International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A Comparative Study for Fault Location Estimation on A HVDC Transmission Line Modeled Using PSCAD

***Mr. Hariom kushwah*[1], *Mr. G. R. Kesheorey*[2], *Dr. A.J. Siddiqui*[3]**

[1]M. Tech Scholar in Power Electronics, VITS, Indore (M.P). E-mail: (harrykush008@gmail.com)

[2]Assistant Professor in Electrical & Electronics Dept. VITS, Indore (M.P). E-mail: (grkvitsin@gmail.com)

ABSTRACT:

Bi-polar transmission line like Rihand-Dadri (Delhi) which is 816 km long and works at 500 kV, with the capacity to move 1500 MW of force, created on PSCAD/EMTDC programming dependent on CIGRÉ benchmark rules. The planned model is additionally recreated for cut off with shortcoming ON obstruction of 0.01 Ω and issue OFF opposition of 1.0 x 10^6 Ω with differing issue area along transmission line at a time frame km. The gained information gathered and handled for include extraction with Wavelet change utilizing Haar wavelet up to the third level. Information from both the closures of the transmission line is utilized for preparing and testing of backpropagation models to be created in the MATLAB interface. Precise issue area assessment of a Bipolar-HVDC transmission line is critical to diminish shortcoming setting aside opportunity and further developing accessibility file of the transmission framework. Regarding recently referenced issues, AI based backpropagation strategies are proposed and executed for precise shortcoming area assessment. A relative report is ready over various AI calculations with and without signal handling of information from two terminal of line. The outcomes exhibit that the AI apparatus alongside legitimate sign handling for include extraction is extremely effective in assessing issue area in bipolar HVDC transmission line. The blunder got during testing are in the scope of 1-2 km, which ends up being an incredible headway.

1.Introduction

Present day electrical energy purchasers are totally reliant upon complex electric network for satisfying every day family cooling and warming, medical care, lighting and modern application to name the trivial few. The matrix establishes of a transmission framework, which is intended to move mass power from creating station to an electric substation for additional circulation to customers [1] [2]. The electrical framework has the property to detreat with time and climate variables and human pain are a portion of the reasons the networks honesty is under pressure. Particularly in metropolitan regions, the circumstance is greater because of its more reliance of framework for power supply making it more vital for eliminate any sort of weakness from the framework [3].

The typically level of voltage in transmission lines is 100kV to 1000kV and these transmission lines are undeniably associated with work in a much steady condition [4]. With ongoing mechanical turn of events, many progressed correspondence organizations and advance sensors are created which has additionally contributed in further developing strength and productivity and dependability of transmission framework [5].

These new Operation innovation gadgets take into consideration a lot of data from various framework frameworks and communicating required data to tasks work force on time that couldn't be imagined when past age and transmission frameworks were planned and fabricated many years prior [6] [7]. Lately, power quality has turned into a fundamental worry in power framework designing – with 85-87% of force framework issues happen on appropriation lines. Nonetheless, the shortcomings that happen on the transmission lines (the transmission network) however less widespreadly affect the buyers [8].

2.Artificial Neural Network (ANN)

AI method isn't new to the area of science and innovation. It has been use by different fields to take care of perplexing algorithmic issues. With is superb advancement it has found its direction in the field of electrical designing additionally [21][22]. It has been generally utilized for load determining, security examination, in taking care of financial burden dispatch issue and so forth to give some examples. Methods like ANN, GA, ANFIS and so forth, which are various types of AI, end up being truly dependable alongside giving quick outcomes to give appropriate control activity against line shortcomings in the field of HVDC transmission [23]. This procedures can get significant data from the profoundly mind boggling non-straight information, henceforth observes its application in the regulator planning for HVDC transmission [24][25]. Such learning in which information of both info and outside is accessible known as directed learning is use in this work. A portion of those calculations are examine in after area.

Neural organization can involve input information as a wellspring of data and gain information on it in determining kind of work. This cycle is finished with the assistance of neuron and its interfacing groups. The preparation is finished by changing the heaviness of association between neurons. While preparing neural organization model loads are change in each progression, subsequently blunder work is limited. [20] [21].

