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Estimating Faults in Bipolar HVDC Transmission Systems using Regression Learning Based ANN.

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Abstract — **In the present era of deregulation and competition, demand from every energy supplier is to have good continuity, dependability and reliability. Fault location can play a vital role in achieving this aim. As uninterrupted power supply is the prime demand by all consumers. However, faults in power system will leads to the interruption in power supply and it will make system vulnerable towards system outrage/collapsing and will lead to damage various electrical peripheral of switch gear/ electrical equipment. Hence all faults are required to be detected and clear as soon as possible to restart power supply to consumer. Having accuracy knowledge of fault location will come very handy in reducing system outrage time and they're by improving continuity and reliability of system. Various researches has been done previously towards finding accurate result. In this paper location detection using various artificial neural network (ANN) techniques is presented. The goal of the work is to prepare a model which can somehow manage to give accurate fault location on HVDC line thus helps in improving the system performance. In this study we are proposing a model formed using ANN model for the purpose of fault location approximation in HVDC transmission line using the information of sending end and receiving end voltage. This proposed work is performed with the help of MATLAB/Simulink environment and simulation using PSCAD software. The results show the superiority in efficiency and precision of present model in fault location detection using ANN than other tools.**

Keywords: Fault location Detection, ANN, trainlm, HVDC, MATLAB, PSCAD/EMTDC.

I. INTRODUCTION

Transmission system plays the vital role in connecting generation station to load. It has the responsibility to supply continuous power from one and two other. Any type of damage to transmission line will lead to an interruption in power supply but in the present era of power system deregulation providing good power quality with continuous supply is main its main priority of all electric utility companies. Hence for this reason focus should be paid in the field of system protection and a proper planning is expected to deal with any unwanted situation.

Relay and circuit breakers play key part in preventing system during any fault condition. Faults are responsible for creating system malfunctioning and their immediate diagnosis is expected is expected to increase reliability.

Normally distance relays are used for locating fault. The working of distance relay is based upon the measured value of impedance between fault point and relay location (that is ratio of voltage and current between these two points). Now this should be giving accurate results, but due to the presence of series capacitor banks for compensation problem will somehow tarnish the accuracy of relay.

Capacitor banks are used because they help in balancing reactive power in transmission line thus helping in increasing line loadability, reducing line losses and increase in system stability.

Jenifer Mariam Johnson and Anamika Yadav [1] in 2016 has presented a method of detecting fault location of $\pm$500 kV HVDC transmission system using artificial neural network (ANN). Author has modelled and simulated $\pm$500 kV bipolar HVDC transmission line over PSCAD/EMTDC software. Author has proposed a model developed using ANN in MATLAB environment, trained and tested using one sided voltage and current magnitude of HVDC transmission line for various fault location. Author has simulated HVDC line model for LG fault at distance of every 2 kilometer of transmission and noted the data corresponding to that. From this model has observed a result with an accuracy of 2-kilometer distance. Model is developed for a HVDC bipolar transmission line of $\pm$500 kV and 936 KM.

Sunil Singh, D. N. Vishwakarma [2] in 2016 has developed a fault location estimation technique for a 300 km, 400 kV transmission line. Author has performed fault analysis at various location of this transmission line in MATLAB environment and the data obtained during simulation at various fault location is stored. This data is than transformed using wavelet analysis for the sole purpose of feature extraction which than can be supplied to ANN for prediction of fault location. After obtaining results from ANN, author came to conclusion DWT and ANN model together are very efficient in predicting exact location of fault with very high accuracy.

Ankita Nag and Anamika Yadav [3] in 2016 has proposed an ANN based protective scheme for the hybrid transmission system both overhead and underground. Author has discussed various advantages of AI has over primitive location detecting techniques like one based on phasor based method which usually utilizes fundamental component of signal and other is traveling wave based method which works on the basis of value of reflected wales. Author has developed and simulated15 kilometer, 132 kV, 50 hz transmission line with 3-kilometer underground cable and 12-kilometer overhead lines for a LG fault. After training and testing author came to conclusion that the output is very accurate compare to other techniques.

Qingqing Yang, Jianwei Li, Simon Le Blond, Cheng Wang [4] in 2016 has developed a model for DC microgrid fault detection and fault location using artificial neural network. The DC microgrid is modelled in PSCAD/EMTDC to simulate various faults.

