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TRANSMISSION LINE FAULT CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK BASED FAULT CLASSIFIER

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ABSTRACT

Transmission line systems are the indispensable link between consumers and generating stations. The intrusion caused to the consumer because of transmission line faults is massive or consequential. A proper and secure protection scheme is mandatory for uninterrupted power supply to the consumer end. This study comes up with a new development of Artificial Neural Network based Fault Classifier (ANNFC) using Discrete Wavelet Transform (DWT); for classification of distinctive faults on three phase transmission line. The proposed ANNFC is trained using discrete sets of data achieved from wavelet analysis taking Db8 as mother wavelet and addition of fifth level detail coefficients of fault transients both for relay terminal and far end terminal for fault classification. The back propagation algorithm along with feed forward neural network is used and a detailed analysis with two hidden layer, one input and one output layer has been performed in order to justify the choice of neural network. The feasibility of the proposed algorithm of fault classification is tested on a 11 KV, 100 MVA, 100 Km long transmission line under various possible fault types and fault impedances in MATLAB environment. The result shows enhanced accuracy and efficient in identifying L-G, L – L, L – L – G, L – L – L faults. Furthermore the performance of ANNFC is compared with the algorithm based fault classifier (AFC) and the results shows that AFC is able to classify the fault with an accuracy of 98% but the proposed ANNFC algorithm, can classify the fault with an efficiency of almost 100%.

Keywords: Transmission Line Faults, Artificial Neural Network based Fault Classifier (ANNFC), Discrete Wavelet Transform (DWT), Algorithm based Fault classifier (AFC), Fault Classification.

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1. INTRODUCTION

To supply interminable electric power to the end users is a very crucial exercise for the power system operators. The origin of the fault may be beyond control, but it is indispensable to diagnose the type of the fault and exactly locate it. The fault is generated whenever conductors contact with each other or ground. Distinctive types of faults are double line-to-ground fault (LLG), single line-to-ground fault (SLG), line-to-line fault (LL), and triple line fault (LLL).

LLG, LL, SLG fault is an asymmetrical fault, whereas LLL fault is symmetrical one [1].

Conventional fault classification algorithms are based on voltage and current of receiving and sending end measurements [2, 3]. To distinguish a fault Increase in current magnitude or decrease in voltage magnitude can be contemplated as a measure. The developed algorithms are reliant on various factors such as source impedance, fault resistance and short circuit capability of power system. For the conventional based fault classifier, magnitudes of voltage and current should be predicated correctly using convenient filtering algorithms [6].

Now a day's power systems is growing in both complexity and size, and due to this more powerful algorithm are necessary to classify and identify different system faults more accurately and faster. Transient based techniques are results of advancement in the algorithm for classifying the faults on the transmission lines [4]. Wavelet Transform (WT) is applied in order to achieve rigorous operation of transient based protection [5]. As indicated in [6] current travelling waves are generated during the fault and an algorithm was developed for classification of faults which utilizes the modulus maxima of current travelling waves as threshold values and WT is used to extract transient signals. In addition wavelet decomposition based algorithm is used which provides more features about the signal [8]. After decomposition with first level maximum detail coefficient energy were calculated for each current signals with or without fault condition and if threshold condition of that maximum detail coefficient is increased to 0.001 this means faulty condition. DWT in conjunction with MRA is applied to conquer the disadvantages of previous techniques [8]. Here DWT is used to decompose current signal into distinct frequency bands using MRA and based on this algorithm fault is classified and the nature of fault is classified meticulously by using details (D1) at the first decomposition level of currents. A new algorithm based on wavelet was presented which is easy to implement and deterministic in nature [9]. In this algorithm phase current data of transmission line is passed through Db4 wavelet transform and based on the mean of the approximate coefficient part of scale 1, the classification is done. This method is thus useful to classify fault but the identification of the faulty phase was uncertain.

Various ANN based algorithm have been implemented and investigated in power systems in recent years. Neural network can be trained with offline data so ANN is useful in power system applications. The masterpiece of ANN based algorithm is that it does not use the impedance information rather it learns from the examples conferred to it during training [14].

In addition author in this paper [10] has considered the use of back propagation neural network (BPNN) as a surrogate method for fault classification in a transmission line. It uses RMS values of phase voltage and phase currents as inputs. The back propagation algorithm with feed forward neural network along has been employed [11] for classification of the fault for analysis of three phase involved. A detailed analysis with varying number of hidden layers has been performed to validate the choice of neural network. The three phase voltages and current are taken as inputs in proposed scheme. Various kinds of faults are simulated in PSCAD [12] presented in the paper. For classification the data was generated for all the types of faults at three different locations (0, 50 and 100km of line) with eight values of fault inception angles at a sampling frequency of 2 khz and two values of fault resistance. Here three configuration of ANN have been attempted with different combination of input.