2.1 Levenberg–Marquardt (LM) Algorithm

It was first proposed by K. Levenberg in 1944 and afterward changed by D. Marquardt in 1963 thus it was named on them. The Levenberg-Marquardt calculation has a forte of having both soundness and speed simultaneously while tackling a second request issue. While addressing with this calculation, the Hessian grid and the angle can be determined by following relations,

$$g = \frac{\partial E(x,w)}{\partial x} = \left[\frac{\partial E}{\partial w_1}\frac{\partial E}{\partial w_2} \quad \cdots \quad \frac{\partial E}{\partial w_N}\right]^T$$

$$W_{k+1} = W_k - \alpha g_k$$

Even if the error curvature is arbitrary, it will become unsteady very speedily. In this development Jacobean matrix is establish as

$$J = \begin{bmatrix} \frac{\partial e_{1,1}}{\partial w_1} & \frac{\partial e_{1,1}}{\partial w_2} & & \frac{\partial e_{1,1}}{\partial w_N} \\ \frac{\partial e_{1,2}}{\partial w_1} & \frac{\partial e_{1,2}}{\partial w_2} & \cdots & \frac{\partial e_{1,2}}{\partial w_N} \\ \cdots & \cdots & & \cdots \\ \frac{\partial e_{1,M}}{\partial w_1} & \frac{\partial e_{1,M}}{\partial w_2} & & \frac{\partial e_{1,M}}{\partial w_N} \\ \cdots & \cdots & & \cdots \\ \frac{\partial e_{P,1}}{\partial w_1} & \frac{\partial e_{P,1}}{\partial w_2} & & \frac{\partial e_{P,1}}{\partial w_N} \\ \frac{\partial e_{P,2}}{\partial w_1} & \frac{\partial e_{P,2}}{\partial w_2} & \cdots & \frac{\partial e_{P,2}}{\partial w_N} \\ \cdots & \cdots & & \cdots \\ \frac{\partial e_{P,M}}{\partial w_1} & \frac{\partial e_{P,M}}{\partial w_2} & & \frac{\partial e_{P,2}}{\partial w_N} \end{bmatrix}$$

Thanfurther, the equation of gradient vector can be further evaluated as

$$g_i = \frac{\partial E}{\partial w_i} = \frac{\partial\left(\frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^2\right)}{\partial w_i} = \sum_{P=1}^{P}\sum_{M=1}^{M}\left(\frac{\partial e_{p,m}}{\partial w_i} e_{p.m}\right)$$

Further, the gradient vector can be evaluated as

$$g = Je$$

Where matrix is formed as

$$e = \begin{bmatrix} e_{1,1} \\ e_{1,2} \\ \cdots \\ e_{1,M} \\ \cdots \\ e_{P,1} \\ e_{P,2} \\ e_{P,3} \\ \cdots \\ e_{P,M} \end{bmatrix}$$

Hence, further hessian matrix can be evaluated as

$$h_{i,j} = \frac{\partial^2 E}{\partial w_i \partial w_j} = \frac{\partial^2\left(\frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^2\right)}{\partial w_i \partial w_j} = \sum_{p=1}^{P}\sum_{m=1}^{M} \frac{\partial e_{p,m}}{\partial w_i}\frac{\partial e_{p,m}}{\partial w_j} + S_{i,j}$$

Where,

$$S_{i,j} = \sum_{p=1}^{P}\sum_{m=1}^{M} \frac{\partial^2 e_{p,m}}{\partial w_i \partial w_j} e_{p,m}$$

The relation between hassian matrix and jacobian matrix can be formed as,

$$H = J^T J$$

Finally, the gauss-newton take the shape as,

$$W_{k+1} = W_k - (J_K^T J_k)^{-1} J_K \, e_k$$

$$H = J^T J + \mu I$$

Hence, finally presenting the Levenberg–Marquardt algorithm as

$$W_{k+1} = W_k - \left[J_K{}^T J_k + ?I\right]^{-1} J_K{}^T e_k$$

The above equation of LM is as described earlier is a mixture of two techniques such that it extracts the speed from gauss newton and it takes property of stability from steepest descent.