Author has discussed the importance of microgrid for present day power system in which penetration of renewable energy is increasing day by day leading to more unpredicted grid behavior and hence making control strategies more complicated. A total of 40 neurons are taken in input layer consisting of 20-20 data from both sending end and receiving end of dc microgrid. Author has obtained results from trained model with an accuracy of one percent error which is very accurate considering distance.

II. METHODOLOGY:

Following techniques are utilized in present work for the purpose of fault location estimation:

Artificial Neural Networks (ANN):

ANN are computing systems or technique that mimic the learning processes of the brain to discover the relations between the variables of a system. They process input data information to learn and obtain knowledge for forecasting or classifying patterns etc. type of work. ANN consists of number of simple processing elements called neurons. All information processing is done within this neuron only. A network of connected artificial neurons can be designed, and a learning algorithm can be applied to train it [5].

Signals (Input data) are passed between neurons over connection links and Each connection link has an associated weight, which in a neural network, multiplies the signal transmitted. The weights represent information being used by the network to solve a problem. Then the weighted sum is operated upon by an activation function (usually nonlinear), and output data are conveyed to other neurons. The weights are continuously altered while training to improve accuracy and generalize abilities [6] [7].

Levenberg–Marquardt (LM) Algorithm: Reducing error function is the main reason to use this algorithm. Levenberg-Marquardt algorithm [8] [9] is a very efficient technique for minimizing a nonlinear function. The algorithm includes many different variables like in present study we have output data, weight between neurons and error function, that determine efficiency and success rate of model. The ideal values of these variables are very dependent on the test function.

Levenberg-Marquardt algorithm is fast [10] and has stable convergence. This algorithm was designed to approach second-order training speed without computing the Hessian matrix. When the performance function has the form of a sum of squares, then the Hessian matrix can be approximated and the gradient can be computer as

$$H = J_x^T J_x \tag{1}$$

$$g = J_x^T e \tag{2}$$

Where J_k is the Jacobian matrix for k[th] input, which contains first order derivatives of the network errors with respect to the weights and biases, e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix. [11]

The Levenberg –Marquardt algorithm is actually a blend of the steepest descent method and the Gauss–Newton algorithm. The following is the relation for LM algorithm computation,

$$W_{k+1} = W_k - [J_K^T J_k + \mu I]^{-1} J_K^T e_k \tag{3}$$

where I is the identity matrix, W_k is the current weight, W_{k+1} is the next weight, e_{k+1} is the current total error, and e_k is the last total error, μ is combination coefficient. [11] [12]

It tries to combine the advantages of both the methods hence it inherits the speed of the Gauss–Newton algorithm and the stability of the steepest descent method.

The combination coefficient μ is multiplied by some factor (β) whenever a step would result in an increased e_{k+1} and when a step reduces e_{k+1}, μ is divided by β. In this study, we used β=10. When μ is large the algorithm becomes steepest descent while for small μ the algorithm becomes Gauss-Newton. [11]

The Neural Network in present study consist of three layers. The first one is Input layer (consist of 4 Neutrons for 4 input element) from where inputs are feed to model for further computation. Then comes second layer called Hidden Layer (consist of 10 Neurons), this is where activation function is used to limit value of output Neuron.

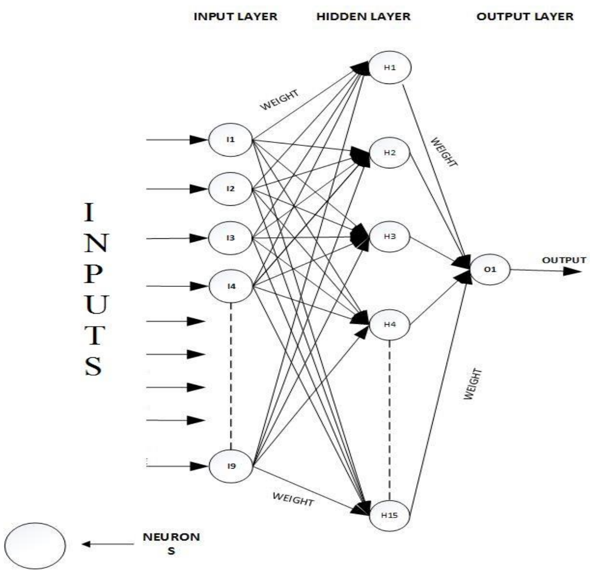

Fig. 1: Working model of an ANN

III. STAGES FOLLOWED IN FAULT LOCATION ESTIMATION

Following stages are followed in same order as mentioned estimating fault location.

