The Journal of CPRI,
Vol. 10, No. 3, September 2014 pp. 441-452

Development of adaptive distance relay for STATCOM connected 220 kv transmission line with wavelet transform and ANN

Ramchandra P Hasabe* and Anil P Vaidya**

A new scheme to enhance the solution of the problems associated with Transmission line protection with Statcom connected is presented in this paper. Static Synchronous Compensator (STATCOM) is a shunt type FACTS device connected at the midpoint of the transmission line to maintain the voltage at desired level by injecting/absorbing the reactive power. This connection affects the performance of distance protection relay during line faults. 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 distance location for all the types of faults for 220 kv transmission line. 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: *Fault detection, fault classification, wavelet Transform, statcom.*

1.0 INTRODUCTION

Protection of transmission lines is one of the important tasks to safeguard electric power systems. The STATCOM is ashunt-connected reactive-power compensation device that is capable of generating or absorbing reactive power. The placement of the STATCOM device depends on the application for which it is installed. Particularly to meet the purpose of increasing the power transfer capability of long transmission lines, the midpoint sitting is the best location for shunt connected STATCOM. This is simply because,with the inclusion of FACTS controllers, transmission systems undergo rapid variations in line impedance, power angle,load currents, and also the transients introduced at the fault occurrence. [1] Therefore, it is essential to study the effect of FACTS devices on the performance of the distance relay,which is used as the main protective gear for long distance power transmission lines.

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 [2], [3]. Neural networks are used for different applications as classification, pattern recognition etc. 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

* Electrical Engineering Department,Walchand College of EngineeringSangli, Maharashtra, India. Email : rphasabe@yahoo.co.in
** Electrical Engineering Department, Walchand College of Engineering Sangli, Maharashtra, India. India. Email : anil.vaidya@walchandsangli.ac.in

listed as [6]–[10]. Takagi et al. [6] use current and voltage phasors from one terminal for their method based on reactive power. Girgis et al. [7], Abe et al. [8], Jianget al. [9] and Gopalakrishnan et al. [10] use voltage and current phasors from both ends.

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 scheme is propose for 220 kv Statcom connected transmission line for fast and reliable fault detection using energy of the detail coefficients of the phase signals, and location using 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.

2.0 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.

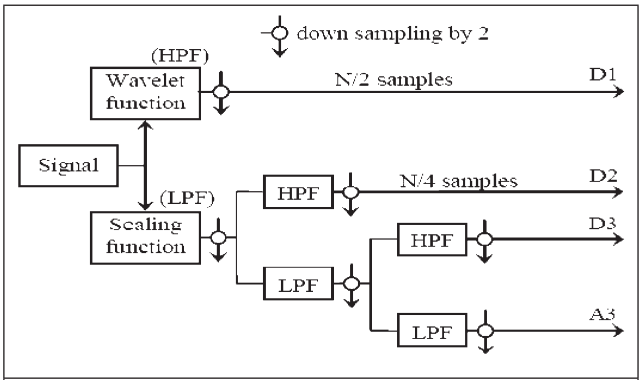

FIG. 1 WAVELET FILTER BANK

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. The signal of desired frequency component can be obtained from repetitive decompositions as shown in Figure 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].

3.0 ARTIFICIAL NEURAL NETWORKS

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 multi layered 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 multi layered feed forward network has been chosen to process the prepared input data obtained from the W.T [15-16].

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

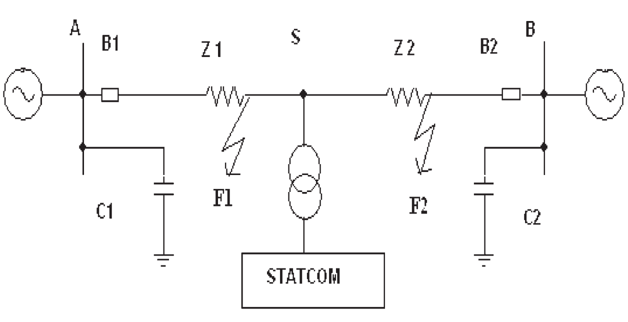

FIG. 2 SINGLE LINE TRANSMISSION MODEL

The system under consideration is 220 KV Karad to Miraj transmission line. The transmission line is 90 Km lone. The detail parameters of transmission line are as follows.