2.2 Bayesian Regularization (BR) Algorithm:

BRANNs are extra enthusiastic than expected back-proliferation organizations and can decrease the need for long cross-approval. BR calculation is an interaction that changes a nonlinear relapse into a "very much displayed" measurable issue in the method for an edge relapse. In this calculation regularization is utilized to work on the organization by streamlining the exhibition work (F(ω)). The presentation work F(ω) is the amount of the squares of the mistakes of the organization loads (Ew) and the amount of squares blunder of the information (ED) [26].

$$F(\omega) = \alpha E_W + \beta E_D$$

Where,

$$E_D = \sum_{k=1}^{n} e_k{}^2$$

$$E_w = \sum_{i=1}^{n} w_i{}^2$$

Where α and βdenotes objective capacity esteems. Bayesian Regularization is a preparation calculation that refreshes the upsides of loads and predisposition as per LM enhancement. In Bayesian Regularized preparing calculation, the loads of the models are considered as irregular at first, and afterward the worth of the organization loads and preparing set are replicated utilizing Gaussian dispersion. The Bayes' hypothesis is utilized to compute α and β boundaries, given by

$$\alpha = \frac{\Upsilon}{2\, E_W}$$

$$\beta = \frac{N_D - \Upsilon}{2\, E_D}$$

$$\Upsilon = \sum_{i=1}^{N_w} \frac{\lambda_i}{\lambda_i + \alpha}$$

ND is the quantity of items, Nw is number of loads, λi is eigen upsides of the information Hessian and Y is the successful number of boundaries vital for the model [27]. As per the Bayes' hypothesis two irregular factors, An and B relates with one another dependent on their earlier (or minor) probabilities and ensuing (or restrictive) probabilities, given as;

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Where P(A|B) is the contingent likelihood of occasion A, contingent upon occasion B, P(B|A) the restrictive likelihood of occasion B, contingent upon occasion A, and P(B) the past likelihood of occasion B. To get the best upsides of loads, execution work F(ω) should be limited, which is the equivalent to boosting the accompanying likelihood work given as:

$$P(\alpha, \beta|D, M) = \frac{P(D|\alpha, \beta, M)\; P(\alpha, \beta|M)}{P(D|M)}$$

Where $\alpha$and β are, the variables on which worth of execution work is reliant and is the one which is required be to enhanced, M is the specific neural organization engineering, D is the weight appropriation, P ($D|M$) is the standardization factor, P ($D|\alpha$, β, M) is the probability capacity of D for given α, β, M and P (α, $\beta|M$) is the unvarying earlier thickness for the regularization boundaries [30]. The further computation is done to assess upsides of α

and β utilizing the given weight. After this the computation the preparation moves towards LM calculation based preparing in which hessian grid is additionally used to refresh loads toward a path where there mistake work which MSE is to be limited [31].

2.3 Wavelet change:

This work proposes signal pre-handling over gathered information of HVDC transmission line from PSCAD programming, to extricate highlights. The most famous apparatus for signal handling is Fourier change (FT). It is a strong numerical device to break down any sign as sine wave of various frequencies. This is on the grounds that it is clear much of the time the recurrence base sign gives better data that time base. Nonetheless, FT has a downside that while changing sign in recurrence space its misfortunes all data connected with time reliance of sign, thus makes it difficult to check happening case of a specific recurrence signal. A changed method called Short Time Fourier Transform (STFT) was create to tackle this issue. The method utilizes windowing approach for breaking down a little segment of sign and giving data over a tiny edge of time with exceptionally restricted accuracy, contingent on picked window size. Implies in the event that we picked restricted measured window, time astute it will give great outcomes however will need giving better goal for recurrence. Likewise, for wide window the other way around will occur. Henceforth, a methodology is required, which not just have better goal for both time and recurrence yet additionally an adaptability towards windows size picked. Thus, prompts the development of Wavelet change (WT) instrument. The strategy just adjust the size of window as indicated by sign and in this manner gives better time and recurrence upset. To do this, wavelet change utilizes mother wavelet (an exceptionally short sign). The WT just believers the first sign as many moved and scaled variants of mother wavelets in continuation [28] [29]. In present work, Haar wavelet is utilized a mother wavelet and change is done up to third even out. Following condition will additionally clarifies the discrete wavelet change [32].

