DETECTION CLASSIFICATION AND LOCATION OF FAULTS ON 220 KV TRANSMISSION LINE WITH STATCOM USING WAVELET TRANSFORM AND NEURAL NETWORK

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ABSTRACT

A new scheme to enhance the solution of the problems associated with Transmission line protection with Statcom connected is presented in this paper. The fault detection is carried out by using energy of the detail coefficients of the phase signals and artificial neutral network algorithm used for fault type classification and fault distance location for all the types of faults for 220 KV transmission line. The energies of the all three phases A, B, C and ground phase are given input to the neural network for the fault classification. For each type of fault separate neural network is prepared for finding out the fault location. An improved performance is obtained once the neutral network is trained suitably, thus performance correctly when faced with different system parameters and conditions.

Keywords — Discrete Wavelet Transform, Fault Detection, Fault Classification, Statcom, Wavelet Transform.

I. INTRODUCTION

Protecting of transmission lines is one of the important tasks to safeguard electric power systems. Wavelet transform has the advantage of fast response and increased accuracy as compared to conventional techniques. The wavelet transformation is a tool which helps the signal to be analyzed in time as well as frequency domain effectively. The detection of fault is carried out by the analysis of the wavelets coefficients energy related to phase currents. ANN based techniques have been used in power system protection and encouraging results are obtained [1], [2],[3]. In classification, the objective is to assign the input patterns to one of the different classes [4], [5]. Fault location in a transmission line using synchronized phasor measurements has been studied for a long time. Some selected papers are listed as [6]–[10]. When a fault occurs, the presence of a shunt compensator in the line creates new problems for fault location algorithms and since the control system of shunt compensator reacts to the fault, the voltages and currents at the fault locator point will be affected in the transient state. In this paper a scheme is propose for 220KV Statcom connected transmission line for fast and reliable fault detection using energy of the detail coefficients of the phase signals, classification and location using neural network. For fault classification current signals (Ia2, Ib2, Ic2, and IG) detail coefficients energy

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values are given as input to the neural network. For each type of fault location separate neural network with different combination of input signals are prepared. In each of these cases, the current, voltage and ground phase current signals detail coefficients energies values of only phase involving in the fault signals are given as input to the neural network. For fault location of line with Statcom, impedance of line up to the fault point is calculated and as per value of line impedance fault is located. The MATLAB 7.10 version is used to generate the fault signals and verify the correctness of the algorithm. The proposed scheme is insensitive to variation of different parameters such as fault type, fault resistance etc.

II. DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform is found to be useful in analyzing transient phenomenon such as that associated with faults on the transmission lines. The fault signals are generally non stationary signals, any change may spread all over the frequency axis. The wavelet transform technique is well suited to wide band signals that may not be periodic and may contain both sinusoidal and non-sinusoidal components. Multi-Resolution Analysis (MRA) is one of the tools of Discrete Wavelet Transform (D.W.T), which decomposes original, typically non-stationary signal into low frequency signals called approximations and high frequency signals called details, with different levels or scales of resolution. The use of detail coefficients for fault detection is discussed in this paper. Detail coefficients contain information about the fault, which is required for fault detection.

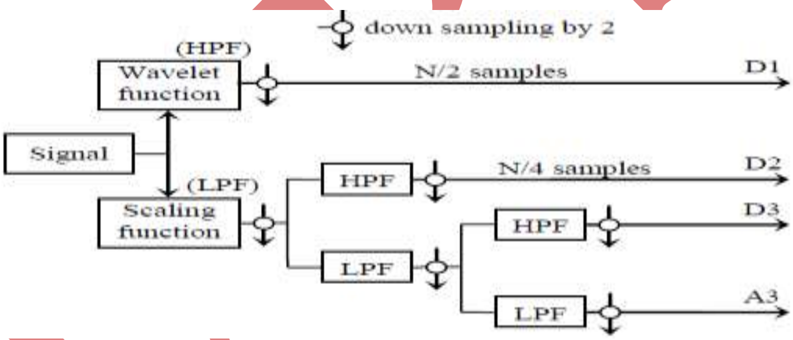

Fig.1. Wavelet Filter Bank

The signal of desired frequency component can be obtained from repetitive decompositions as shown by Fig.1. The mother wavelet determines the filters used to analyze signals. In this paper Db4 (Daubechies 4) wavelet was chosen because of its success in detecting faults [4], [5].

III. ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks simulate the natural systems behavior by means of the interconnection of basic processing units called neurons. ANNs have a high degree of robustness and ability to learn [8]. Once the network is trained, it is able to properly resolve the different situations that are different from those presented in the learning process. The multilayered feed forward network has the ability of handling complex and nonlinear input-output relationship with hidden layers. In this method, errors are propagated backwards; the idea of back-propagation algorithm is to reduce errors until the ANN learns the training data [13] [14]. The multilayered feed forward network has been chosen to process the prepared input data obtained from the W.T.

VI. Transmission Line Model

In Fig.2, model of 220kv, 90 km transmission line from A to B is chosen. Generator of 500MW is connected at one end and loads are connected at 220kv.

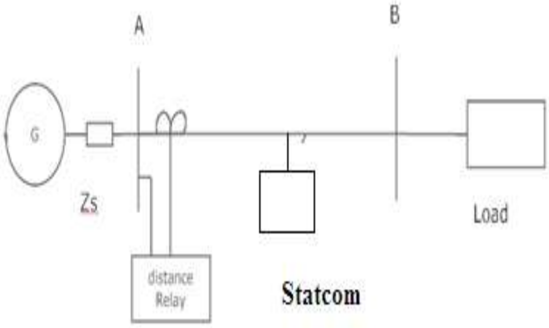

Fig.2. Transmission Line Single Line Mode

Various faults are simulated on that line by varying various parameters. Ratings of power system model are shown in Table I. As shown in Fig.2 a transmission line model is prepared in MATLAB7.10. The transmission line positive and zero sequence parameters are R1=0.10809Ω/km, R0=0.2188Ω/km, L1=0.00092H/km, L0=0.0032H/km, C1=1.25*10^{-8} f/km,0=7.85*10^{-9} f/km. The distributed parameter model of transmission line is considered for analysis. The current signals are sampled at sampling frequency of 20 kHz.

Table I . Model Parameters

1.	Generator	500MVA, 13.8kv, 50Hz, synchronous generator pu model
2.	Transformer1	13.8kv/220kv, 500MVA.
3.	Transfomer2	220kv/13.8kv, 500MVA.
4.	Load1	50MW, 220kv, 1Mvar, RL load.
5.	Load2	150MW, 220kv, , 1MVar, RL load
6	Load3	100MW, 220kv, , 1MVar, RL load
7	Transmission line	Length=90 km.

V. DESIGN OF FAULT DETECTION, CLASSIFICATION AND LOCATION

The design process of proposed fault detection, classification and location approach is as above. Combination of different fault conditions are to be considered and training patterns are required to be generated by simulating different kinds of faults on the power system. The fault resistance, fault location, and fault type are changed to generate different training patterns.

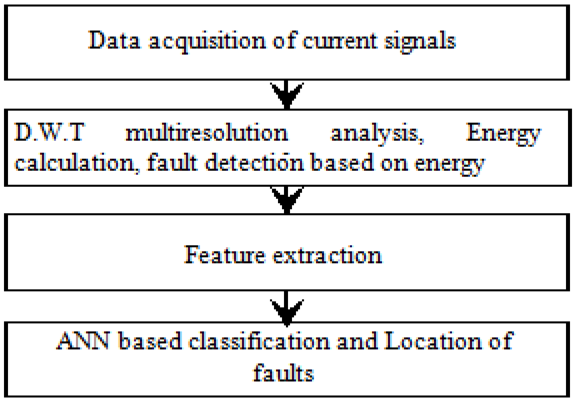

Fig.3. Process Of Fault Detection, Classification And Location.