TABLE 1

MODEL PARAMETERS

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

Voltage Rating: - 220 KV, System frequency: - 50 Hz, Length of Transmission Line:- 90 km. Line Constants are used as per conductor data. e.g. Zebra, Dear, ACSR conductor. For Deer conductor positive and zero sequence parameters are R_1 = 0.07973 Ω/Km, L_1 =1.27e-3 H/Km, C_1 = 0.012 e-6 F/Km, R_0 =0.22826 Ω/Km, L_0 =3.91e-3 H/Km, C_0= 0.0083 e-6 F/Km. The current transformer ratio is 800/1 A and the Voltage transformer ratio is 220 kV/110V.

Various faults are simulated on that line by varying various parameters. Ratings of power system model are shown in Table 1. As shown in Figure 2 a transmission line model is prepared in MATLAB 7.10. The distributed parameter model of transmission line is considered for analysis. The current signals are sampled at sampling frequency of 20 kHz.

4.0 DESIGN OF FAULT DETECTION AND LOCATION

The design process of proposed fault detection, classification and location approach is as shown in Figure 3. 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.

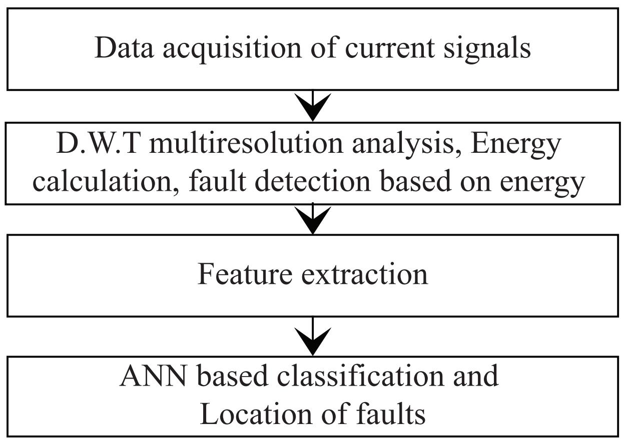

FIG. 3 PROCESS OF FAULT DETECTION, CLASSIFICATION AND LOCATION

5.0 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 the 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. 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 Figure 4 Here, for detecting the fault, difference of energies between two adjacent windows has been considered. The energy of detail coefficients for ak^th window is given by equation (1),

$$E_d = \sum_{i=1}^{N} D_l^2(i) \quad \text{....(1)}$$

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 Figure 5.

$$F.D(k) = F.D(k-1) + [E_d(k) - E_d(k-400)] \quad \text{....(2)}$$

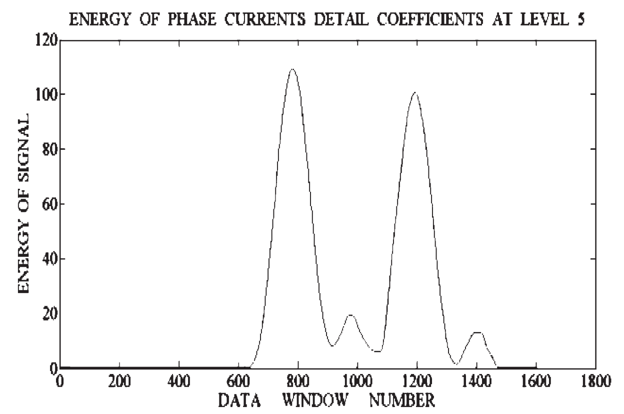

FIG. 4 ENERGY OF THE DETAIL LEVEL 5 VS. WINDOW NUMBER

In this sampling frequency of 20 kHz gives 400 samples for each cycle of 20 ms. Here, moving window slides taking only 1 new sample at each move and keeping 399 previous samples. So one cycle corresponds to nearly 400 data samples.