The discrete wavelet change is having two-part initial one is scaling part and the subsequent one is wavelet part. In DWT S (n) in example of sign, where, n = 0, 1, 2… M-1, where j is scaling component and k is moving element.

3. Results and Discussion

In the figure 1 below, the designed Bipolar HVDC model in PSCADEMTDT software is shown.

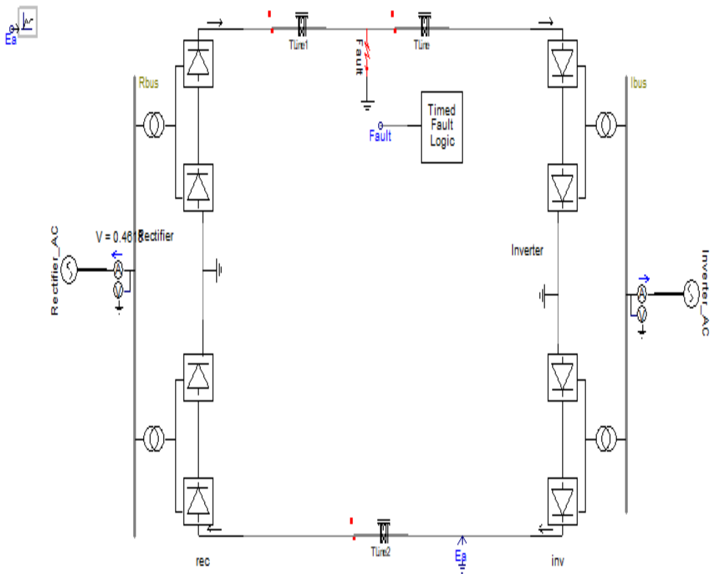

Figure 1: Bipolar HVDC model for Fault Simulation

Information is the essential wellspring of data needed to prepare and test any neural organization model. The information must be precise for legitimate preparing. The explanation for is that is information will be erroneous or inadequate then model will be empower give right result because of fragmented preparing or wrong preparing. From wrong preparing implies mis-estimation of loads, which further prompts wasteful anticipating. Subsequently, information ought to be handled prior to taking care of it to arrange as an info. The initial phase in treatment of information is information assortment. For this review, information utilized are taken transmission line boundaries acquired by mimicking transmission line model for LG issue at a hole 1 km.

