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Wavelet Based Fault Detection & ANN Based Fault Classification In Transmission Line Protection Scheme

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Abstract— **To improve the speed of detection, operation and accuracy of the fault in transmission line protection, distance relay used highly complicated algorithm due to application of advance signal processing. Wavelet transform is an advanced signal processing tool which enhance the speed of processing signal in occurrence of fault and detected very quickly. In modern transmission line get complicated due to rapidly increasing connections at both ends which get unstable and get effected due to delay in faulty section isolation by relays. For fault classification algorithm on application of artificial neural networks (ANN) for transmission line protection is presented in this paper, which uses the online fundamental components of voltage and current signals of each section measured at one end of transmission line to classify the faults. The ability to classify the nonlinear relationship between measured signals is done by identifying different patterns of the associated signals. The adaptive protection scheme based on application of ANN is tasted for shunt faults, varying fault cases such as different fault resistance and fault inception angle gives improved accuracy. Once the neural network trained adequately which gives accurate results and improved performance when faced with different system parameters and conditions. The entire test results clearly show that the fault is classified within one cycle. So the proposed adaptive protection technique is well suited for transmission line circuit for fault detection and classification in distance relaying scheme. Simulation results of performance studies show that the proposed wavelet and neural network based module can improve the accuracy and speed of the performance of conventional fault section algorithm.**

Keywords— ***Wavelet transform, Multiresolutin analysis Artificial neural network, shunt faults, Levenberg-Marquardt training algorithm***

IV. INTRODUCTION

The growing and improved demand of electrical power has resulted in an increase in the power transfer capability of power systems in both size and complexity enhances the need for accuracy of relays to protect major equipments and maintain system stability when the faults are occurred in transmission line. So the protection of multi terminal line is not simple as that two terminal transmission line which enhances the use of development of more complex algorithms can be implemented for improvement of speed and accuracy with the use of advance signal processing and artificial intelligence Hence, it is necessary to detect the fault and its type on the line and clear the fault as soon as possible in order not to cause such damages. Flashover, lightning strikes and birds, Natural phenomena of wind, snow, ice-load lead to short circuits and Deformation of insulator materials also leads to shunt faults. It is essential to detect the fault quickly and separate the faulty section of the transmission line as early as possible. Locating ground faults quickly is very important to economy and safety of power quality index. Wavelet theory is the mathematics which deals with building a model for processing of non-stationary signals, using a set of components that look like small waves, called wavelets of signal. It has become a well-known advanced signal processing tool which is helpful, especially in signal processing in complex algorithm [2].[3].

In [14] the high frequency traveling-wave information contained in post fault voltage and current signals are used for protection of transmission line circuits. The main drawback of the traveling wave method is that it requires high sampling rates and has a difficulty in distinguishing between traveling waves from the fault and the remote end of the line. The wavelet transform analysis [3,4] give the high-frequency components of the fault generated signals on each terminal of the system. The limitation stated is that at low signal-noise ratio (SNR), the method becomes inefficient for fault diagnosis.

The DWT is easier to implement than Continuous Wavelet Transform CWT because CWT is computed by changing the scale of the analysis window and shifting the window in time or multiplying the signal and the information of interest is often a combination of features that are most speedy. This requires the use of analysis methods sufficiently in which it is versatile to handle signals in terms of their localization of time-frequency. . Frequency based analysis has been common since Fourier's time. These results in a very wide frequency spectrum in the analysis of transients Fourier techniques cannot simultaneously achieve good localization in both time and frequency resolution for a transient waves. [15].The main advantage of WT over Fourier Transform is that the size of analysis window varies in proportion to the frequency analysis at which WT can offer a better compromise in terms of localization. [6]