Stage 1: Data Collection Stage

First stage of present work is to collect data for Neural network training and testing. For this a bipolar HVDC transmission line is simulated for fault at a step of 1 km in PSCAD/EMTDC software and data of both sending end and receiving end is collected. This data is input data for Neural Network. In the present study a line of DC voltage of $\pm$500kV 816 km is taken. This line is a prototype of India first bipolar line i.e. Rihand-Dadri HVDC line. A case study is done for same line in present work. Fault location value is target data for neural network. Hence all data is collected using multiple simulation and presented to neural network.

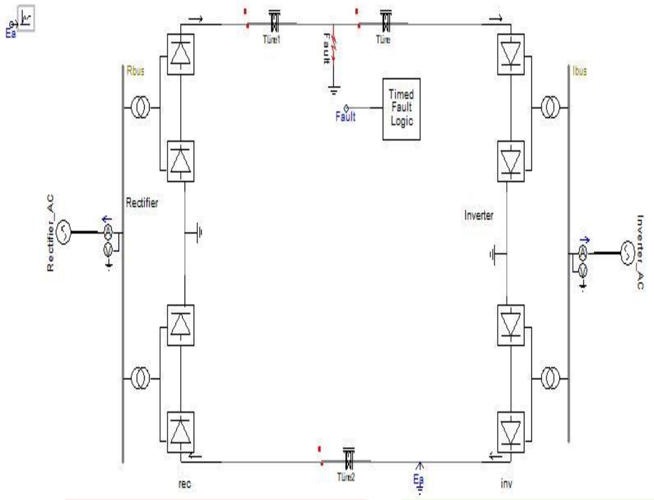

Fig. 2: $\pm$500kV HVDC Bipolar line model in PSCAD.

Stage 2: Data pre-processing stage

In this stage, all the data extracted in previous stage are organized and pre-processed for further stages. In this stage first all the data is copied in single ms excel sheet, with each column representing value of each input parameter. A search is to be performed to check for empty data cells in sheet for better performance. This data is than inserted in Matlab workspace using drag and drop method for using in developing model. This data is then divided in to input and target data. This two are further divided in to two parts one for training and other for testing. Approximate to 3:1 is kept for dividing data for training and testing.

Stage 3: Neural Network Training Stage

In this stage we will feed input data to input layer of present designed model and target is fitted to output layer. We have used LM and BR training algorithm for training. It is this stage in which model is prepared and value of weights are optimized for better performance according to input and target data samples.

Stage 4: Neural Network Testing and validation stage

At this stage, the second part of dataset is used. Although only inputs are provided to already trained neural network and output is calculated from neural networks. These is then compared to original target fault distance to observe the closeness between the two.

The below figure shows a training GUI of neural network, which will give all details of related to training. We have taken 10 hidden layer neurons 4 input layer neurons and 1 output layer neuron