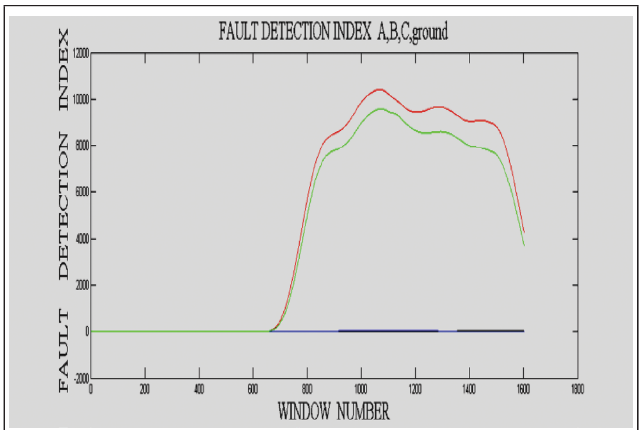

FIG. 5 F.D INDEX FOR SINGLE LINE TO GROUND FAULT VS. WINDOW NUMBER

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].

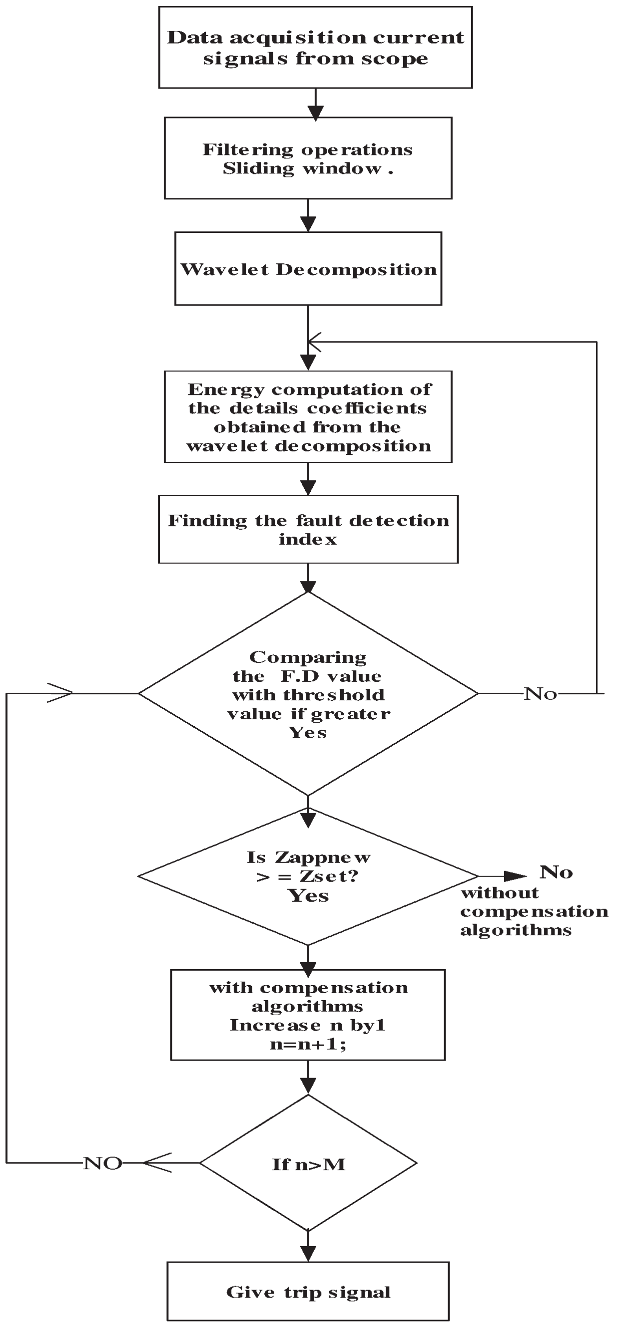

FIG. 6 FLOW CHART OF PROPOSED ALGORITHM

Figure 6 shows the flow chart of algorithm for the proposed distance relay scheme. The voltage and current phasors are estimated using Discrete wavelet Transform (DWT) at the relaying bus and at the 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 Z appnew is then calculated and compared with the relay setting Z set for the zones of protection of the transmission line. If the measured impedance is less than or equal to the Z set value then the uncompensated line algorithm is running while measured impedance is greater than set value then compensated line algorithm is running .

6.0 DEVELOPMENT OF ADAPTIVE DISTANCE PROTECTION SCHEME

The relay will under reach in the presence of STATCOM only for the faults occurring beyond the midpoint of the line. This is shown with the help of simulation in the next section. In this section an adaptive scheme is developed to mitigate the under reaching effect. Equivalent circuit diagram of the power system for faults appearing beyond 50% of the line from relay location can be as shown in the Figure 7.

