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Fault Location Estimation for a Bipolar HVDC transmission line using different Back propagation Algorithms of ANN

Authors: Ms. Shivani Jharbade[1], Ms. Neha Shrivastava [2]

[1] M. Tech Scholar in Power System, REC, Bhopal, (M.P). E-mail: (Shivani0158@gmail.com)

[2]Assistant Professor, Electrical & Electronics Dept. REC, Bhopal, (M.P). E-mail: (vastavaneha@gmail.com)

Abstract — In electrical transmission system uninterrupted supply is a primary demand from system. But every system under go some type of situation where supply gets disconnected for some time based on severity of problem. In HVDC transmission system main problem arises due to line to ground fault. Now the first step to resolve this situation is to locate the exact location of fault occurrence. During this situation for a line long enough, it is very difficult to manually check the whole because that will take long time. Hence a technique is to be derived which has the ability to find the location so as to do the required maintenance as soon as possible and continue the supply again. In this work an attempt is made to resolve this problem with the help of artificial neural network.

Two different algorithms of ANN are utilized in this work to calculate fault location of Bipolar HVDC transmission line. 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. After collection of data further modelling of neural network model is done in neural network toolbox in MATLAB software. The results show that BR will give more accurate results than LM thus proving to be more efficient method.

Keywords: *Fault location Detection, Artificial Neural Network, Levenberg–Marquardt(LM), Bayesian Regularization(BR), Bipolar 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 others. 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.

Nabamita Roy & Kesab Bhattacharya [5] has presented a technique for detecting fault, classifying it had then forecasting fault location. Various techniques author has used in this work is s-transform and wavelet transform for feature extraction purpose. Values of this features is used for both classification and locating fault in this work. Author has concluded that above following techniques includes BPNN techniques has developed a model which has great speed of computation and very high accuracy.

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Liang Yuansheng, Wang Gang, and Li Haifeng [6] has discuss a noble algorithm to detect fault location. Author has performed a mix of travelling wave theory and Bergeron times domain fault location method. The value of voltage and current from both sides is taken as input parameters. In this study a self-adopted filter is also utilized which has ultimately improved performance of the algorithm. After the simulation and performing all tests related to fault at different location, author came to conclusion that this method is efficient for faults location detection for unsynchronized two end measurements on HVDC lines.

S. F. Alwash, Member, V. K. Ramachandara murthy, and N. Mithulananthan [8] has developed an algorithm for identification of all shunt type fault location. This work mainly presented a scheme where author has used impedance method for fault location. This method is tested for IEEE 34 bus distribution system designed and simulated in PSCAD/EMTDC software. In the study author has computed a method which has capability to identify faults location irrespective of type of shunt fault.

Jae-Do Park, Member, IEEE, Jared Candelaria, Liuyan Ma, and Kyle Dunn [9] a DC microgrid system's fault location technique is proposed. In this work author has used intelligent electronic devices for the controlling and monitoring all nodes. The author has successfully implemented proposed algorithm/technique both in hardware and simulation experimentally.

M Ramesh, A. Jaya Laxmi [10] has presented an overview of various intelligent technique for detecting fault in HVDC. In study author has discussed drawbacks of primitive fault detection techniques in HVDC. Then author has provided an overview to various Artificial intelligent techniques in view to identify fault of HVDC transmission system. The study concluded that the rule based linear fuzzy logic controller can be used to achieve the desired fault detection of the HVDC link.

Eisa Bashier M. Tayeb, Orner AI Aziz Al Rhirn [11] discussed that in power system are always exposed to abnormal conditions, which are the reason for the damage of transmission line and other electrical equipment's of power system. These abnormalities are termed as faults. These faults are required to be detected and classified for better performance of transmission line. In this paper author has presented a Back-Propagation technique of Artificial Neural Network as an alternative for transmission line fault detection, classification and isolation.

II. METHODOLOGY:

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

Artificial Neural Networks (ANN):

The evolution of ANN has been dated way back in 1980's with the evolutions of computers. From the very same process of evolution, the term artificial neural network is been derived. The word artificial is basically used to denote the capability of this model to replicate the working of human brain. Usually machines possess a property work according to pre-defined instruction saved in it. However, this is not how human works. The brain of any human has the capacity to take decision based on its experience which we call training in computers language. Hence, it gives capability to brain to take decision that too right in cases which are new to it. Therefore, machine learning is a method by which we inherit this specialty of human biological thinking system and try to replicate same in computer/machine.