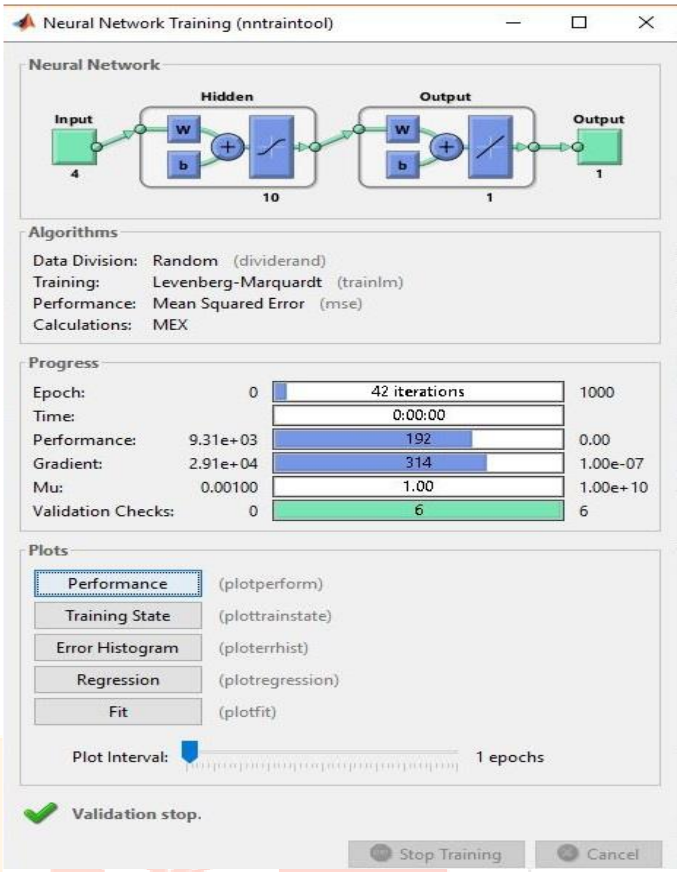

Fig. 3: GUI of ANN during training.

IV. RESULTS

With trainlm >>

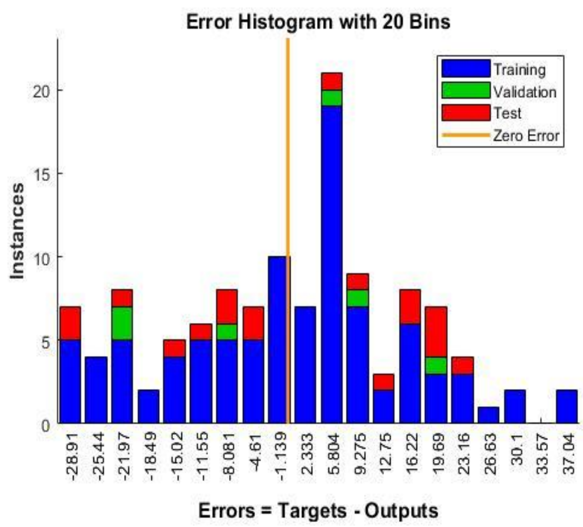

Fig. 4: Error histogram employing the proposed model using LM training.

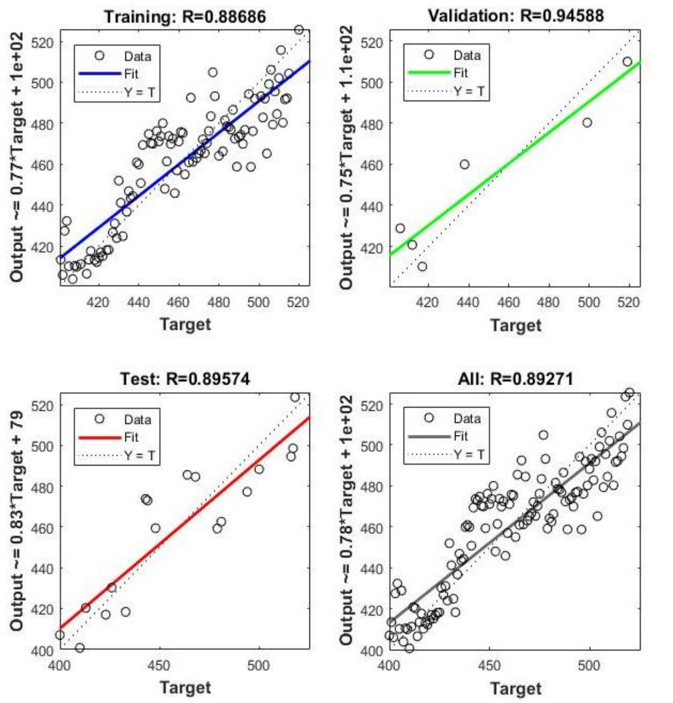

Fig. 5: Regression plot during training, testing & validation for Proposed LM training algorithm.

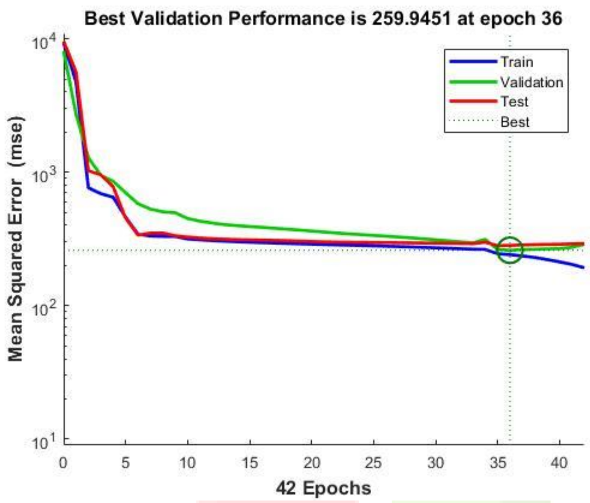

Fig. 6: Neural network performance during training, testing & validation.