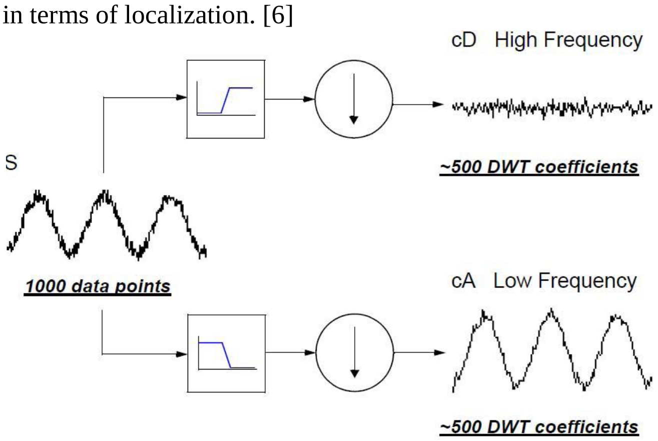

Fig. 1. Analyses of signal using wavelet transform

The wavelet transform decomposes transients into a series of wavelet components having each of which corresponds to a time domain s ignal that covers a specific octave frequency band containing more detailed information. Such wavelet Components appear to be useful for detecting and classifying the sources of surges. Hence, the WT is feasible and practical for analyzing power system transients and disturbances [1-6].

The discrete wavelet transform (DWT) is normally implemented by Mallat's algorithm its formulation is related to Multiresolution analysis theory. Wavelet transform is largely due to this technique, which can be efficiently implemented by using only two filters, one high pass (HP) and one low pass (LP) at level (k) at which fundamental components generate. The results are down-sampled by a factor two and the same two filters are applied to the output of the low pass filter from the previous stage of the signal. The high pass filter is derived from the wavelet function (mother wavelet) and measures the details in a certain input having low pass filter on the other hand delivers a smoothed version of the input signal and is derived from a scaling function associated to the mother wavelet. The idea is illustrated in Figure.2. This mathematically is expressed as:

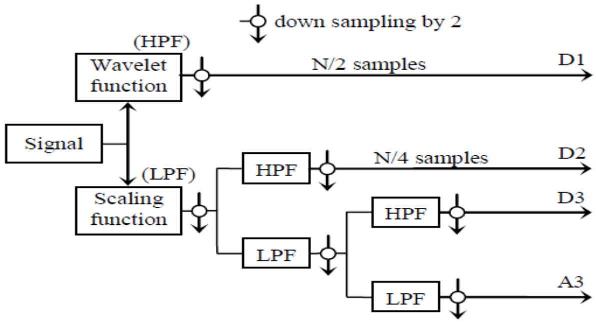

Fig.2.DWT multilevel decomposition

In this analysis, results are carried out by using the db4 as Mother wavelet for signal analysis .The wavelet energy is the sum of square of detailed wavelet transform coefficients. The energy of wavelet coefficient is varying over different scales depending on the input signals which contain energy of signal is contained mostly in the approximation part and little in the detail part-as the approximation coefficient at the first level having much more energy than the other coefficients at the same level of the decomposition tree-but because the faulty signals have high frequency dc components and harmonics, it is more distinctive to use energy of detail coefficients. The basic algorithm for the DWT is not limited to dyadic length and is based on a simple scheme: down sampling and convolution. As usual, when a convolution is performed on finite-length signals of border distortions arise. In this work the extension of DWT is Daubechies ('db') method which assumes that signals can be recovered outside their original support by symmetric boundary value although Symmetrization.

The fundamental voltage and current phasors are estimated using Discrete Fourier Transform based algorithm which mitigates the effects of exponentially decaying DC offsets.

The scheme is tested for different types of fault with varying fault incidence angles and fault resistances using typical transmission line model in Fig.6. The DFT have some disadvantages that overcome by using DWT. The system is modeled in MATLAB SimPowersystems environment. Results indicate that the proposed scheme is reliable, fast and highly accurate

V. FAULT DETECTION BY USING ENERGY OF THE DETAIL COEFFICIENTS

When fault occurs within the power network, the transient voltage and current signal in the fault section contain predominant high frequency components. This is due to superimposed reflection of the fault signals the fault point The energy of these high frequency signals is used as indicator of the fault occurrence in circuit.

The fault detection rules are established by means of the analysis of the current waveforms in time domain and in the first decomposition level of the DWT. This level contains highest frequency components. In order to compute the wavelet coefficients energy, a moving data window goes through the current wavelet coefficients shifts one coefficient at a time shown in given equation.

$$\mathrm{Ew} = \sum_{k=1}^{Nw} [\mathrm{dw(k\,)}]^2$$

Where dw(k) is the Kth wavelet coefficient within the wth window and Nw is the window length which computed as

$$\mathrm{Nw = Ns/2}$$

Where Ns is the number of samples within one cycle of the fundamental frequency of 50 Hz.