Now let's understand how human brain works to form exact algorithm which can give similar outputs. Brain consist of billions of neurons, which are interconnected with each other. These interconnections have a certain strength, which makes our memory storage. Based on these memories we take decision over everything in real time. The strength of these connections depends mainly on signal from various cells/neurons situated in each part of our body. These neurons continuously send signal according to sense organs response to brain in the form of electromagnetic pulses. These pulses are passed to brain through a series of chain of cells linking brain with sense organs. These chains of cells have two responsibility to transfer signal from one part of body to other and second to modify the signal in such a manner that brain will take the decision instantaneously.

Now the objective of formation of neural network is to reproduce the same scenario in computer based upon programming, algorithms, processor and memory, which is discussed in detail in next section.

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Levenberg–Marquardt (LM) Algorithm: The algorithm used in this work is Levenberg–Marquardt (LM) Algorithm which a type of back propagation algorithm. The reason behind using this algorithm is due to its exceptional ability to extract information from a nonlinear data with great stability which keeping speed of convergence intractably high. The algorithm is a combination of two different algorithms proposed by two mathematicians Levenberg and Marquardt and hence the named over them. The drawback of prior one is remove by the advancement of second. The equation were derived back in mid-20th century for the sake of 1st order error reduction purpose. However, with the invention of computers and high-level computation problem this algorithm is evolved in to a great tool for time series forecasting. 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,

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

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]

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=l0. When μ is large the algorithm becomes steepest descent while for small μ the algorithm becomes Gauss-Newton. [11]

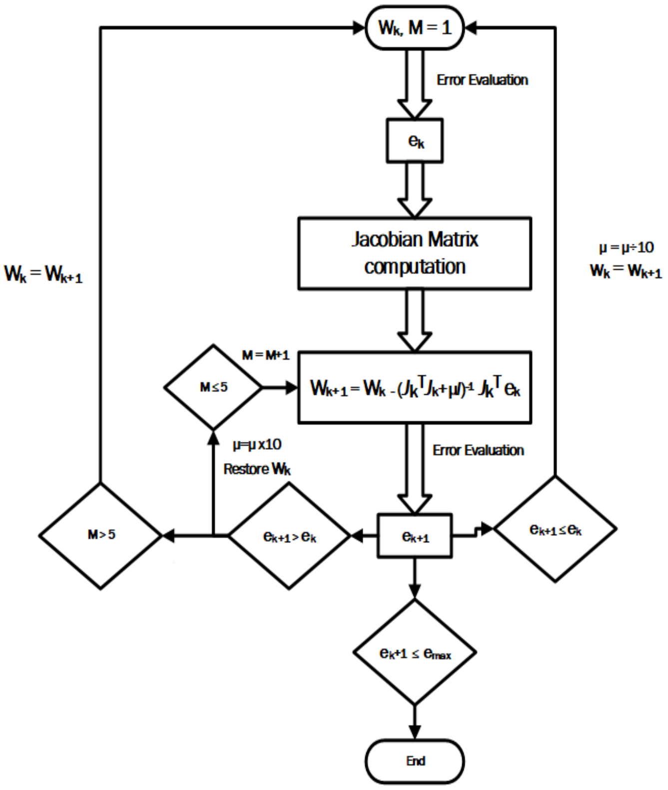

Fig. Flow chart of LM algorithm

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Bayesian Regularization (BR) Algorithm: BRANNs are extra vigorous than usual back-propagation networks and can lessen the necessity for long cross-validation. BR algorithm is a process that changes a nonlinear regression into a "well-modelled" statistical problem in the means of a ridge regression. In this algorithm regularization is used to improve the network by optimizing the performance function (F(*ω*)). The performance function F(*ω*) is the sum of the squares of the errors of the network weights (E_W) and the sum of squares error of the data (E_D) [13] [14]:

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

Where, $E_D = \sum_{k=1}^{n} e_k^2 \qquad E_w = \sum_{i=1}^{n} w_i^2$

Both α and β are the objective function parameters. In the BR framework, the weights of the network are viewed as random variables, and then the distribution of the network weights and training set are considered as Gaussian distribution. The α and β factors are defined using the Bayes' theorem. The Bayes' theorem relates two variables (or events), A and B,