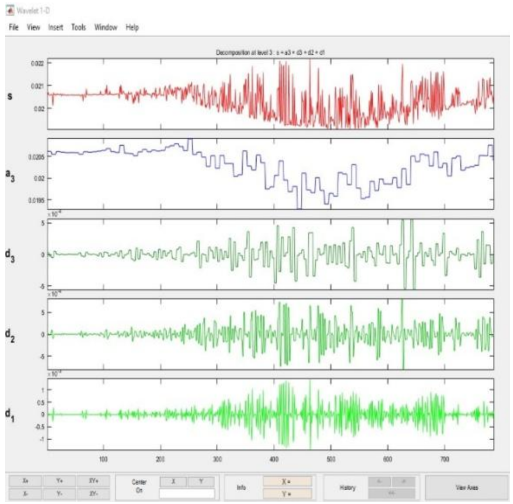

Figure 2: Wavelet transform of a signal

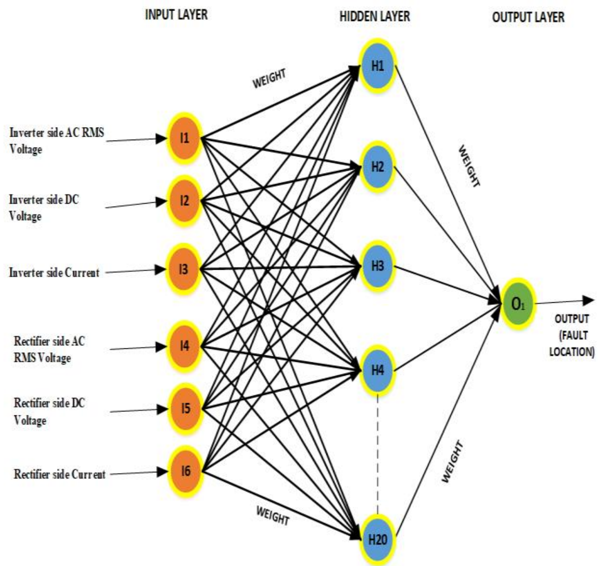

Figure 3: Working model of an ANN

Figure 3 shows the working ANN model implemented for present study. It is consist of 6 input neurons, 20 hidden layer neurons and 1 output layer neuron. The data obtained from PSCAD simulation and wallet transform are provided to neural network model for training and testing.

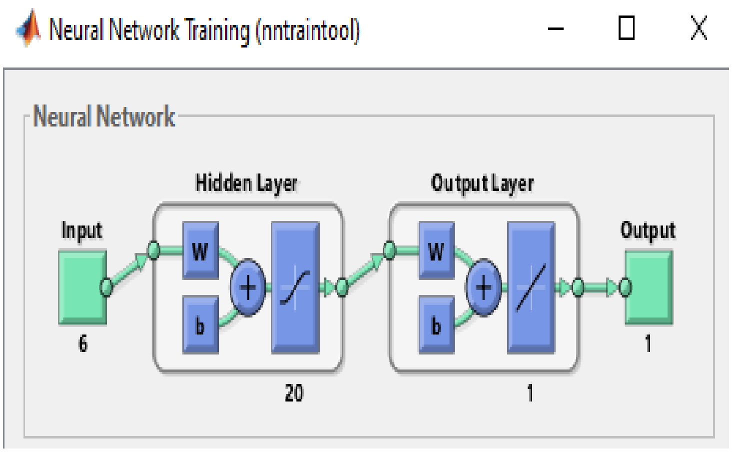

Figure 4: Design of Model in nntool in MATLAB

The results obtained are shown in table 1 below:

Table 1: Obtained Results

Actual fault location (in km)	With LM algorithm		With BR algorithm	
	Fault location estimated (in km)	Error (km)	Fault location estimated (in km)	Error (km)
159	147.588505848081	-11.4114941519194	164.240012804077	5.24001280407728
302	286.888881178689	-15.111118823114	281.447639602167	-20.5523603978329
346	348.808442546749	3.76370643562950	348.468325701315	2.46832570131488
458	450.576283109639	2.80844254674884	442.014650460553	-15.9853495394468
576	585.811032956771	-7.42371689036060	579.027626278063	3.02762627806283
684	673.373218444357	9.81103295677144	695.440184930823	11.4401849308229
727	730.763706435630	-10.62678155 6432	731.324509972039	4.32450997203898
Mean absolute error		**8.7 km**		**9.0055 km**

Actual fault location (in km)	With WT-LM algorithm		With WT-BR algorithm	
	Fault location estimated (km)	Error (km)	Fault location estimated (km)	Error (km)
159	160.560148789004	1.56014878900382	160.492688100455	1.49268810045496
302	301.376511935045	-0.623488064955097	300.525582654671	-1.47441734532947
346	344.320427072465	-1.67957292753550	344.494750239424	-1.50524976057574
458	455.680697228701	-2.31930277129942	456.494380893382	-1.50561910661781
576	576.848083446189	0.848083446188980	576.475663532224	0.475663532224189
684	684.014800053345	0.0148000533453114	684.465636126392	0.465636126391587
727	727.678941291362	0.678941291362321	728.511177515595	1.51117751559457
Mean absolute error		**1.1035 km**		**1.2044 km**