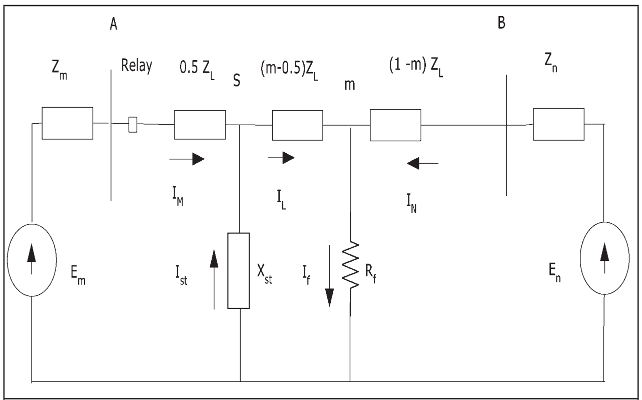

FIG. 7 EQUIVALENT NETWORK OF FAULT AFTER STATCOM

The measured impedance at the relay point before STATCOM is:

$$Z_{Mrelay} = V_M / I_M = m\,Z_L + R_f\,(I_f / I_M) \quad ....(3)$$

Obtained from Figure 7, the voltage at the relay point is:

$$V_M = 0.5 Z_L I_M + (m-0.5) Z_L I_L + I_f R_f \quad ....(4)$$

According the relationship of those current, getting:

$$I_L = I_M + I_{st}$$
$$I_f = I_M + I_N + I_{st} \quad ....(5)$$

Using equation (5) in equation (4), getting:

$$V_M = m\,Z_L\,I_M + (m - 0.5)\,Z_L\,I_{st} + I_f\,R_f \quad ....(6)$$

Then, the measured impedance at the relay point is:

$$Z_{relay} = V_M / I_M = m\,Z_L + (m - 0.5) Z_L\,(I_{st} / I_M) + R_f\,(I_f / I_M) \quad ....(7)$$

Examining equation (3) and equation (7), we can see that apart from the additional impedance generated from the fault resistance, there is additional impedance generated from STATCOM. This additional impedance is

$$Z_{error} = (m - 0.5)\,Z_L\,(I_{st} / I_M) \quad ....(8)$$

The term in equation (8) represent the error in the measurement of the apparent impedance due to the shunt FACTS device. The error (Zerror) due to the shunt-FACTS is proportional to the fault location (m) and the ratio of the current in the shunt FACTS device and the relay. The positive value of this current ratio, as a result of current injection by the FACTS device, would lead to higher impedance seen by the relay, which would result in relay under-reach. As a result, the STATCOM is expected to introduce a larger under-reaching effect. On the other hand, the negative value of the current ratio would result in relay seeing fault at a closer location than the actual fault location and hence would lead to an over-reaching effect. This would occur if the shunt-FACTS absorbed the reactive current instead of injecting current.

For solid line to ground faults Rf=0, substituting this in equation (7) and after rearranging the terms, equation for computation of actual fault impedance can be written as

$$mZL = \frac{Zrelay + 0.5\, ZL\, I_{RATIO}}{1 + Iratio} \qquad ....(9)$$

Where, I ratio = IST/IM is called the current ratio factor.

The current ratio factor (I ratio) can be calculated by using equations (10) and (11), for phase to ground and phase to phase mho relay units respectively.

For R phase to ground fault

$$(I_{ratio})_{\{PhaseR\}} = \frac{Ist\{phase\ R\} - Ist(0)}{I\{phase\ R\} + KIo} \qquad ....(10)$$

For R phase to Y phase fault

$$(I_{ratio})_{\{PhaseR\}} = \frac{Ist\{phase\ R\} - Ist(0)}{I\{phase\ R\} + KIo} \qquad ....(11)$$

Similarly I ratio for other faults are calculated. where

k = Zero sequence compensation factor of transmission line

Ist (phase R) = STATCOM phase R current

I (phase R) = Phase R current at relay location

I0 = Zero sequence current at relay location

Ist (0) = STATCOM zero sequence current

The relay will automatically adapt equations (10) & (11) for apparent impedance calculation as soon as the distance measured by the conventional distance relay exceeds 50% of the total line impedance.