In this paper we attempt to develop ANNFC algorithm, which is trained using discrete sets of data available from wavelet Db8 as mother wavelet and addition of fifth level detail coefficients of fault transients for both relay terminal and far end terminal for fault classification. The suggested ANNFC algorithm abide of time-frequency division of fault generated transients using Wavelet transform, supersede by pattern recognition using ANN. The performance of ANNFC is compared with the algorithm based fault classifier (AFC) and the results shows that AFC is able to classify the fault with an accuracy of 98% but the proposed scheme ANNFC, can classify the fault with an efficiency of almost 100%. The MATLAB/SIMULINK is used to generate the fault signals and verify the correctness of the algorithm.

Composition of this paper is as follows. Section II indicates about algorithm based approach which includes wavelet transform and AFC. Section III explains about ANN based approach and also includes ANN and ANNFC algorithm for fault classification. The analysis of algorithm and simulation are discussed and presented in section IV. Last the paper is encapsulated in section V.

2. ALGORITHM BASED APPROACH

The development of algorithm for classification of power system transmission line faults which is deterministic in nature and easy to implement. The proposed method uses the sum of detail coefficient, calculated from DWT of each phase current upto scale 5, to define the wavelet based classification scheme.[13]

2.1. Wavelet Transform

Signal processing was introduced into transmission line protection to improve the reliability of the protection algorithms. Wavelets are a class of functions used to localize a given function in both scaling and position. They are used in applications such as time series analysis and signal processing. Wavelets form the basis of the wavelet transform which "cuts up data of operators or functions into different components of frequency, and then studies each component with a resolution matched to its scale" (Dr I. Daubechies [16]). In the context of signal processing, the wavelet transform depends upon two variables: time and scale (or frequency).

There are two main types of wavelet transforms: discrete (DWT) and continuous (CWT). The first deals with functions that are defined over a range of integers (usually $t = 0, 1. . . N - 1$, where N denotes the number of values in the time series).The second is designed to work with functions defined over the whole real axis.

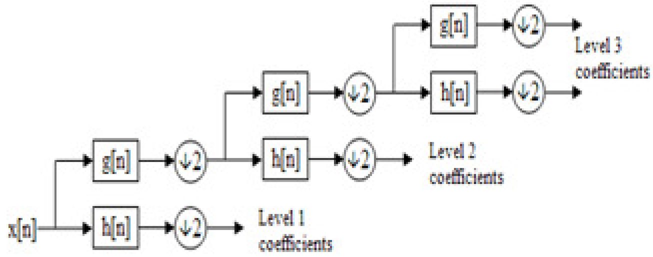


Fig. 1 Filter Bank Wavelet

Filter bank approach is an efficient way of splitting a signal into various bands. To give an example, suppose if we split a 1MHz signal into 4 bands, each with 0.25MHz bandwidth. Brute force, you design four filters, apply the 1MHz signal to each filter and you are done. If you apply multi-rate signal processing theory, you need to design only one filter (like one mother wavelet) and apply decimated copies of signal to the filter (like the decimation you do in wavelet analysis) and get output at 1/4th the input rate (different time scale than the input). In this paper Daubechies 8 as a mother wavelet was chosen because of its success in classifying faults.

2.2. Algorithm based Fault Classifier

Here classification of fault is done adopting wavelet transform coefficients. Db8 wavelet is used as a mother wavelet. Summation of level fifth detail coefficients is used for classification of fault. Algorithm for classification of fault is presented in fig. 4. Table 1 shows the recorded value of summation of fifth level detailed coefficient for different fault conditions at 20km from relay terminal. Similarly Table II shows the energy values for fault at 80km from relay terminal. The fault resistance is fixed 100Ω.

Table 1 Addition of energy level upto 5 detail coefficients for the line currents from both relay terminal and far end terminal for 20km from relay terminal

Fault	E_A	E_B	E_C	E_{SUM}
AG	0.4600	13.9179	13.0024	27.3804
BG	26.0874	1.4743	27.3491	54.9109
CG	7.6106	8.3304	0.2757	16.2166
ABG	1.5653	1.5813	8.9307	12.0772
BCG	17.5198	1.5027	1.0458	20.0683
CAG	0.2342	36.6347	0.3341	37.2030
AB	1.8520	2.3395	0.0069	4.1984
BC	0.0015	1.5482	1.9358	3.4855
CA	0.0377	0.0112	0.0307	0.0796
ABC	0.8241	2.3183	0.4319	3.5823

Table 2 Addition of energy level upto 5 detail coefficients for the line currents from both relay terminal and far end terminal for 80km from relay terminal.

