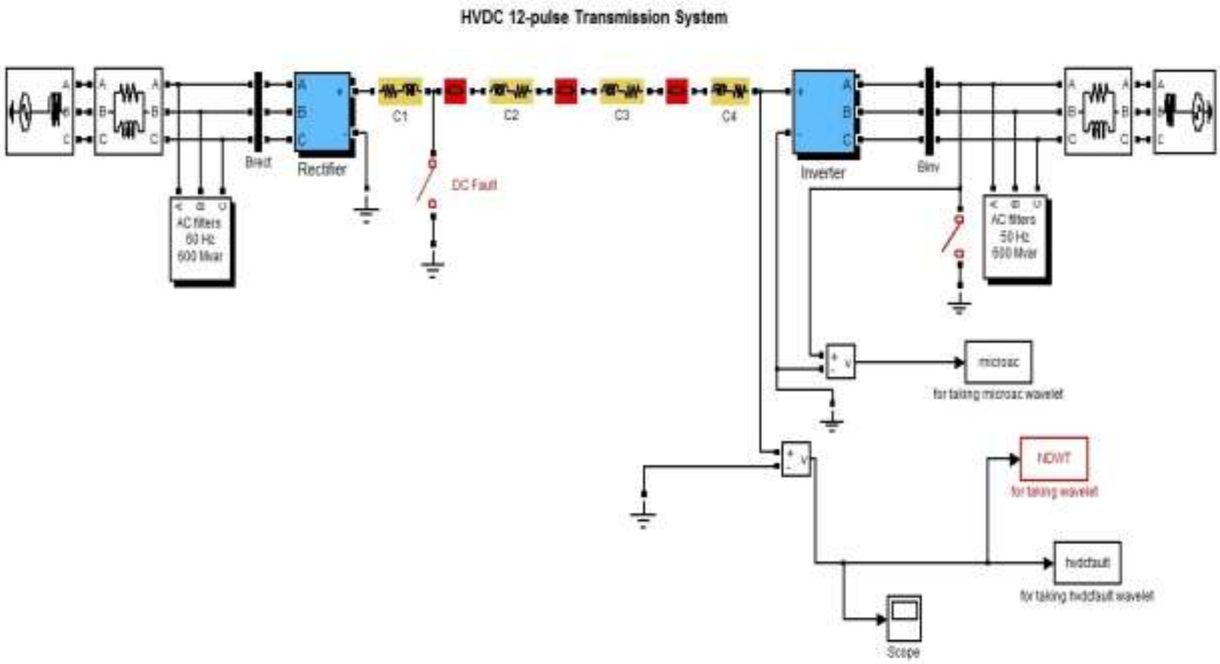

Fig 2: HVDC transmission Link

V. WORK METHODOLOGY

A. HVDC Transmission System

The HVDC system used as work background is shown in the Simulink model [34] in Fig 2. The HVDC link utilizes 12-pulse rectifier. The fault location is done in 300 km DC transmission line between source side to the load side. A 1000 MW (500 kV, 2 kA) DC interconnection is used to transmit power from a 500 kV, 5000 MVA, 60 Hz system to a 345 kV, 10000 MVA, 50 Hz system. The AC systems are represented by damped L-R equivalents with an angle of 80 degrees at fundamental frequency (60 Hz or 50 Hz) and at the third harmonic. AC filters are used to prevent the odd harmonic currents from spreading out on the AC system. The filters are grouped in two subsystems. These filters also appear as large capacitors at fundamental frequency, thus providing reactive power compensation for the rectifier consumption due to the firing angle α. Two circuit breakers are used to apply faults: one on the rectifier DC side and the other on the inverter AC side.

B. Fault location scheme

Step 1: Model the Transmission system, and divide the transmission line to different zone.

Step 2: Generate training data for faulty and normal cases. Then preprocess the data.

Step 3: Train the networks with the data and examine the output for faulty zones and normal cases for understanding the neural network output for each cases.

Step 4: Test the model and validate the scheme.

The above scheme is implemented using algorithms, for each step, explained in the following subsections.