6.1 Shunt compensator is not in fault loop:

Consider the fault at point 'F1' (refer Figure 2) wherein compensator is not in the fault loop. Figure 8 shows the impedance trajectories of a-phase for SLG fault on a-phase at 25 % of line length with fault resistance 0.01 ohm. Extensive case studies have been carried out and it is observed that, when compensator is not in the fault loop, the operating points are very close to each other for uncompensated line, compensated line and compensated line with correction. Similar observations are confirmed with capacitive compensation.

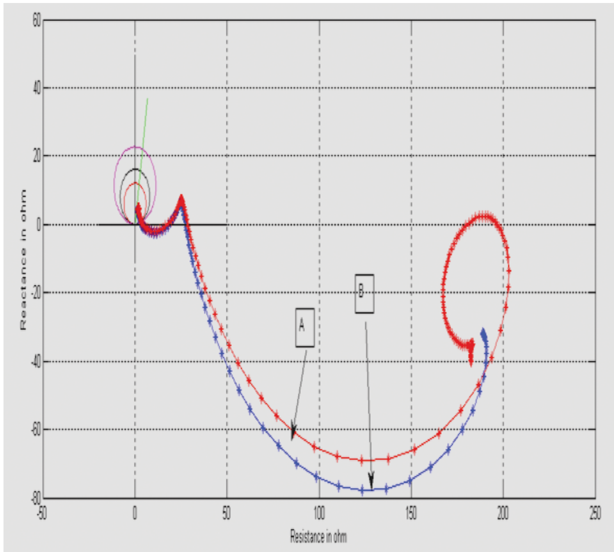

FIG. 8 IMPEDANCE TRAJECTORIES OF A-PHASE FOR SLG FAULT ON A-PHASE AT 25 % OF LINE LENGTH WITH FAULT RESISTANCE 0.01 OHM (A) COMPENSATED LINE, (B) UNCOMPENSATED LINE

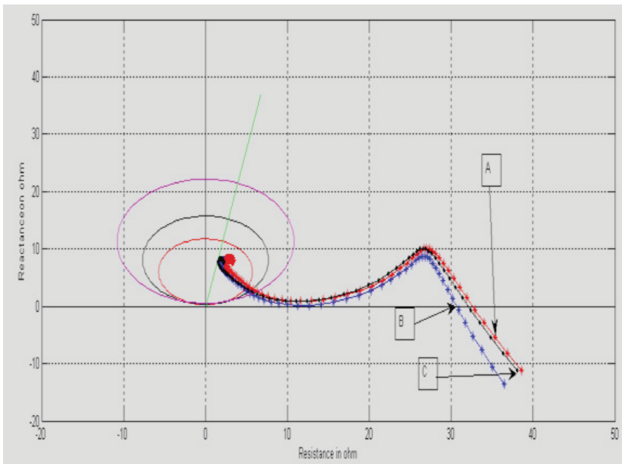

FIG. 9 IMPEDANCE TRAJECTORIES OF A-PHASE FOR SLG FAULT ON A-PHASE AT 30 % OF LINE LENGTH WITH FAULT RESISTANCE 0.01 OHM(A)COMPENSATED LINE, (B) UNCOMPENSATED LINE (C) COMPENSATED LINE WITH PROPOSED SCHEME

Figure 9 shows the impedance trajectories of a-phase for SLG fault on a-phase at 30 % of line length with fault resistance 0.01 ohm with proposed scheme

6.2 Shunt compensator is in fault loop:

Consider the fault at point 'F2' (refer Figure 2) wherein the compensator is in the fault loop. Figure 10 shows the impedance trajectories of a-phase for SLG fault on a-phase at more than 120 % of line length with fault resistance 0.01 ohm. Figure 11 shows the impedance trajectories of phase-a for SLG fault on a-phase at more than 90 % of line length with 0.01 ohm fault resistance. The compensation is adjusted (inductive) and relay is set to 90 %. It can be observed from Figure 10, that even the fault is in the zone of protection, the conventional distance relay locates the fault out of the zone of protection and hence mal-operates in the form of under reaching the fault point. But with the proposed algorithm the relay does not mal-operates even though the shunt compensator is present in the fault loop. Similar observations are confirmed for non-zero fault resistance shown in Figure 10. When shunt compensator is present in the fault loop and supplying inductive compensation, the measured impedance deviates from actual value. The inductive compensation has more impact on the measured reactance while it has less impact on the measured resistance which is observed.