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based on their prior (or marginal) probabilities and posterior (or conditional) probabilities as [15]:

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

Where P(A|B) is the conditional probability of event A, depending on event B, P(B|A) the conditional probability of event B, depending on event A, and P(B) the previous probability of event B. In order to get the best values of weights, performance function F(ω) (11) needs to be minimized, which is the equal to maximizing the following probability function given as:

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

Where α and β are, the factors on which value of performance function is dependent and is the one which is needed be to optimized, M is the particular neural network architecture, D is the weight distribution, P $(D|M)$ is the normalization factor, P $(D|\alpha,\ \beta,\ M)$ is the likelihood function of D for given α, β, M and P $(\alpha,\ \beta|M)$ is the unvarying prior density for the regularization parameters.

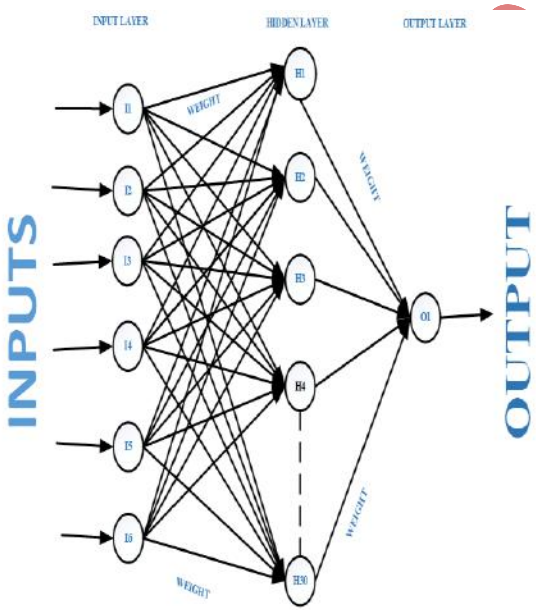

Fig. : Working model of an ANN

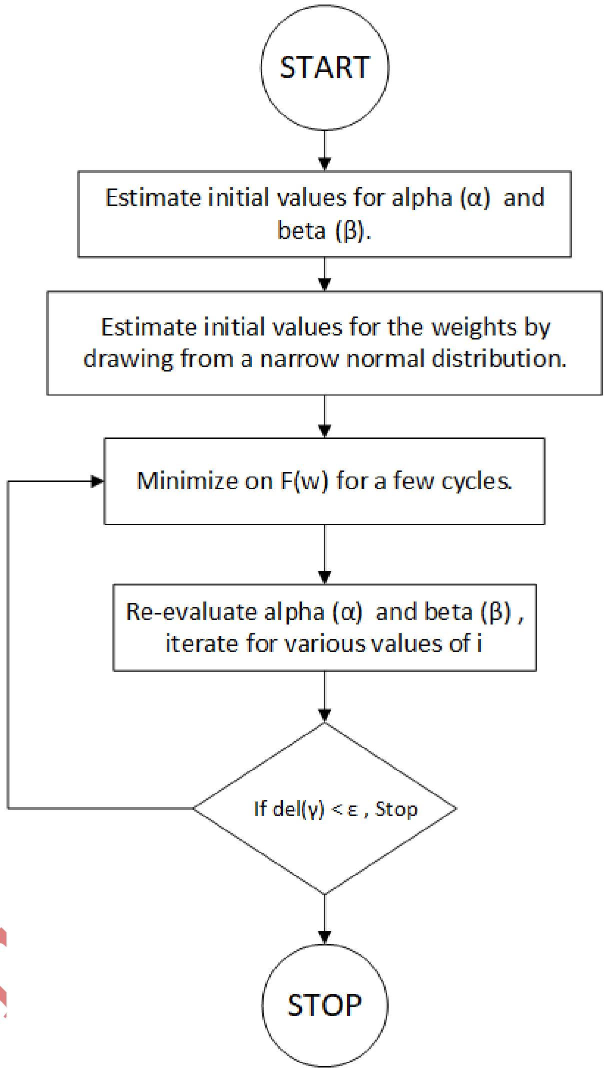

Fig. Flow chart of BR algorithm

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.