VI. FAULT DETECTION

The signals taken from the scope are filtered, sampled at 20 kHz sampling frequency. Then DWT is applied up to level 5, and detail coefficients and approximate coefficients are calculated and detail coefficients energy is calculated. Then, we come to know that detail level 5 contains highest amount of energy than the level 4 [11], [12]. A moving data window of one cycle (400 samples) is taken and decomposition is done and energy of the details coefficients at level 5 is obtained for each data window. As the fault signals contain the high amount of harmonic components, the energy of the signal increases at the occurrence of fault as shown in Fig.4 Here, for detecting the fault, difference of energies between two adjacent windows has been considered. The energy of detail coefficients for a k^{th} window is given by equation (1),

$$E_d = \sum_{i=1}^{N} D_l^2(i) \qquad (1)$$

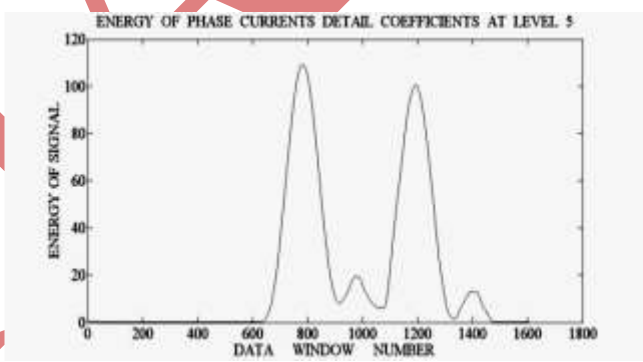

Fig. 4.Energy Of The Detail Level 5 Vs. Window Number

Where, k=window number, l=level of the DWT, N=length of Detail coefficients at level l. For accurately detecting the presence of faults, the difference between the two consecutive energies of the moving windows is calculated by (2) and shown in Fig.5.

$$F.D(k) = F.D(k-1) + [E_d(k) - E_d(k-400)] \qquad (2)$$

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In this sampling frequency of 20 kHz gives 400 samples for each cycle of 20ms. Here, moving window slides taking only1 new sample at each move and keeping 399 previous samples. So one cycle corresponds to nearly 400 data samples.

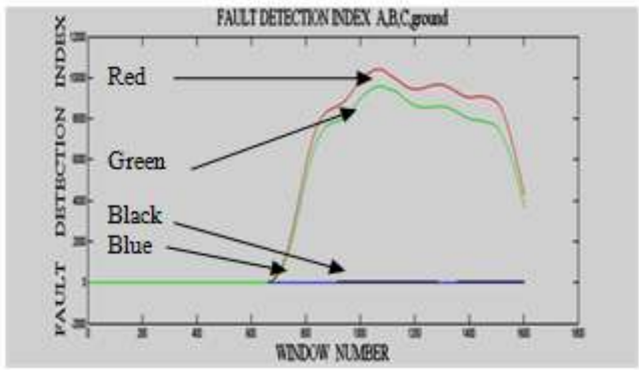

Fig. 5.F.D Index For Single Line To Ground Fault Vs. Window Number

The fault is present on R-phase and ground (G) for the present case. Red colour shows the R phase, green colour shows the ground (G) phase, black colour represents the Y phase and blue colour shows the B phase.The Fault Detection value is compared with threshold value for consecutive 10 data windows, and then decision is made whether fault is permanent or temporary. By using these Fault Detection values the faults can be accurately detected [7].