CONCLUSION

From the above conversation, obviously AI approaches are far superior performing when clubbed with legitimate information pre-handling instrument. Since information got is non-occasional, Wavelet change has advantage over Fourier change. Henceforth, wavelet-based neural organization is planned in this work. Four sorts of blends are prepared and tried in this work. The outcomes got from LM procedure gives a mean outright blunder of 8.7 km. The outcomes acquired from BR strategy gives a mean outright blunder of 9.0055 km. The outcomes acquired from WT-LM strategy gives a mean outright mistake of 1.1035 km. The outcomes got from WT-BR method gives a mean outright blunder of 1.2044 km.

On contrasting outcomes one can accompany end the WT-LM is a superior performing model with a precision of 1.1035 km mistake, which ended up being an incredible advancement in contrast with different strategies in the field of HVDC shortcoming area assessment

REFERENCES:

[1] Mishra, D.P., P. Ray,“Fault detection, location and classification of a transmission line”, Neural Comput&Applic, Springer, Volume 30, PP. 1377–1424, 2018.

[2] Pasad, A., J.Belwin Edward, K.Ravi, “A Review on Fault Classification Methodologies in Power Transmission Systems: Part - I”, Elsevier, Volume 5, Issue 1, Pages 48-60, May 2018.

[3] Souza, P.,Eliane da Silva Christo and Aryfrance Rocha Almeida, “Location of Faults in Power Transmission Lines Using the ARIMA Method,” Energies 2017, volume 10, 1596, 2017.

[4] Jia, H., “An Improved Traveling-Wave-Based Fault Location Method with Compensating the Dispersion Effect of Traveling Wave in Wavelet Domain” ,Hindawi, Mathematical Problems in Engineering, Volume 2017, Article ID 1019591, 11 pages.

[5] Santo, S., Carlos Eduardo de Morais Pereira, “Fault location method applied to transmission lines of general Configuration”, Electrical Power and Energy Systems 69, ScienceDirect, pp. 287–294, 2015.

[6] Evrenosoglu, H., “A single-ended fault location method for segmented HVDC transmission line”, Electric Power Systems Research, ScienceDirect, Volume 107, Pages 190-198, February 2014.

[7] Yusuff, A., A.A.Jimoh, J.L.Munda, “Fault location in transmission lines based on stationary wavelet transform, determinant function feature and support vector regression”,Electric Power Systems Research, ScienceDirect,Volume 110, Pages 73-83, May 2014.

[8] Yadav, A., and YajnaseniDash, “ An Overview of Transmission Line Protection by Artificial Neural Network: Fault Detection, Fault Classification, Fault Location, and Fault Direction Discrimination” , Advances in Artificial Neural Systems, Volume 2014, Article ID 230382, 20 pages, Hindawi Publishing Corporation, 2014.

[9] Huang, Q., Wei Zhen, and Philip W. T. Pong, “A Novel Approach for Fault Location of Overhead Transmission Line With Noncontact Magnetic-Field Measurement”, IEEE Transactions On Power Delivery, Vol. 27, issue NO. 3, pp. 1186-1195, July 2012.

[10] Bao, J.,Zhong Tingjian Ye Mao, “A Fault Location and Realization Method for Overhead High Voltage Power Transmission”, Procedia Engineering 15, Elsevier, pp. 964 – 968, 2011.

[11] Suonan, J., Shuping Gao, Guobing Song, Zaibin Jiao, and Xiaoning Kang,“A Novel Fault-Location Methodfor HVDC Transmission Lines”, IEEE Transactions on Power Delivery, Volume 25, Issue 2, pp 1203 – 1209, 2010.

[12] Giorgi, M., Antonio Ficarella, Marco Tarantino, “Error analysis of short term wind power prediction models”. Appl. Energy 88, pp. 1298–1311, 2011.