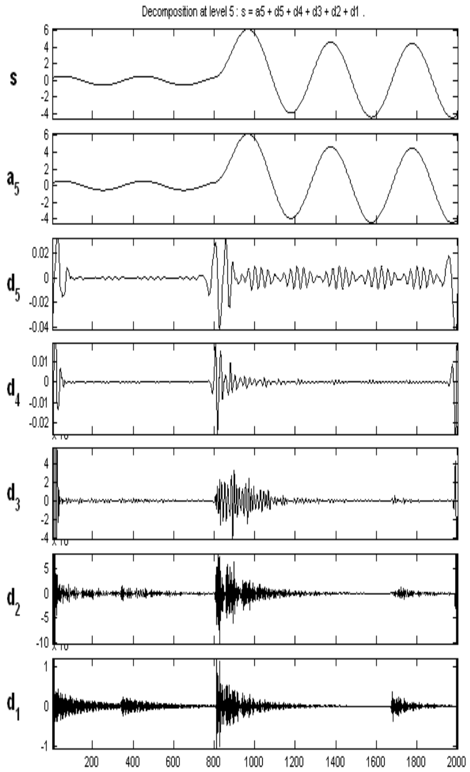

Fig.3. Detail coefficient at Single phase to ground (A-G) fault

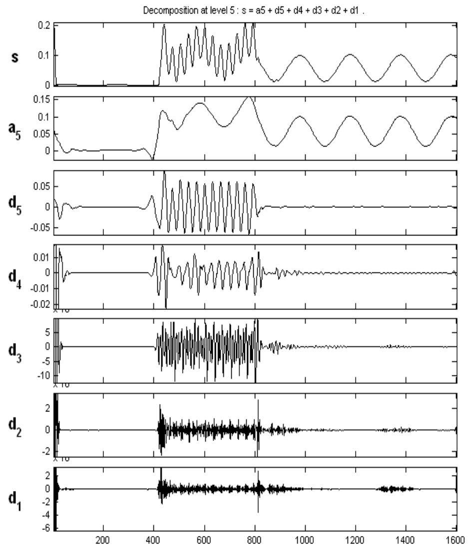

Fig.4. Detail coefficient at Single phase to ground (B-G) fault

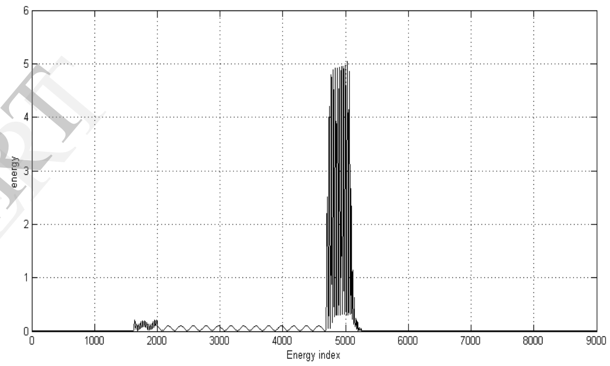

Fig 5 Energy index of fault

The simulation time was at 50μs and resistance fault equal 1ohm in which three phase current signals at normal condition were recorded and decomposed using DWT (db4 level 1) to get there details coefficient, energy of these signals and then making compression of these signals and take the ratio of energy change from the first level with keeping approximation with no change because fault inception have great effect on detail coefficient as it generate a high frequency component to signals. First Faults were created at a line for one cycle, analysis these signals before the realizing and switching off the circuit breaker.

Different types of faults were simulated using MATLAB simulation [6] and after recorded transient signals they were decomposed using wavelet toolbox to get there details coefficient shown in fig.3,4, energy of these signals shown in fig.5 .and then making compression to these signals to get the energy change from the first level and how faults make changes to the energy of these signals. Simulation was carried out for all different single phase to ground fault but only shown here is Phase-A to ground shown in fig.