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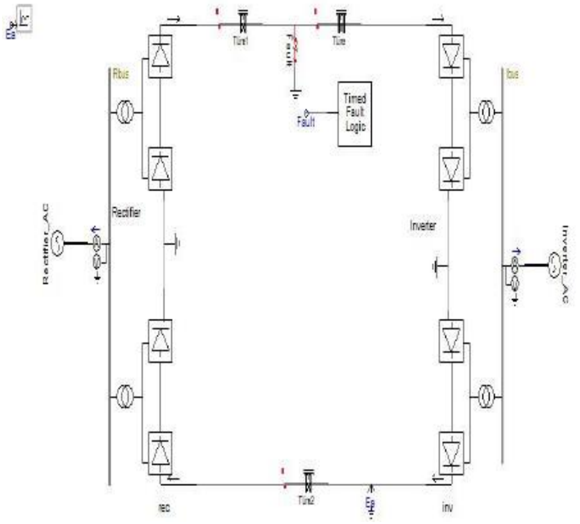

Fig. 2: ±500kV HVDC Bipolar line model in PSCAD.

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.

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 train 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 30-20 hidden layer neurons 6 input layer neurons and 1 output layer neuron

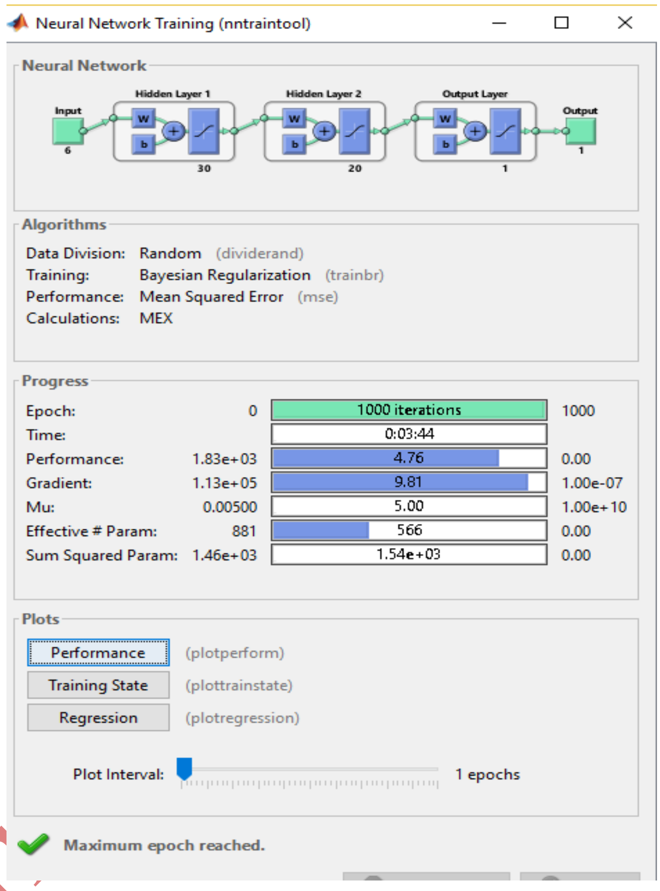

Fig. 3: GUI of ANN during training.

IV. RESULTS

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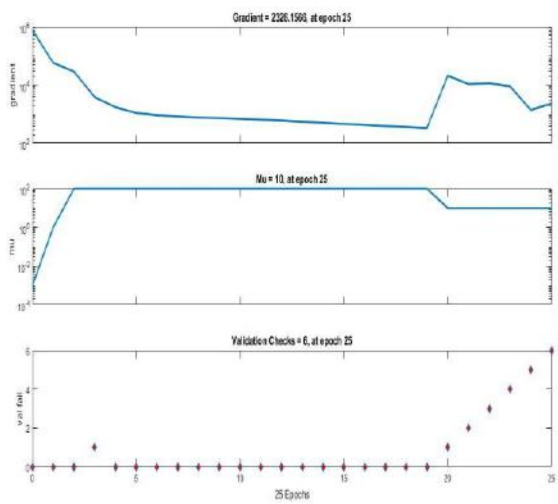

Fig. 4: Training states employing the proposed model using LM training.