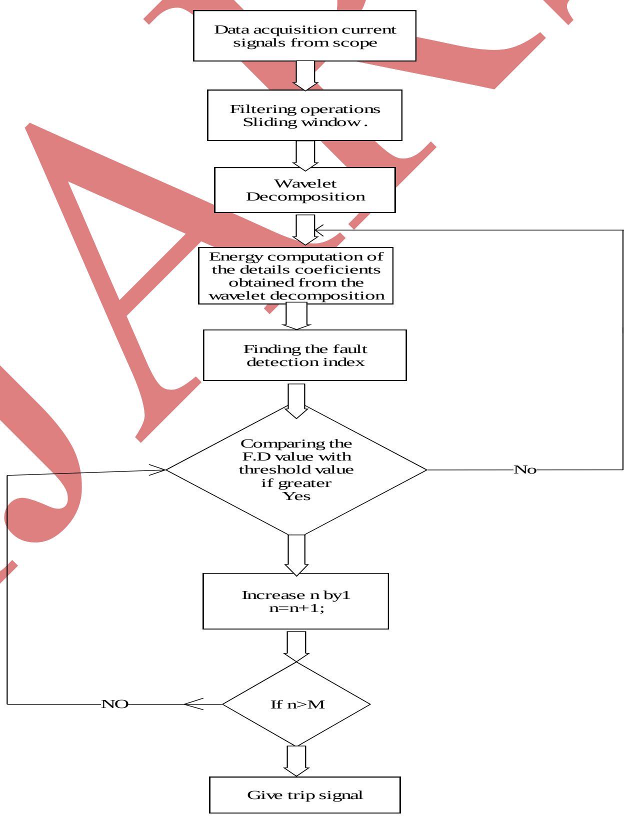

Fig. 6. Flow Chart Of Proposed Algorithm.

Fig. 6 Shows The Flow Chart Of Algorithm Of The Distance Relay For The Proposed Scheme. The Voltage And Current Phasors Are Estimated Using Discrete Wavelet Transform (DWT) At The Relaying Bus And At The

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Terminal Of The Compensator. The Estimated Voltage And Current Phasors Of The Compensated Terminal Is Communicated At The Relaying Bus Using Fast Data Communication Link Like Fiber Optics, Etc. The Apparent Impedance Zappnew Is Then Calculated And Compared With The Relay Setting Zset For The Zones Of Protection Of The Transmission Line. If The Measured Impedance Is Less Than Or Equal To The Zset Value Then The Uncompensated Line Algorithm Is Running While Measured Impedance Is Greater Than Set Value Then Compensated Line Algorithm Is Running .

VII. NEURAL NETWORK BASED FAULT CLASSIFICATION

All different faults are simulated for different conditions and training patterns are generated from the energy values of the detail coefficients. The 4 input neurons and 4 output neurons are selected. Feed forward multilayer back propagation neural network is selected. The average values of energies of current signals, half cycle after the occurrence of fault are given as input to the neural network, along with the three lines energies, zero sequence current energy is also given as fourth input to the neural network. Three outputs show the statuses of the three phases, if fault is present it is shown by the presence of '1', otherwise with presence of '0'. Similarly fourth output indicates the ground fault. If ground is involved in the fault will be indicated by the presence of '1', otherwise it is presented by '0'. Generation of different training patterns is done as shown in Table II.

Table II. Training Patterns

Type of fault	LG, LLG, LL, LLL.
Location of fault (%) from busbar P.	20,30,40,50,60,70,80
Fault resistance	5,10,15,20 Ω.

For training neural network different fault conditions are simulated, features are extracted and network is trained. At 7 different locations on the transmission line fault is created, at 20, 30, 40, 50, 60, 70, 80% of the transmission line length from the sending end, 4 different values of fault resistances can be used and total 10 different faults are created, and this gives 7*4*10=280 cases for training neural network.

The different training algorithms are presented to train the neural network; they use the gradient of the performance function to determine how to adjust the weights to minimize a performance function. The gradient is determined using back propagation technique, which involves performing computations backwards through the network. A variation of back propagation algorithm called Levenberg-Marquardt (LM) algorithm was used for neural network training, since it is one of the fastest methods for training moderate-sized feed forward neural networks [15].

LM algorithm to weight update is given by (3),

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} * J^T * e \qquad (3)$$

Where J is Jacobean matrix that contains first derivatives of the network error with respect to the weights and biases, e is a vector of network errors. $J^T J$ is an approximation of the Hessian Matrix, $J^T e$ is the gradient and μ is the scalar affecting performance function. LM algorithm based method for training neural network is much faster than the other methods. Fig.7 shows the Multilayered Feed forward Neural Network (M.F.N.N.)