Making compression of current signals using threshold energy with the first energy level for all current signals with keeping approximation with no change to compute the threshold of energy change, if any energy exceed this level this means that there is a faulty condition to that phase of line. Secondly to decide if this double phase or double phase to ground fault it was very cleared that if the fault is double phase the energy will be the same for these two faulty phases with comparison with the energy of double faulty phases when there is double phase to ground fault these energy were not same, were some different.

VI. ANN BASED FAULT CLASSIFICATION

There has been a very limited attention to the use of artificial neural network for protection of teed transmission circuit [24]. Eyada et. al [25] use radial basis function neural network for fault distance location in transmission line circuits and also detects the fault but the network does not identify the phase in which the fault occurs.

ANN is powerful in pattern recognition, classification and generalization. ANN-based techniques show a great enhancement in the accuracy of fault classification and location in comparison with the conventional techniques. This is due to the features of ANN which do not exist in the conventional methods such as the capability of non-linear mapping, learning, parallel processing and generalisation. In this work, we present an extension to our work which addresses double circuit transmission lines fault detection and classification based artificial neural network [26]. The pattern classifier, i.e. the Protection technique, is tested for shunt faults (LG: single phase to ground, LLG: double phase to ground, LL: phase to phase, LLLG: three phase to ground fault) under different fault locations, fault resistances, and fault inception angles. A 400 kV transmission line circuit configuration is simulated using MATLAB®-Simpower and Simulink software for observation of results.

VII. TRANSMISSION LINE MODELLING

The transmission line system studied is composed of 400kv transmission line circuit with section lengths 120 km (section-1), 80 km (section-2) , connected to sources at one end and load of 400kv at another end. The single line diagram of the transmission line circuit is shown in Fig. 1. Short circuit capacity of the equivalent thevenin sources on each sides of the line is considered to be 1.15 GVA and X/R ratio is 7. The transmission line is simulated with distributed parameter line model using MATALB® software as shown in Fig.2. The transmission line parameters are shown in Table 1. Preprocessing is a useful method that significantly reduces the Size of the neural network and improves the performance and speed of training process [27]. Three phase current and three phase voltages input signals were sampled at a sampling frequency of 2 kHz and further processed by simple 2nd-order low-pass filter with cut-off frequency of 300 Hz. Subsequently, one full cycle Discrete Fourier transform is used to calculate the fundamental component of voltages and currents. The input signals were normalized in order to reach the ANN input level (±1).

Table 1 Transmission line parameters

Positive sequence resistance R1,Ω/km	0.01273 ohms/km
Zero sequence resistance R0,Ω/km	0.3864 ohms/km
Positive sequence inductance L1,H/km	0.9337e-3 H/km
Zero sequence induction L0,H/km	4.1264e-3H/km
Positive sequence capacitance C1,F/km	12.74e-9 F/km
Zero sequence capacitance C0,F/km	7.751e-9 F/km