Fault	E_A	E_B	E_C	E_{SUM}
AG	0.4295	15.8718	14.1853	30.4865
BG	26.2883	1.5339	27.4816	55.3038
CG	7.5332	8.4055	0.2179	16.1567
ABG	1.5577	1.5237	10.2317	13.3131
BCG	18.1588	1.4671	1.2459	20.8718
CAG	0.2112	33.7558	0.2975	34.2646
AB	1.5599	1.9707	0.007	3.5376
BC	0.0015	1.3317	1.6697	3.0028
CA	0.0401	0.0112	0.0330	0.0843
ABC	0.7542	2.1330	0.3911	3.2782

Let E_{A1}, E_{A2}, E_{B1}, E_{B2}, E_{C1}, E_{C2} are the summed coefficient of fifth level detail Coefficient for both end and at each phase current of line.

$$E_A = E_{A1} + E_{A2} \quad (1)$$

$$E_B = E_{B1} + E_{B2} \quad (2)$$

$$E_C = E_{C1} + E_{C2} \quad (3)$$

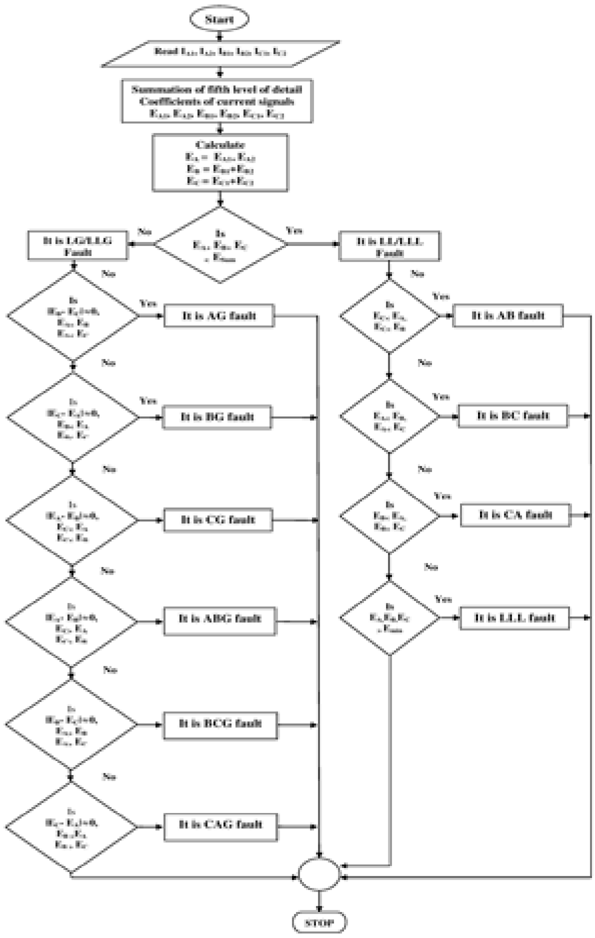


Fig 2 Flow Chart of Fault Classification

3. ANN BASED APPROACH

3.1. Artifical Neural Network

The biological neural network structure gives the mathematical structure of Artificial Neural Networks (ANN) where neurons are interconnected among each other. Fig.3 shows model of a back propagation ANN consisting of output layer, input layer and hidden layer. For power system applications back propagation neural network model of NN is widely used. In the work presented below, neural network toolbox in MATLAB has been used for training process where the output layer transfer function as liner and the transfer function in the first layer have been considered tan-sigmoid. One output layer with four outputs one input layer with four inputs and two hidden layer with 40 and 20 neurons is considered for designing the neural network. The steepest descent method is used to train the network. E_1, E_2, E_3 and E_{sum} have been taken as four inputs (sum of energy of detail coefficients Db8 as mother wavelet) and four fault classifier outputs have been taken for fault classification.