The proposed scheme measures impedance very accurately and the effect due to the inductive shunt impedance on the measured reactance and resistance is corrected very accurately.

It is observed that when fault resistance is not zero the operational condition of power system and compensation both affect the measured impedance. The operational condition has great effect on the measured resistance while compensation has great impact on measured reactance. But with the proposed scheme both the effects are nullified very accurately and very accurate results are obtained.

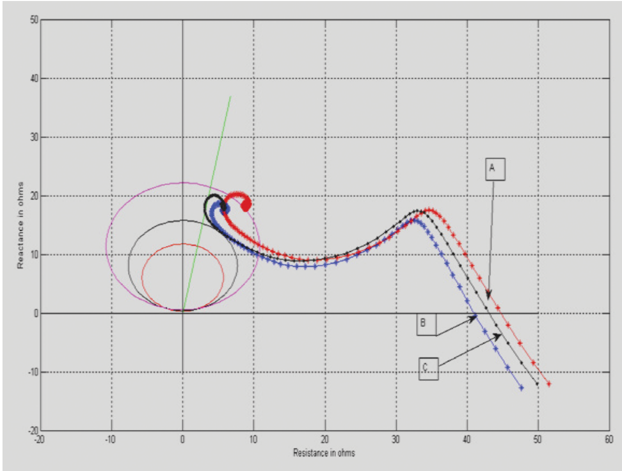

FIG. 10 IMPEDANCE TRAJECTORY FOR L-G FAULT AT 120 % OF LINE WITH 0.01 OHM FAULT RESISTANCE AND
(A) COMPENSATED LINE,
(B) UNCOMPENSATED LINE,
(C) COMPENSATED LINE WITH PROPOSED SCHEME

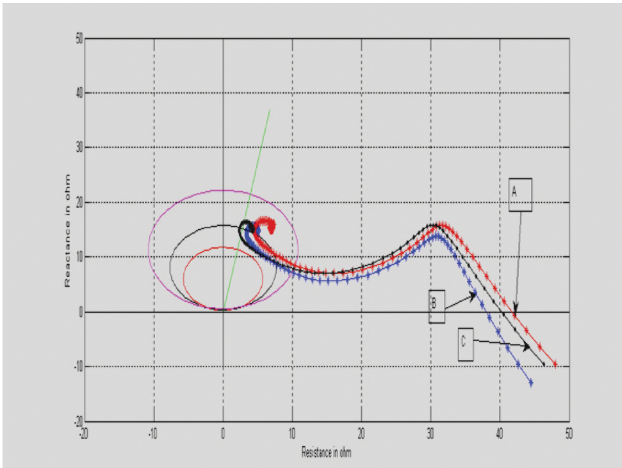

FIG. 11 IMPEDANCE TRAJECTORY FOR L-G FAULTS AT MORE THAN 90 % OF LINE WITH 0.01 OHM FAULT RESISTANCE
(A) COMPENSATED LINE,
(B) UNCOMPENSATED LINE,
(C) COMPENSATED LINE WITH PROPOSED SCHEME

7.0 ANN BASED FAULT DISTANCE LOCATOR

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

7.1 Selecting the right architecture

One factor in determining the right size and structure for the network is the number of inputs and outputs that it must have. However, sufficient input data to characterize the problem must be ensured. The network inputs chosen here are the magnitudes of the detail coefficients energies fundamental components (50 Hz) of phase voltages and currents measured (AG-Ia_2, Va_2, IG) 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 V_{a2}, V_{b2}, V_{c2}, I_{a2}, I_{b2}, I_{c2} and I_G as per faults. (i)

Output Lf = Fault distance in KM. (ii)