V. CONCLUSION

In the present research, an attempt is made to predict fault location for a HVDC link using ANN models by utilizing receiving end and sending end data to train ANN model. The model developed is able to predict fault location accurately. The developed ANN model with the configuration of 4-10-1 is trained using back propagation algorithm LM. The results show that LM will give accurate results and thus proving to be very efficient method.

REFRENCES

[1] Jenifer Mariam Johnson and Anamika Yadav, "Fault Location Estimation in HVDC transmission line using ANN" First International Conference on Information and Communication Technology for Intelligent Systems: Volume 1, Springer, 2016.

[2] Sunil Singh D. N. Vishwakarma, "ANN and Wavelet Entropy based Approach for Fault Location in Series Compensated Lines", 2016.

[3] Ankita Nag and Anamika Yadav, "Artificial Neural Network for Detection and Location of Faults in Mixed Underground Cable and Overhead Transmission Line", International Conference on Computational Intelligence and Information Technology, CIIT, 2016.

[4] Qingqing Yang, Jianwei Li, Simon Le Blond, Cheng Wang, "Artificial Neural Network Based Fault Detection and Fault Location in the DC Microgrid", Energy Procedia 103, pp 129 – 134, ScienceDirect, 2016.

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

[6]. Giorgi, M.G.D., Ficarella, A., Tarantino, M. "Error analysis of short term wind power prediction models, Appl. Energy 88, pp. 1298–1311, 2011.

[7]. P. M. Fonte, Gonçalo Xufre Silva, J. C. Quadrado, Wind Speed Prediction using Artificial Neural Networks, 6th WSEAS Int. Conf. on Neural Networks, Lisbon, Portugal, June 16-18, pp. 134-139, 2005.

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

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

[10]. A Method of Accelerating Neural Network Learning, Neural Processing Letters, Springer, pp. 163–169, 2005.

[11]. M. T. Hagan and M. B. Menhaj, Training feedforward networks with the Marquardt algorithm, IEEE Transactions on Neural Networks, vol. 5, no. 6, pp. 989–993, 1994.

[12]. Bogdan M. Wilamowski and Hao Yu, Improved Computation for Levenberg–Marquardt Training, IEEE Transactions on Neural Networks, Vol. 21, No. 6, 2010.

[13]. Mackay, D.J.C., Bayesian interpolation, Neural Computation, Vol. 4, pp 415-447, (1992).

[14]. Zhao Yue; Zhao Songzheng; Liu Tianshi, Bayesian regularization BP Neural Network model for predicting oil-gas drilling cost, Business Management and Electronic Information (BMEI), 2011 International Conference on 13-15, vol.2, pp. 483-487, 2011.

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

[16] Nabamita Roy & Kesab Bhattacharya, "Detection, Classification, and Estimation of Fault Location on an Overhead Transmission Line Using S-transform and Neural Network", Electric Power Components and Systems, 43(4), pp 461–472, Taylor & Francis, 2015.

[17] Liang Yuansheng, Wang Gang, and Li Haifeng, "Time-Domain Fault-Location Method on HVDC Transmission Lines Under Unsynchronized Two-End Measurement and Uncertain Line Parameters", IEEE Transactions on Power Delivery 1, 2015.

[18] Pu Liu, Renfei Che, Yijing Xu, Hong Zhang, "Detailed Modeling and Simulation of ±500kV HVDC Transmission System Using PSCAD/EMTDC", IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), 2015

[19] S. F. Alwash, V. K. Ramachandaramurthy, and N. Mithulananthan, "Fault Location Scheme for Power Distribution System with Distributed Generation", IEEE Transactions on Power Delivery, 2014.

[20] Jae-Do Park, Jared Candelaria, Liuyan Ma, and Kyle Dunn, "DC Ring-Bus Microgrid Fault Protection and Identification of Fault Location", IEEE Transactions on Power Delivery, Vol. 28, NO. 4, 2013.