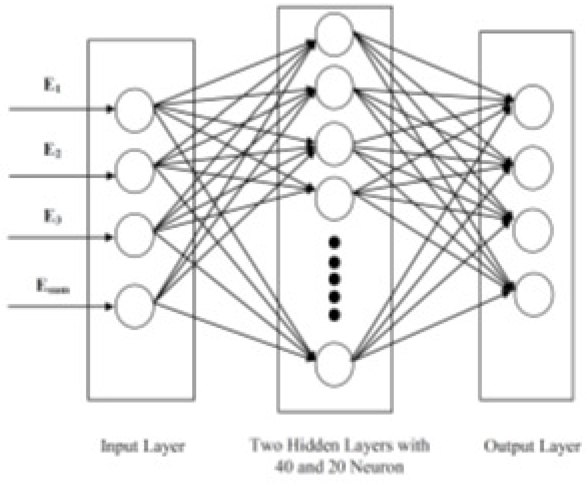


Fig. 3 Neural Network

3.2. ANN based Fault Classifier

The designed neural network takes in the sets of four inputs as explained earlier are sum of energy level upto 5 detail coefficients for the line currents. The neural network has four outputs, each of them corresponding to the fault condition of each of the three phases and one output for the ground line. Hence the outputs are either 1 or 0 denoting the presence or absence of a fault on the corresponding line (A, B, C or G where A, B and C denote the respective three phases of the transmission line system and G denotes the ground). Hence the various possible permutations can represent each of the various faults accordingly. The proposed neural network should be capable to accurately distinguish between the ten possible categories of faults. The truth table representing the faults and the ideal output for each of the faults is illustrated in Table 3.

The training set contains total 100 inputs and output pattern (10 for each type of fault).

Table 3 For various faults ANN output

Type of Fault	Phase A	Phase B	Phase C	Ground
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
CB	0	1	1	0
AC	1	0	1	0
ABG	1	1	0	1
CBG	0	1	1	1
ACG	1	0	1	1
ABC	1	1	1	0

Neural networks with a variation of composition of hidden layers and the distinct number of neurons in each hidden layer were evaluated. Of those, the one that achieved satisfactory performance was the neural network 4-40-20-4, i.e. four neurons in the output layer, four neurons in the output layer and two hidden layers with 40-20 neurons in it.

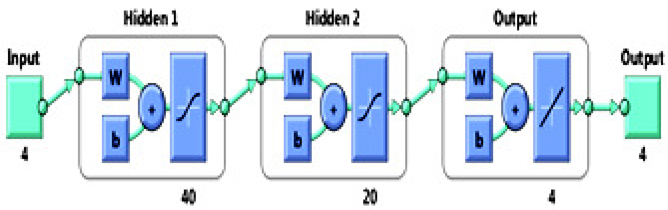


Fig.4 Developed Back Propagation Neural Network model in Simulink

The overall mean square error of the trained neural network is 0.028434 and from Figure 5 it can be seen that the testing and the validation curves have analogous characteristics which is an implication of efficient training.

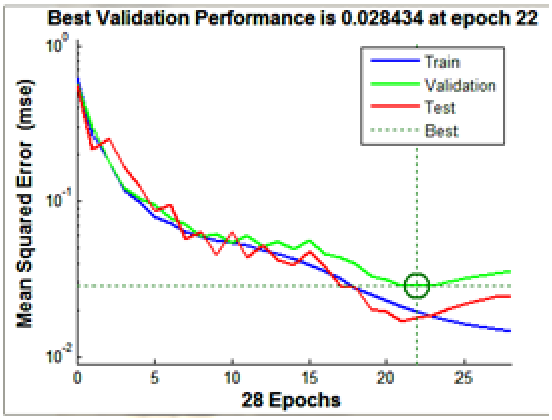


Fig.5 Mean-square error performance of the network

Figure 7 shows the regression plot. The three plots shows training, testing and validation data. The performance of the trained neural network is tested in two ways, i.e. first by plotting the linear regression that relates the targets to the outputs as shown in Figure 7. The correlation coefficient in this case was found to be 0.95668 which indicates satisfactory correlation between the targets and the outputs.

Figure 8 shows the confusion matrix here we can see that the efficiency of the trained network in terms of classification of the fault, which is 81.7 percent. It is achieved that the neural network can differentiate among the all ten available types of transmission line faults.