1. MODELLING

The HVDC transmission system was developed in MATLAB SIMULINK as described in the beginning of V.1.The Full transmission link was then divided to 3 zones, as A, B, C [28]. Hence 4 models were developed for each of these three zones with DC fault injected at the corresponding zones and a normal model, with no fault in between the transmission line. The Distance for each zone was decided after checking the fault voltage and its wavelet. In the present work, zone A extends to 50km, Zone B to 150km, Zone C to 100 km.
The line distances where intentionally made different, to make the input data to the neural network have characteristic difference, so that the classification becomes more perfect. The large zone distance is not a limitation, since our objective is to demonstrate that location of zone is made accurate with the present methodology.
Also the number of zones can be increased according to the work background.

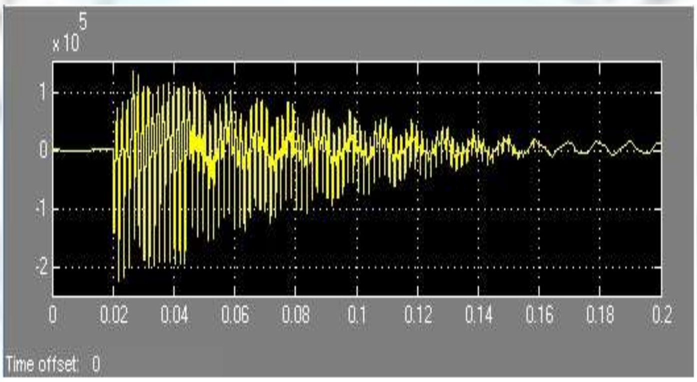

Fig 3: Zone A DC fault

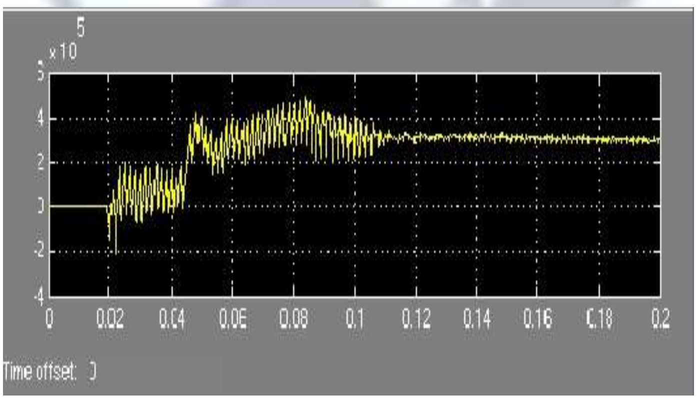

Fig 4: Zone B DC fault

A sample of fault signal voltages for zone A and zone B are shown in above Figures 3 and 4 respectively.

2. GENERATION OF TRAINING DATA

The Data is generated by the following algorithm, by running the models described in the previous section. The algorithm for generating data from a particular zone is given below:

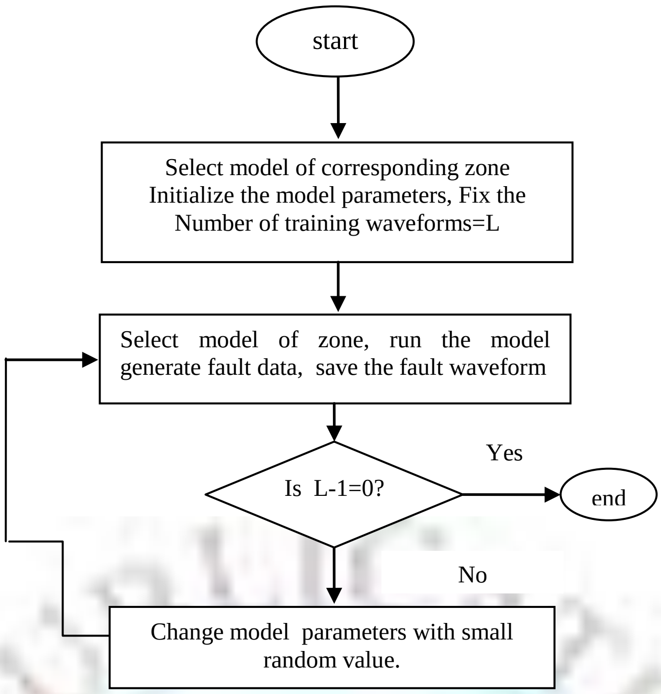

Fig 4: Algorithm for generating data

The above data is preprocessed with Haar wavelet (Section IV) and appropriate features (appropriate length and amplitude of the coefficients) are selected. This is used for training the neural network architecture system described in Section III. The system architecture for training the neural and testing for locating the zone A is shown below.