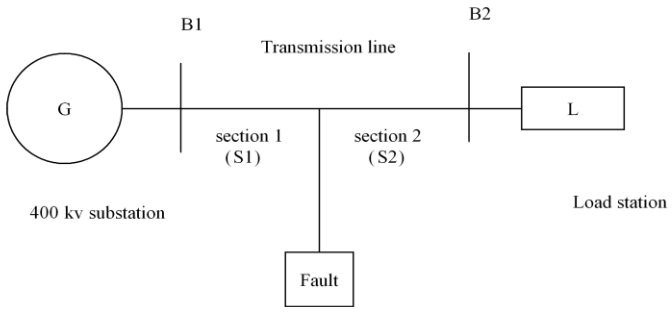

Fig.6.single line diagram of power system under study

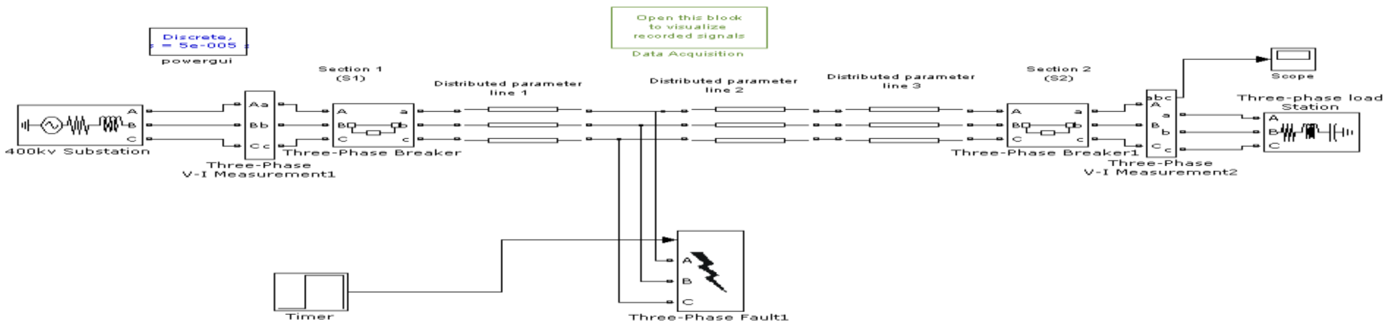

Fig.7.Power system model simulated in MATLAB Simulink software

V. PROPOSED ANN BASED FAULT CLASSIFIRER

The different steps used to implement a neural network in the fault classification algorithm in circuit of transmission line are described below.

A. Designing the ANN architecture

The network inputs chosen here are the magnitudes of the fundamental components (50 Hz) of three phase voltages and three phase currents of each section measured at one end of transmission line. The basic task of fault classification is to determine the type of fault along with the phase; the outputs of the ANN are: three outputs corresponding to three phases, one output to represent whether neutral is involved in the fault loop and three outputs to represent in which line section fault is present shown in data acquisitions system. Thus, total six outputs were considered to be provided by the network for fault classification. The input U_1 and output V_1 for the fault classification networks is given by

$$U_1 = [V_{a1}, V_{b1}, V_{C1}, I_{a1}, I_{a2}, I_{a3}, V_{a2}, V_{b2}, V_{c2}, I_{a2}, I_{b2}, I_{c2}] \quad (1)$$

$$V_1 = [A, B, C, G, S_1, L] \quad (2)$$

Similarly, for fault location task, where we have to determine the accurate distance to the fault which was decided that 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 P_2 and the output Q_2 for the fault location network is given by,

$$U_2 = [V_{a1}, V_{b1}, V_{C1}, I_{a1}, I_{a2}, I_{a3}, V_{a2}, V_{b2}, V_{c2}, I_{a2}, I_{b2}, I_{c2}] \quad (3)$$

$$V_2 = [\ L_f\ ] \quad (4)$$

For formation of hidden layer the number of neurons is determined empirically by experimenting with various network configurations in ANN. Through a series of trials and modifications of the ANN architecture, the best performance was achieved by using a three layer network with 12 neurons in the input layer, 13 neurons in the hidden layer, and 6 neurons in the output layer as shown in Fig. 3. The final determination of the neural network requires the relevant transfer functions in the hidden and output layers to be established. Activation function of the hidden layer is hyperbolic tangent sigmoid function.

Neurons with sigmoid function produce real valued outputs that give the ANN ability to construct complicated decision boundaries in an n-dimensional feature space. This is important because the smoothness of the generalization function produced by the neurons, and hence its classification ability, is directly dependent on the nature of the decision boundaries. Saturating linear transfer function (Satlin) has been used in the output layer as shown in Fig. 3.

Depending on the fault type which occurs on the system, various outputs of the network should be 0 or 1. For fault distance classification task, three layer network with 12 neurons in the input layer, 13 neurons in the hidden layer and 6 in the output layer was found to be suitable with pure linear function "Satlin" in the output layer as shown in Fig. 3.