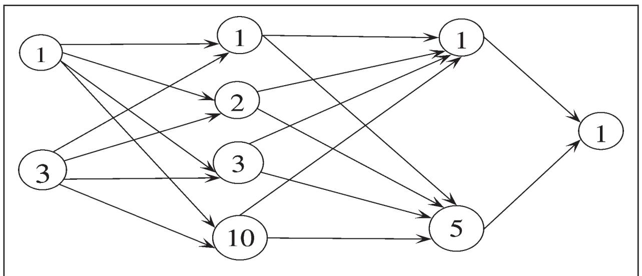

FIG. 12 STRUCTURE OF THE CHOSEN ANN WITH CONFIGURATION FOR LG FAULT

For each type of fault separate neural network is prepared for finding out the fault location. The ANN architecture, including the number of inputs to the network and the number of neurons in hidden layers, is determined empirically by experimenting with various network configurations. 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 Figure 12. The final determination of the neural network requires the relevant transfer functions in the layers to be established. After analysing the various possible combinations of transfer functions normally used, such as log sig, tan sig and linear functions, the tan sig function was chosen as transfer function for the hidden layer, and pure linear function "purelin" in the output layer.

7.2 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.

7.3 Training process

To train the network, a suitable number of representative examples of the relevant phenomenon must be selected so that the network can learn the fundamental characteristics of the problem and, once training is completed, provide correct outputs in new situations not used during training. To obtain enough examples to train the network, a software package MATLAB® 7.10 is used. All the ten types of fault at different fault locations between 0-100% ofline length and different fault resistance have been simulated as shown in Table 2. 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 I_{a2}, I_{b2}, I_{c2},

V_{a2}, V_{b2}, V_{c2} 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 Figure 13.

TABLE 2

TRAINING PATTERNS GENERATION

Sr. No.	Parameter	Set value
1	Fault type	LG:A_G-I_{a2}, V_{a2}, IGBG-I_{b2}, V_{b2}, I_G CG-I_{c2}, V_{c2}, I_G LL: AB- I_{a2}, V_{a2}, I_{b2}, V_{b2}, LLG:ABG -I_{a2}, V_{a2}, I_{b2}, V_{b2}, IG LLL: ABC- I_{a2}, V_{a2}, I_{b2}, V_{b2}, I_c2, V_{c2} LLLG:ABCG-I_{a2}, V_{a2}, I_{b2}, V_{b2}, I_{c2}, V_{c2}, I_G
2	Fault (Lf in KM) location	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.

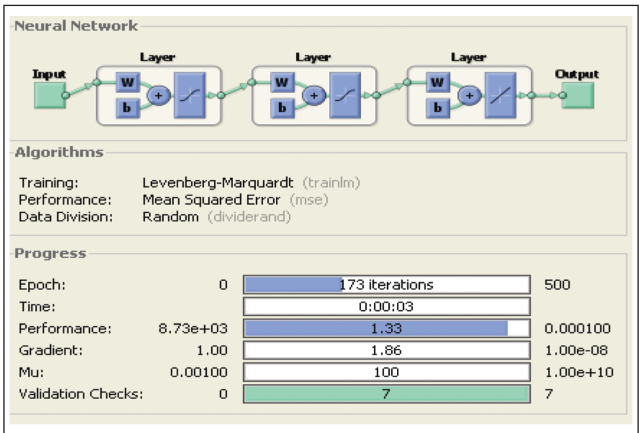

FIG. 13 OVERVIEW OF THE CHOSEN ANN (3-10-5-1)

Figure 14 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.

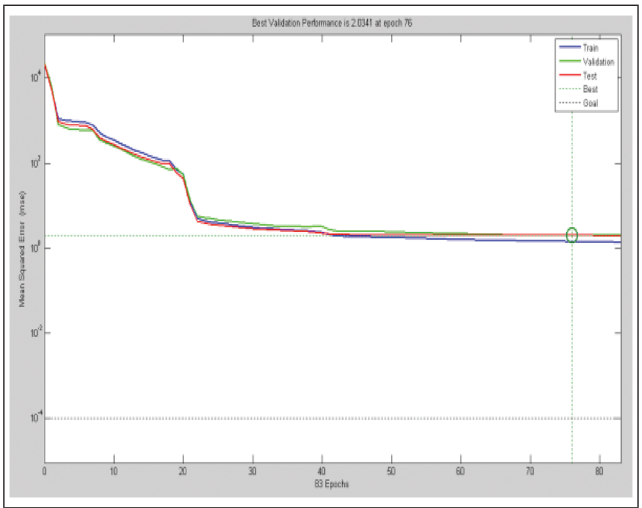

FIG. 14 MSE PERFORMANCE OF THE NETWORK WITH CONFIGURATION(3-10-5-1)

7.4 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 (L_f=0-90KM), fault resistances (R_f=1,2,3 etc)

Table 3 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 La.