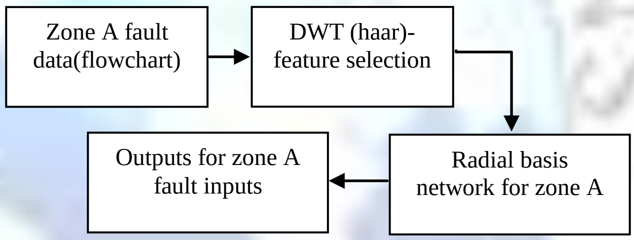

Fig 5: Training Architecture

Separate radial basis networks are created for each zone. This zone are then feeded the wavelet data for all faulty zones and the normal transmission links for setting the threshold value for localizing the faulty zone.

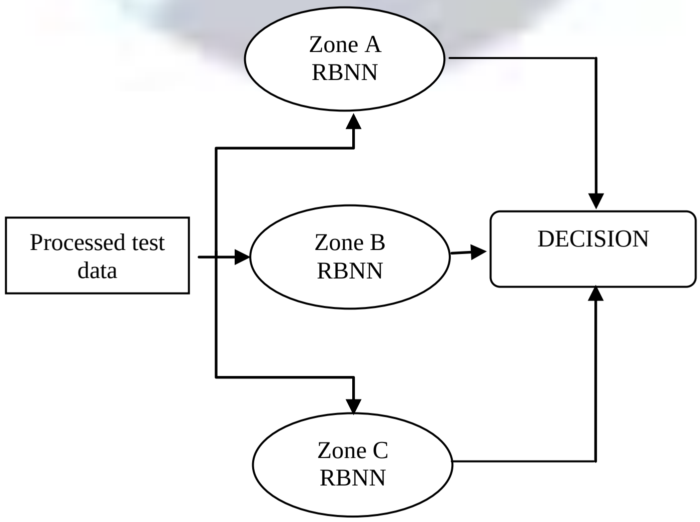

Fig 6: Testing Architecture

International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463
Vol. 2 Issue 11, November-2013, pp: (97-104), Available online at: www.erpublications.com

From the training architecture each network is trained and fed input from all four models. The characteristic output for each network is determined for the particular zone. In other words, each network is tuned for producing a unique output when the fault corresponding to that zone is fed. This information is used in the decision making block in the testing architecture.

For locating the zone .or testing the system the test signal is generated from the model. The Processed test signal can be either normal (no fault) or corresponding to a particular zone. This is passed to the neural network bank. The outputs from the neural network bank is compared and accurate zone is decided. The sample outputs are shown below.

RBNN A	RBNN B	RBNN C
-0.1443	1	1
-0.0333	1	1
-0.2109	1	1

Table 1: Network bank output for zone A fault.

RBNN A	RBNN B	RBNN C
1	-0.1221	1
1	-0.0999	1
1	-0.1887	1

Table 2: Network bank output for zone B fault.

RBNN A	RBNN B	RBNN C
1	1	-0.3221
1	1	-0.0399
1	1	-0.1287

Table 3: Network bank output for zone C fault.

RBNN A	RBNN B	RBNN C
1	1	1
1	1	1
1	1	1

Table 4: Network bank output for normal input.

The above results show that for a normal input, network bank produces a common high value 1 in the present case. The fault for a particular zone when fed to the network bank produces a low output for the network tuned for that particular zone and high for other zones network. Hence, decision making become more robust and easy resulting in accurate fault location.