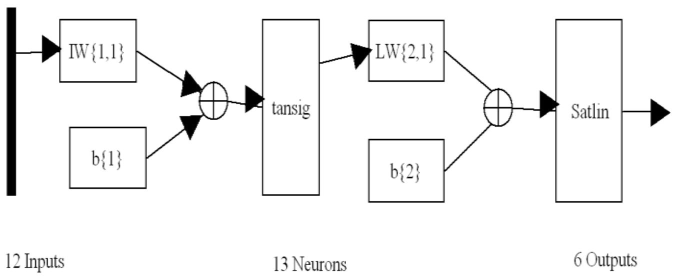

Fig.3 Structure of ANN Based Fault Classifier

B. ANN Training Process

By using SIMULINK & SimPowerSystem toolbox of MATLAB each type of fault (SLG, LLG, LL, LLLG each section of transmission line) at different fault inception angles between 0 & 90° and fault resistance 0.001 to 40 have been simulated as shown below in Table 2. The number of fault simulated for single phase to ground faults (AG, BG, and CG for each section) are: 360 for section 1 (= 3*15*4*2) i.e. (types of fault *number of fault locations*fault resistances*fault inception angles), 120 (= 3*5*4*2) for section 2. Thus, the total number of fault cases simulated for single phase to ground faults is 480. The number of cases simulated for double phase to ground faults (ABG, BCG and CAG) for each section is: 360 (3*15*4*2 for section 1), 120 (3*5*4*2 for section 2) forming total number of fault cases simulated for double phase to ground faults as 480. The number of cases studied for phase to phase faults (AB, BC, CA) for each section are: 450 (3*15*5*2 for section 1), 150 (3*5*5*2 for section 2) forming total number of fault cases simulated for phase to phase faults are 600. Similarly, the number of cases simulated for three phase to ground faults are 150(1*15*5*2 for section 1), 50 (1*5*5*2 for section 2) From each fault case ten numbers of post fault samples

Sr.No.	Parameters	Set values
1.	Fault Type	AG,BG,CG,ABG,BCG.ACG, AB,BC,AC,ABCG
2.	Fault location in km	Section1-0,10,20,30,..180 km Section2-0,10,20,30,..110 km
3.	Fault inception angle	0^0 and 90^0
4.	Fault resistance	0,0.01,20,30,….50Ω

Table 2 .Pattern Generation

The networks for fault classification were trained using Levenberg–Marquardt training algorithm of neural network toolbox in MATLAB [28]. Architectures of ANN based fault classifier modules are shown in Table 3. The number is epochs required for training varies from 50 to 350 to reduce the mean square error below 0.001. As the training is done off line, the iterations and time required for training are not of great concern. The trained network is tested for new cases, not covered in training pattern to demonstrate the viability of the proposed network

Table.3 Architecture of ANN based fault classifiers

Type of Network	Number of neurons			M.S.E	No. Of epoch
	I\P layer	Hidden layer	O\P layer		
LG classifier	12	13	6	1.58018e-04	61
LLG classifier	12	13	6	1.08275e-26	65
LL classifier	12	13	6	2.63620e-04	34
LLLG classifier	12	13	6	2.0867e-004	55

have been extracted to form the data set for neural network algorithm. 45 samples during no fault are also collected for the fault classification task. Thus, the total number of patterns generated for training is 2500 for the fault classification task of ANN algorithm. When network was trained with large training data set, it requires large memory and large computing time of training process. Therefore, speed of training is very low. In order to compensate for this four different modules i.e. single phase to ground, double phase to ground, phase to phase and three phase to ground fault classifiers are designed for fault classification task to train ANN algorithm.

VI. SIMULATION TEST RESULTS OF ANN BASED FAULT CLASSIFIER

The ANN based Fault classifier modules were then extensively tested using independent data sets consisting of fault scenarios never used previously in training of ANN. Fault type, fault features, fault inception angle and fault resistance were changed to investigate the effects of these factors on the performance of the proposed ANN algorithm.

A. Test results of single phase to ground faults(LG)

The network was tested by presenting different single phase to ground fault cases with varying fault inception angles (Φ_i =0 & 90°). Table.4. show the test results of the ANN based fault classifier module respectively for "B" phase to ground fault in section-1 at 80km, for fault inception time 70ms (Φ_i = 90°) and fault resistance $R_f = 50\Omega$. It is clear from Table 4 that all the outputs of ANN are low (0) before the inception of fault and further after the inception of fault at 70 ms the output of the corresponding phase "B", ground "G" and the faulty section "S1" becomes high (1) at 91ms time i.e. within one cycle time and all other outputs are low. Thus, the fault is simultaneously detected and classified.

B. Test results of double phase to ground faults(LLG)

The ANN network is tested for a double phase to ground fault "ABG" fault in section-2 at 90km, fault inception time is 60ms (Φ_i =0°) and fault resistance R_f = 30Ω. Table.4. shows the test results of the ANN based fault detector, classifier module. The output of ANN becomes high after 75ms time in corresponding phases A, B, ground "G" and section-2 and all other outputs are low in the graph.