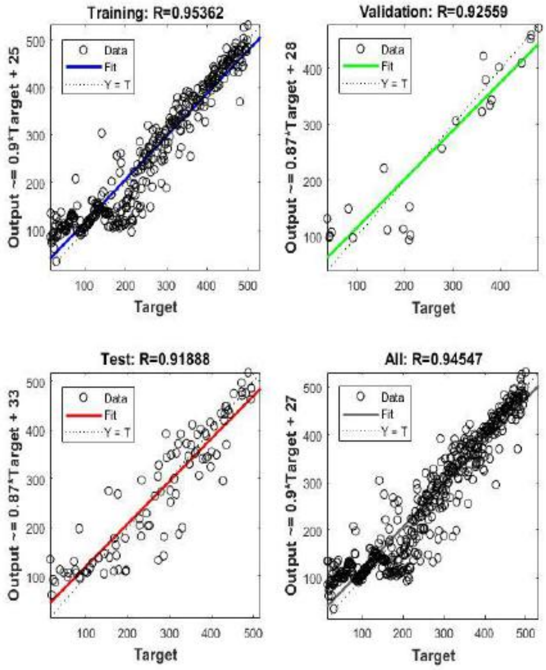

Fig. 5: *Regression plot during training, testing & validation for Proposed LM training algorithm.*

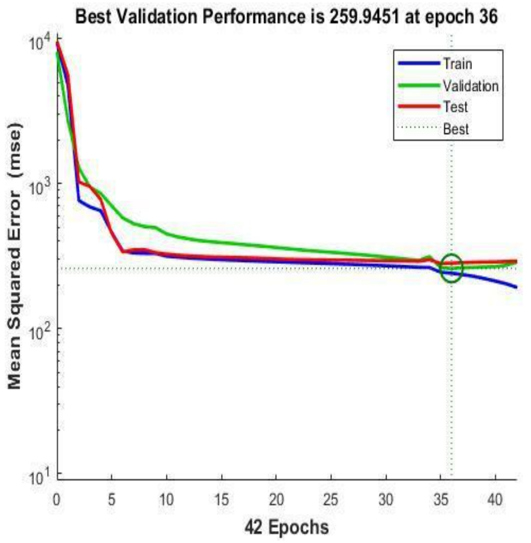

Fig. 6: Neural network performance during training, testing & validation.

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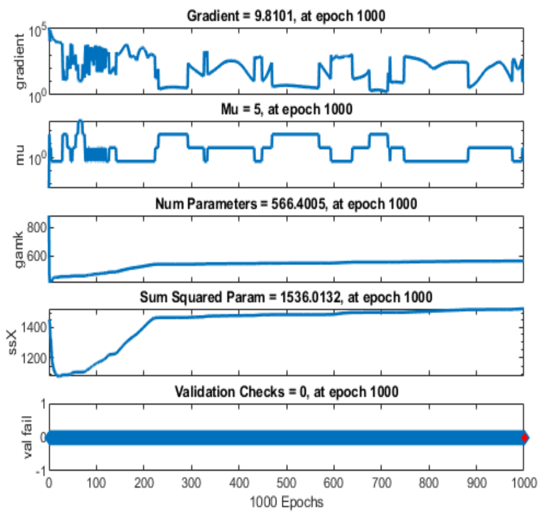

Fig. 7: Training states employing the proposed model using LM training.

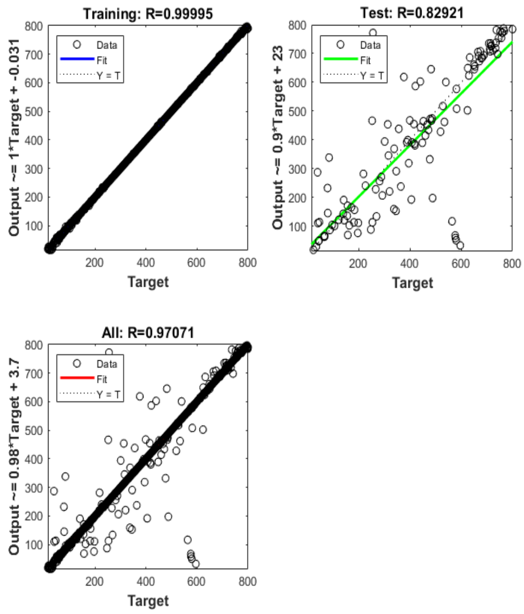

Fig.8: Regression plot during training, testing & validation for Proposed for Proposed Levenberg-Marquardt (LM) training algorithm.

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Fig. 9: 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 6-30-20-1 is trained using LM back propagation algorithm, proving to be efficient method.

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