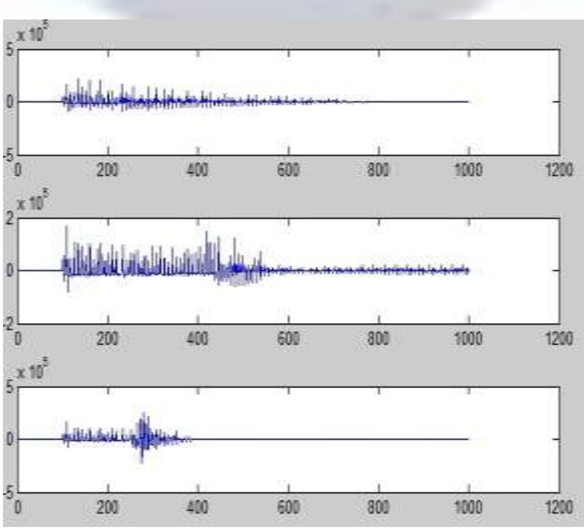

Fig 7: Haar output for faulty inputs for different zone

The testing for faults resulted in nearly hundred percent accuracy in fault location for the above work background. The accuracy of location classification depends on the preprocessing with proper selection of wavelet coefficients. A sample output is shown in Fig.7 above.

VI. CONCLUSION

A novel fault location strategy for HVDC transmission line is presented. The fault signal is preprocessed with wavelets and fed to the neural network bank tuned for each zones. The outputs shows that proposed fault location technique result in accurate decision making for fault localizing. The use of Radial basis network saves time as well as memory, and fast creation of network objects.

REFERENCES

[1] A. Swetha, P. Krishna Murthy, N. Sujatha and Y. Kiran ," ARPN Journal of Engineering and Applied Sciences a novel technique for the location of fault on a hvdc transmission line", vol. 6, no. 11, November 2011.

[2] Kasson Nanayakkara, A.D. Rajapakse, Randy Wachal," Fault Location in Extra Long HVDC Transmission Lines using Continuous Wavelet Transform", International Conference on Power Systems Transients (IPST2011) in Delft, the Netherlands June 14-17, 2011 ,[online].

[3] Shang,Herold,"High speed fault identification and protection for HVDC line using wavelet technique",proto power tech 2001,Portugal [online].

[4] Pannala Krishna Murthy,Amarnath," Wavelet Transform Approach for Detection and Location of Faults in HVDC System", 2008 IEEE Region 10 Colloquium and the Third ICIIS, Kharagpur, INDIA December 8-10.

[5] K.Rajesh," fault identification using wavelet transform ", 2005 IEEE/PES Transmission and Distribution Conference & Exhibition: Asia and Pacific Dalian, China.

[6] Kai Liao, Xiaopeng Li," A Fault Location Method Based on Traveling Wave Natural Frequency Used On ±800kV UHVDC Transmission Lines "5652978-1-4244-8165-1/11/ ©2011 IEEE.

[7] O. M. K. Kasson Nanayakkara," Location of DC Line Faults in Conventional HVDC Systems with Segments of Cables and Overhead
Lines Using Terminal Measurements", IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 27, NO. 1, JANUARY 2012.

[8] B. Ravindhranath Reddy1, Dr. M. Vijay Kumar2," detection & localization of faults in transmission lines using wavelet transforms (coif let & Mexican hat)", Journal of Theoretical and Applied Information Technology © 2005 - 2009 JATIT [online].

[9] B. Ravindranath Reddy, Dr. M. Vijaya Kumar," fault detection, classification and location on transmission lines using wavelet transform ,2009 Annual Report Conference on Electrical Insulation and Dielectric Phenomena, [online].

[10] Feng Liang and B. Jeyasurya," Transmission Line Distance Protection Using Wavelet Transform Algorithm ", IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 19, NO. 2, APRIL 2004
.
[11] F. B. Costa, B. A. Souza, and N. S. D. Brito," A Wavelet-Based Method for Detection and Classification of Single and Cross country Faults in Transmission Lines "Presented at the International Conference on Power Systems Transients (IPST'09) in Kyoto, Japan on June 3-6, 2009 [online].

[12] Anuradha S Deshpande, Grishma S. Shah**,"** Transmission Line Protection based on Travelling Waves", WSEAS TRANSACTIONS on CIRCUITS and SYSTEMS [online].

[13] Amir Ttabatabaei, Mohammad-reza Mosavi," Fault Location Techniques in Power System based on Traveling Wave using Wavelet Analysis and GPS Timing:, PRZEGLĄD ELEKTROTECHNICZNY (Electrical Review), ISSN 0033-2097, R. 88 NR 6/2012 [online].