[13] Ramesh, M., A. Jaya Laxmi, “Fault Identification in HVDC using Artificial Intelligence - Recent Trends and Perspective”, International Conference on Power, Signals, Controls and Computation, IEEE, 2012.

[14] Bashier, E., M. Tayeb, Orner AI Aziz Al Rhirn, “Transmission Line Faults Detection, Classification and Location using Artificial Neural Network”, International Conference & Utility Exhibition on Power and Energy Systems: Issues and Prospects for Asia (ICUE), IEEE,2012.

[15] Park, J., Jared Candelaria, Liuyan Ma, and Kyle Dunn, “DC Ring-Bus Microgrid Fault Protection and Identification of Fault Location”, IEEE Transactions On Power Delivery, Volume 28, Issue 4, pp. 2574 – 2584, 2013.

[16] Batra, H.,Rintu Khanna, “Study of Various Types of Converter Station Faults”, International Journal of Engineering Research & Technology (IJERT), Vol. 2 Issue 6, June - 2013.

[17] Alwash, S.F., V. K. Ramachandaramurthy, and N. Mithulananthan, “Fault Location Scheme for Power Distribution System with Distributed Generation”, IEEE Transactions on Power Delivery,Volume 30, Issue 3,pp 1187 – 1195, 2014.

[17] David, J., “Artificial Neural Networks: Methods and Applications”.

[18] Alexiadis, M.C., P.S. Dokopoulos, H.S. Sahasamanoglou, I.M Manousaridis, “Short-term forecasting of wind speed and related electrical power”, Solar Energy, Volume 63, pp. 61–68, 1998.

[19] Giorgi, M.AntonioFicarella, Marco Tarantino, “Error analysis of short term wind power prediction models”. Appl. Energy 88, pp. 1298–1311, 2011.

[20] Hyndman, R. and Koehler A. "Another look at measures of forecast accuracy”, International Journal of Forecasting 22, pp. 679 – 688, 2006.

[21] Marquardt, D., “An algorithm for least-squares estimation of nonlinear parameters,” SIAM J. Appl. Math., Volume 11, pp. 431–441, 1963.

[22] Levenberg, K., “A method for the solution of certain problems in least squares”, Quart. Appl. Mach., Volume 2, pp. 164–168, 1944.

[23] Sotirov, S., “A Method of Accelerating Neural Network Learning”, Neural Processing Letters, Springer, Volume 22, pp. 163–169, 2005.

[24] Hagan, M.T. and M. B. Menhaj, “Training feedforward networks with the Marquardt algorithm”, IEEE Transactions on Neural Networks, Volume 5, pp. 989–993, 1994.

[25]Wilamowski, M. and Hao Yu, “Improved Computation for Levenberg–Marquardt Training”, IEEE Transactions on Neural Networks, Volume 21, pp. 930 – 937, 2010.

[26] Miranda, M. S. and R. W. Dunn, “One-hour-ahead wind speed prediction using a Bayesian methodology,” IEEE Power Engineering Society General Meeting, pp. 1-6, 2006.

[27] Kisi, O., ErdalUncuoghlu, “Comparison of three backpropagation training algorithms for two case studies,” Indian Journal of Engineering & Materials Sciences, Volume 12, pp. 434-442, 2005.

[28] Daubechies, I.,“Ten Lectures on Wavelets”, Society for Industrial and Applied Mathematics, Philadelphia, PA, 1992.

[29] Mallat, S.,"A Wavelet Tour of Signal Processing", Academic Press, San Diego, CA, 2001.
[30] Yue, Z., Zhao Songzheng; Liu Tianshi, "Bayesian regularization BP Neural Network model for predicting oil-gas drilling cost", Business Management and Electronic Information (BMEI), International Conference on 13-15 May 2011, Volume 2, pp. 483-487, 2011.
[31] Mackay, D.J.C., "Bayesian interpolation", Neural Computation, Volume 4, pp. 415-447, 1992.
[32] Rioul, O. and M. Vetterli, Wavelets and signal processing, IEEE Signal Processing Magazine, vol. 8, no. 4, pp. 14–38, October 1991