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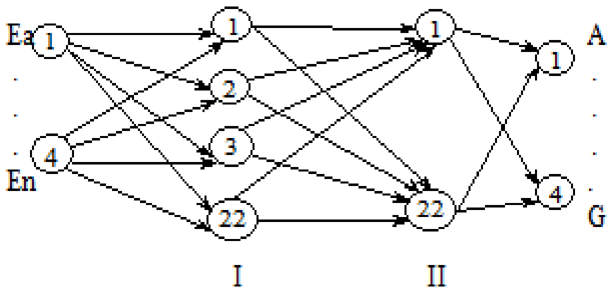

Fig.7. Multilayer Feed Forward Network For Fault Classification

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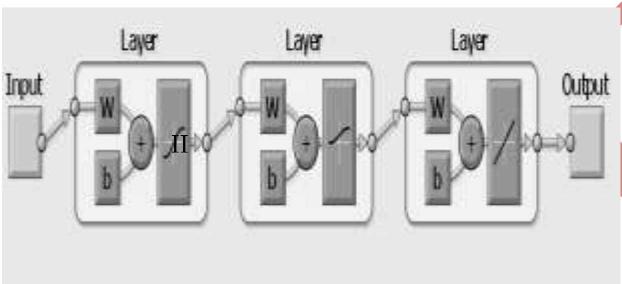

Fig.8. 4-22-22-4 'Tansig', 'Logsig', 'Purelin' Configuration.

Network with 2 hidden layers worked out to be better than the 1 hidden layer network.4-22-22-4 configuration give better results than the 4-22-4, 4-10-4 configurations. Activation functions used for the hidden layers I, II and output layer are 'tansig', 'logsig' and 'purelin' respectively. The Fig.8 shows the neural network.

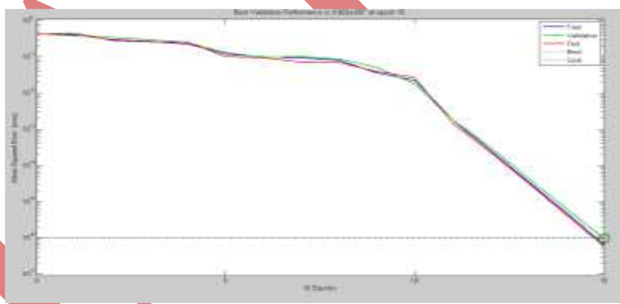

Fig.9. Performance Curve

The data used for training data division is done randomly; training function used is LM algorithm. Performance function used is Mean least square error method. The performance goal chosen is10^{-6} . Fig.9 shows the performance curve.

VIII. TEST RESULTS

A validation data set consisting of different fault types was generated using the transmission line model shown in Fig.2. The validation test patterns were different than they were used for the training of the neural network .For different faults on the model system, fault type; fault location and fault resistance values are changed to investigate the effects of these factors on the performance of the proposed algorithm. Test results are as shown in

Table III. These results show the accuracy of neural network for varying fault location values and varying fault resistance value.

The output layer activation function used is 'Purelin', because of its success in the classification of faults correctly. The tansig and logsig transfer functions did not show a good classification capability. The output layer transfer function is fixed at 'Purelin' and the hidden layer transfer function was changed.

If the transfer functions of the hidden layers I and II are chosen as 1) Tansig-Tansig. 2) Logsig-Logsig. 3) Tansig-Logsig, the Table IV test result shows that the accuracy obtained with the Tansig-Logsig type of neural network is more and it is having good generalization capability. The classification results for almost all types of faults are satisfactory.

Table III. Testing Results

Fault type	Fault location from P(%)	Fault resistance Ω.	Output of neurons			
			A	B	C	G
AG	30%	10	1.0001	2*10^-3	4*10^-3	1.00
BCG	50%	15	0	1.00	0.9989	1.00
CAG	50%	10	1	0	1.00	0.998
CG	50%	10	1*10^-3	0.000	1.00	1.00
ABC	30%	10	1.00	1.00	0.999	0.00
ACG	70%	5	0.9996	-3*10^-4	0.997	1.000
AB	70%	5	1.018	1.0847	0.1587	0.052

Table IV. Comparison Of Transfer Functions

Transfer Functions for hidden layers. No. neurons in hidden layers.	Tansig-tansig. 22-22	Logsig-logsig. 22-22	Tansig-logsig. 22-22.
Performance error of test results	2.9*10^(-7)	5.5*10^(-7)	5.39*10^ (-8).