[14] P. S. Bhowm,ik, Member, IEEE, P. Purkait, Member, IEEE and K. Bhattacharyya," Proposal for a Distance Relaying Scheme based on Wavelet Assisted Neural Network", 2008 IEEE [online].

[15] Mamta Patel, R. N. Patel," Fault Detection and Classification on a Transmission Line using Wavelet Multi Resolution Analysis and Neural Network", International Journal of Computer Applications (0975 – 8887) Volume 47– No.22, June 2012.

[16]. Hanif Livani, Student Member, IEEE and Cansin Yaman Evrenosoglu, Member, IEEE," A Traveling Wave Based Single-Ended Faul Location Algorithm using DWT for Overhead Lines Combined with Underground Cables", 978-1-4244-6551-4/10 ©2010 IEEE.

[17] Paraskevas E. Argyropoulos, Hanoch Lev-Ari" Customized Wavelets for Fault Location in Power Systems," [online].

[18] Fernando H. Magnago and Ali Abur,"fault location using wavelets", IEEE Transactions on Power Delivery, Vol. 13, No. 4, October 1998.

[19] Urmil B. Parikh, Biswarup Das, Member, IEEE, and Rudra Prakash Maheshwari," Combined Wavelet-SVM Technique for Fault Zone Detection in a Series Compensated Transmission Line", IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 23, NO. 4, OCTOBER 2008.

[20] Alberto Borghetti, Mauro Bosetti, Mauro Di Silvestro, Carlo Alberto Nucci,and Mario Paolone, Continuous-Wavelet Transform for Fault Location in Distribution Power Networks: Definition of Mother Wavelets Inferred From Fault Originated Transients", IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 23, NO. 2, MAY 2008.

[21] V.S.Kale, S.R.Bhide, P.P.Bedekar and G.V.K.Mohan,"Detection and Classification of Faults on Parallel Transmission Lines using Wavelet Transform and Neural Network", International Journal of Electrical and Computer Engineering 3:16 2008.

[22] Syed Muhammad Atif Saleem**,"** FFT and wavelet transform based artificial neural networks' pattern recognition schemes for high impedance arc faults, master's thesis, [online] .

[23] Suhaas Bhargava Ayyagari,"artificial neural network based fault location for transmission lines", University of Kentucky Master's Theses [online].

[24] Soumyadip Jana, Sudipta Nath, Aritra Dasgupt," transmission line fault classification based on wavelet entropy and neural network", international journal of electrical engineering & technology (IJEET), Volume 3, Issue 2, July – September (2012), pp. 94-102.

[25] K. **G.** Narendra V. K. Sood* (Senior Member) K, Khorasani R. Pate1 (Fellow),"Application of radial basis function basis neural network for fault diagnosis in a HVDC system. 0-7803-2795-0 ,IEEE [online].

[26] P. K. Dash, A. K. Pradhan, and G. Panda," Application of Minimal Radial Basis Function Neural Network to Distance Protection", ieee transactions on power delivery, vol. 16, no. 1, january 2001.

[27] Hadi Zayandehroodi, Azah Mohamed," Performance Comparison of MLP and RBFNeural Networks for Fault Location in Distribution Networks with DGs", 978-1-4244-8946-6/10, 20210 IEEE.

[28] Hadi Zayandehroodi," An Automated Protection Method for Distribution Networks with Distributed Generations Using Radial Basis Function Neural Network", 978-1-4577-0354-6/11©2011 IEEE.

[29] Hade Zayandehroodi," Determining Exact Fault Location in a Distribution Network in Presence of DGs Using RBF Neural Networks", IEEE IRI 2011, August 3-5, 2011, Las Vegas, Nevada, USA 434 978-1-4577-0966-1/11/ ©2011 IEEE.

[30] N. Rezaei, S. A. M. Javadian," Diagnosis of Impedance Fault in Distribution System with Distributed Generations Using Radial Basis Function Neural Network", 1-4577-1314-9/11 ©2011 IEEE.

[31] S.R. Samantaray, Fault classification and location using HS-transform and radial basis function neural network",DSPACE, [online].

[32] http://mathworld.wolfram.com/HaarFunction.html.