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 1.11% to +6%.

TABLE 3. Percentage errors as a function of fault distance and fault resistance for the ANN chosen for single phase fault location.

TABLE 3

Fault Distance (Km)		Measured Fault Location (Km)		Percentage Error (%)	
RF=1Ω	RF=4Ω	RF=1Ω	RF=4Ω	RF=1Ω	RF=4Ω
9	9	8	7.3	1.11	1.8
18	18	15	15.5	3	2.7
54	54	52	51	2.22	3
63	63	60	57	3	6
72	72	70.5	70	1.6	2

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.

8.0 CONCLUSION

In this paper accurate fault detection, 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.

REFERENCES

[1] Albasri F A, Sidhu T S, Varma R K, "Mitigation of Adverse Effects of Midpoint Shunt- FACTS Compensated Transmission Lines on Distance Protection Schemes," Power Engineering Society General Meeting Rep. pp 1-8, 2007

[2] K Gayathri and N Kumarapan, "Comparative Study of Fault Identification and Classification on EHV Lines Using Discrete Wavelet Transform and Fourier Transform Based ANN", World Academy of Science, Engineering and Technology, pp.822-831.2008.

[3] D V Coury, D C Jorge,"Artificial Neural Network Approach To Distance Protection Of Transmission Lines." IEEE Transactions on Power Delivery, Vol. 13, No. 1, January 1998.

[4] H Khorashadi-Zadeh, M R Aghaebrahimi, "A Novel Approach to Fault Classification and Fault Location for Medium Voltage Cables Based on Artificial Neural Network", World Academy of Science, Engineering and Technology, pp.1100-1103.2008.

[5] V S Kale, S R Bhide, P P Bedekar, "Faulted Phase Selection on Double circuit Transmission Line using Wavelet Transform and Neural Network",Third International Conference On Power Systems, Kharagpur, INDIA.

[6] A Abdollahi, S Seyedtabaii, "Comparison of Fourier & Wavelet Transform Methods for Transmission Line Fault Classification", The 4th International Power Engineering and Optimization Conf. (PEOC2010), Shah Alam, Selangor, MALAYSIA: 23-24 June 2010.

[7] K Takagi, Y Yomakoshi, M Yamaura, R Kondow, and T Matsushima, "Development of a new type fault locator using the one terminal voltage and current data," IEEE Trans. Power App. Syst., vol. PAS-101, pp. 2892–2898, Aug. 1982.

[8] A Girgis, D Hart, and W Peterson, "A new fault location technique for two- and three-terminal lines," IEEE Trans. Power Delivery, vol. 7, pp. 98–107, Jan. 1992.

[9] M Abe, T Emura, N Otsuzuki, and M Takeuchi, "Development of anew fault location system for multi-terminal single transmission lines,"IEEE Trans. Power Delivery, vol. 10, pp. 159–168, Jan. 1995.

[10] J A Jiang, J Z Yang, Y H. Lin, C W. Liu, and J C Ma, "An adaptive PMU based fault detection/location technique for transmission lines part I: Theory and algorithms," IEEE Trans. Power Delivery, vol. 15, pp. 486–493, Apr. 2000.

[11] A Gopalakrishnan, D Hamai, M Kezunovic, and S McKenna, "Fault location using the distributed parameter transmission line model," IEEE Trans. Power Delivery, vol. 15, pp. 1169–1174, Oct. 2000.

[12] V S Kale, S R Bhide, P P Bedekar, 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, pp.1063-1067, 16, 2008.

[13] N Zamanan, M Gilany, "A Sensitive Wavelet-Based Algorithm for Fault Detection in Power Distribution Networks" ACEEE Int. J. on Communication, Vol. 02, No. 01, Mar 2011.pp.46-50.

[14] S Haykin, Neural Networks, IEEE Press, New York, 1994.

[15] H Demuth and M Beale, "Neural Network Toolbox Matlab" 1992.

[16] Mamta Patel, R N Patel,"Fault Detection and Classification on a Transmission Line using Wavelet Multi Resolution Analysis and Neural network.