IX. ANN BASED FAULT DISTANCE LOCATOR

In this paper single line to Ground fault locator explains in detail.

Single Line to Ground Faults Locator

9.1. Selecting The Right Architecture

The network inputs chosen here are the magnitudes of the detail coefficients energies fundamental components (50 Hz) of phase voltages and currents measured at the relay location. As the basic task of fault location is to determine the distance to the fault, the distance to the fault, in km with regard to the total length of the line, should be the only output provided by the fault location network. Thus the input and the output for the fault location network are:

Input = different combinations of □ Va2, Vb2, Vc2, Ia2, Ib2, Ic2 and IG as per faults. (1)

Output Lf = Fault distance in KM. (2)

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For each type of fault separate neural network is prepared for finding out the fault location. Through a series of trial and error, and modifications of the ANN architecture, the best performance is achieved by using a four layer neural network with 3 inputs and 1 output as shown in Fig. 10. After analysing the various possible combinations of transfer functions normally used, such as logsig, tansig and linear functions, the tansig function was chosen as transfer function for the hidden layer, and pure linear function "purelin" in the output layer.

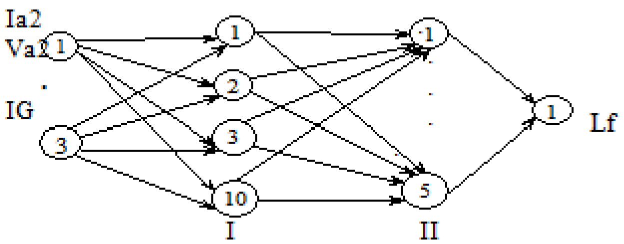

Fig.10 Structure Of The Chosen Ann With Configuration For Lg Fault

9.2. Learning Rule Selection

The back-propagation learning rule can be used to adjust the weights and biases of networks to minimize the sum-squared error of the network. The simple back-propagation method is slow because it requires small learning rates for stable learning, improvement techniques such as momentum and adaptive learning rate or an alternative method to gradient descent, Levenberg–Marquardt optimisation, can be used. Various techniques were applied to the different network architectures, and it was concluded that the most suitable training method for the architecture selected was based on the Levenberg–Marquardt (Trainlm) optimization technique.

9.3. Training Process

Using SIMULINK & SIMPOWERSYSTEM toolbox of MATLAB all the ten types of fault at different fault locations between 0-100% of line length and different fault resistance have been simulated as shown below in Table V. Feed forward back-propagation network have been surveyed for the purpose of single line-ground fault location, mainly because of the availability of the sufficient relevant data for training. In order to train the neural network, several single phase faults have been simulated on transmission line model. For each of the three phases, faults have been simulated at every 10 km on a 90 km transmission line. Total of 648 cases have been simulated with different fault resistances 1, 2, 3 ohms respectively. In each of these cases, the current and voltage signals detail coefficients energies of only phase involving in the fault and ground phase current signals given as input to the neural network such as Ia2, Ib2, Ic2,Va2 ,Vb2, Vc2 and IG. The output of the neural network is the distance to the fault from the sending end of the transmission line. The ANN based fault distance locator was trained using Levenberg–Marquardt training algorithm using neural network toolbox of Matlab as shown in Fig. 11

Table V. Training Patterns Generation

Sr. No.	Parameter	Set value
1	Fault type	LG: AG-Ia2, Va2, IG BG- Ib2, Vb2, IG CG -Ic2, Vc2, IG LL: AB- Ia2, Va2, Ib2, Vb2, LLG: ABG -Ia2, Va2, Ib2, Vb2, IG

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		LLL: ABC- Ia2, Va2, Ib2, Vb2, Ic2, Vc2 LLLG:ABCG- Ia2, Va2, Ib2, Vb2, Ic2, Vc2, IG
2	Fault location (Lf in KM)	10, 20, 30, …80 and 90 km
3	Fault resistance (Rf)	1, 2, 3 ohm

Once the network is trained sufficiently and suitably with large training data sets, the network gives the correct output after one cycle from the inception of fault.