C. Test results of phase to phase faults(LL)

The test results of the ANN based fault classifier module for "CA" fault in section-2 at 160 km, fault inception time =

70ms (Φ_i = 90°) and fault resistance R_f = 30Ω are shown in table 4. The output of ANN becomes high (1) at 95ms in corresponding phases "C and A" and section-2 within one cycle time from the inception of fault and all other outputs are low.

D. Test results of double phase to ground fault (LLLG)

The Table 4 show the test results of the ANN based fault classifier module for "ABCG" fault in section-1 at 70km for fault inception time of 70ms (Φ_i= 90°) and fault resistance R_f = 50Ω. The output of ANN shown in table 4.becomes high (1) at 85ms in corresponding phases "A, B, C, G" ground and section-2 within one cycle time from the inception of fault and all other outputs are low. It is clear from test results shown above that, the faults are correctly classified and faulty section is identified accurately. In the some test results of ANN based fault classifier modules are shown in Table 4 and 5. During training of the neural network, samples of fault cases with only two values of fault inception angle (0° and 90°) and three values of the fault resistance (0, 10 and 50 Ω) have been taken. However, while testing the neural network wide variation in fault inception angle (0-90°) and fault resistance (0-50Ω) have been studied as shown in Table 4

Table 4 Test result of ANN based fault classifier

Sr.No.	Fault type	Fault inception angle in^0	Fault location in km	Fault resistance in Ω	ANN based fault classifier output					
					A	B	C	G	S1	S2
1	AG	0	130	0.01	1	0	0	1	1	0
	BG	0	70	10	0	1	0	1	1	0
	CG	0	90	20	0	0	1	1	1	0
	ABG	0	30	30	1	1	0	1	1	0
	BCG	0	70	40	0	1	0	1	1	0
	ACG	0	90	50	1	0	1	1	1	0
	AB	0	30	10	1	1		0	1	0
	BC	0	70	20	0	1	1	0	1	0
	AC	0	110	30	1	0	1	0	1	0
	ABCG	0	170	40	1	1	1	1	0	1
2	AG	90	90	40	1	0	0	1	1	0
	BG	90	180	30	0	1	0	1	0	1
	CG	90	40	20	0	0	1	1	1	0
	ABG	90	50	10	1	1	0	0	1	0
	BCG	90	60	50	0	1	1	1	1	0
	CAG	90	70	40	1	0	1	1	1	0
	AB	90	90	10	1	1	0	0	1	0
	BC	90	45	20	0	1	1	0	1	0
	CA	90	85	30	1	0	1	0	1	0
	ABCG	90	155	40	1	1	1	1	1	1
3	BG	0	75	10	0	1	0	1	1	0
	CG	90	95	0.01	0	0	1	1	1	0

	ABG	0	100	50	1	1	0	1	1	0
	BCG	90	110	10	0	1	1	1	1	0
	CAG	0	120	0.01	1	0	1	1	1	0
	BC	90	130	50	0	1	1	0	1	0
	AC	0	180	10	1	0	1	0	0	1

VII. CONCLUSION

The speed and accuracy of algorithm and ANN architecture for fault classification for shunt faults on transmission line fed from sources on one end and the load at another is presented in this work. The online data sheet used to input to the algorithm employs the fundamental components of three phase voltage and three phase currents of each section measured at one end at source side, thus require less communication and data acquisitions. The ANN classification algorithm provides automatic determination of fault type, faulted phases after one cycle from the inception of fault at any fault resistance. The algorithm effectively eliminates the effect of varying fault parameters such as fault inception angle and fault resistance on transmission line protection scheme. The performance of the proposed scheme has been investigated by a number of offline tests in desired fault condition. The complexity of the possible types of faults (LG, LLG, LL, and LLLG for each section) of transmission line, varied fault inception angles (0 & 90°) and fault resistance (0-50Ω) are investigated and tested. The proposed scheme allows the protection engineers to increase the reach setting i.e. a greater portion of line length can be protected as compared to earlier techniques in transmission line distance protection.

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