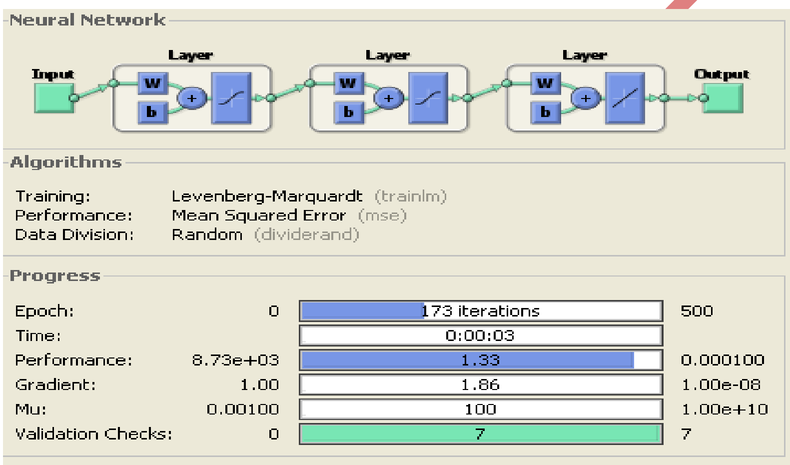

Fig. 11 Overview Of The Chosen Ann (3-10-5-1).

Fig. 11 plots the mean square error as a function of time during the learning process and it can be seen that the achieved MSE is about 2.61.

9.4 Test Result Of Ann Based Fault Distance Locator

Once training was completed, ANN based Fault distance locator was then extensively tested using independent data sets consisting of fault scenarios never used previously in training. For different faults of the validation/test data set, fault type, fault location, and fault resistance were changed to investigate the effects of these factors on the performance of the proposed algorithm. The network was tested and performance was validated by presenting all the ten types of fault cases with varying fault locations (Lf=0-90KM), fault resistances (Rf=1,2,3 etc) Table VI shows some of the test results of ANN based fault locator under different fault conditions. It can be seen that all results are correct with reasonable accuracy. At various locations different types of LG faults were tested to find out the maximum deviation of the estimated distance Lf measured from the relay location, from the actual fault location. Table VI. Percentage errors as a function of fault distance and fault resistance for the ANN chosen for single phase fault location.

Table VI. Result

Fault Distance (Km)		Measured Fault Location (Km)		Percentage Error (%)	
RF=1Ω	RF=4Ω	RF=1Ω	RF=4Ω	RF=1Ω	RF=4Ω
9	9	8.5	8	0.55	1.1

18	18	16	15.5	2	2.7
54	54	52	51	2.22	3
63	63	62	60	1	3.33
72	72	70.5	71	1.6	1.6

Then the resulted estimated error “e” is expressed as a percentage of total line length L In all the fault cases, the results have shown that the errors in locating the fault are less than 0.55% to +3.33%.

Table VI can show the percentage errors in fault location as a function of Fault Distance and Fault resistance. Different cases are shown with different fault resistances. Thus, the neural network performance is considered satisfactory and can be used for the purpose of single line- ground fault location.

X. CONCLUSION

In this paper accurate fault detection, classification and location technique is discussed. This technique depends upon the current and voltage signals. The features are extracted from the current and voltage signals by using wavelet transform. The feature vector is then given as input to the neural network. The capabilities of neural network in pattern classification were utilized. Simulation studies were performed and the performance of the scheme with different system parameters and conditions was investigated. The test result shows that the accuracy obtained for fault classification with the “tansig-logsig” transfer function for hidden layers I and II is satisfactory. For fault location after analysing the various possible combinations of transfer functions normally used, such as logsig, tansig and linear functions, the tansig function was chosen as transfer function for the hidden layer I and II, and pure linear function “Purelin” in the output layer gives satisfactory results.

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