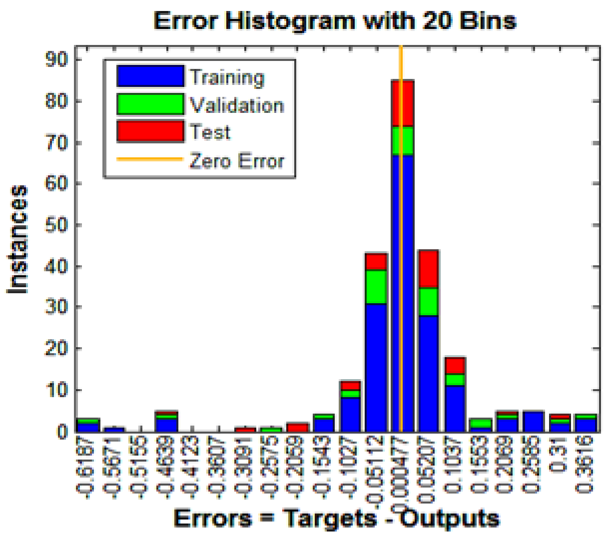


Fig 6 ANN Training Error Histogram

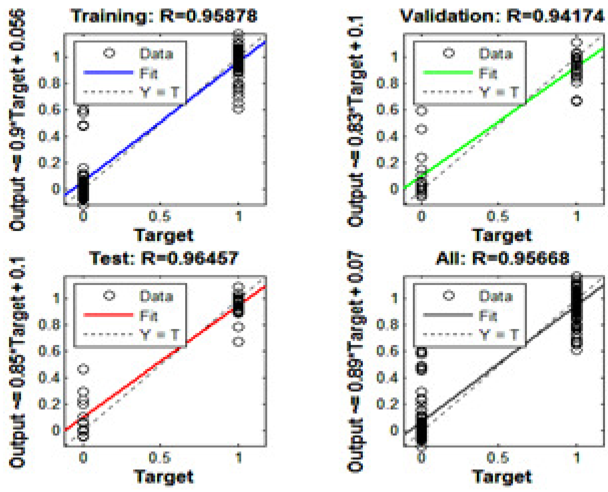


Fig. 7 Regression Plot for the outputs vs. targets of the proposed ANN.

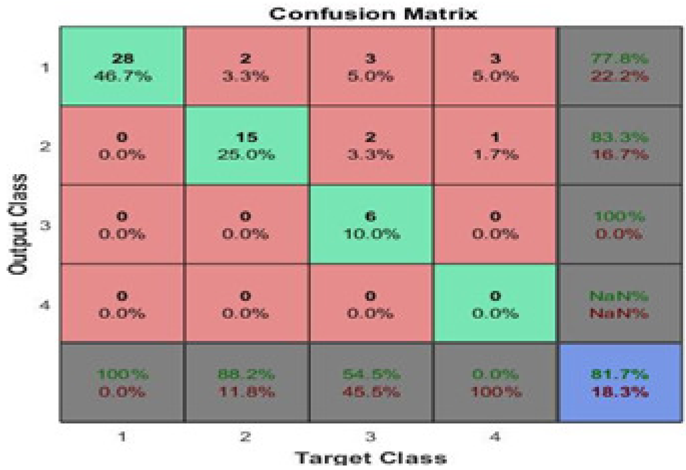
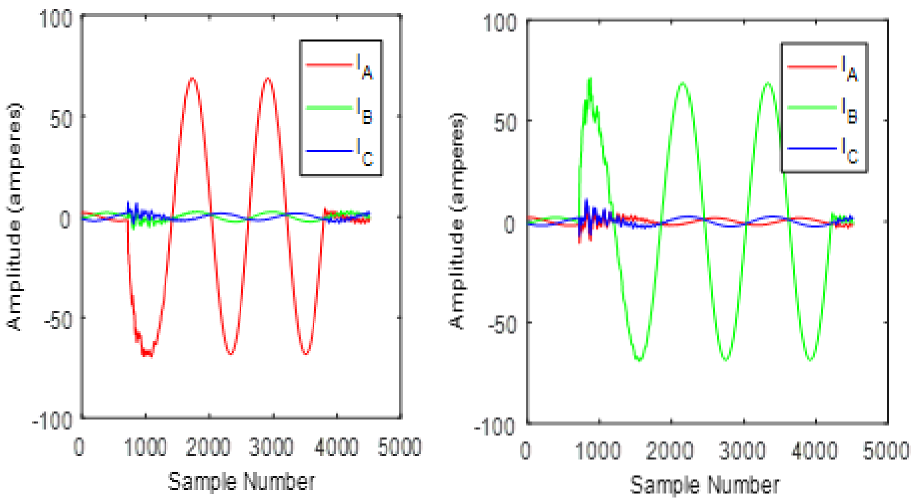
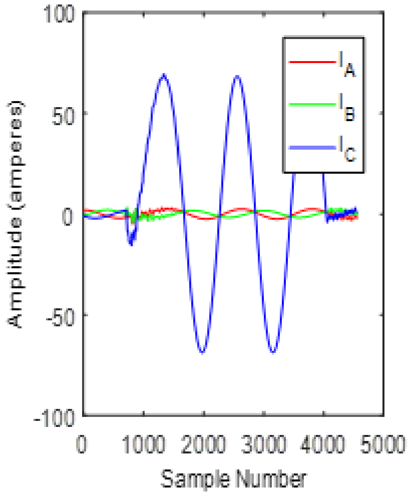


Fig. 8 : Confusion matrix

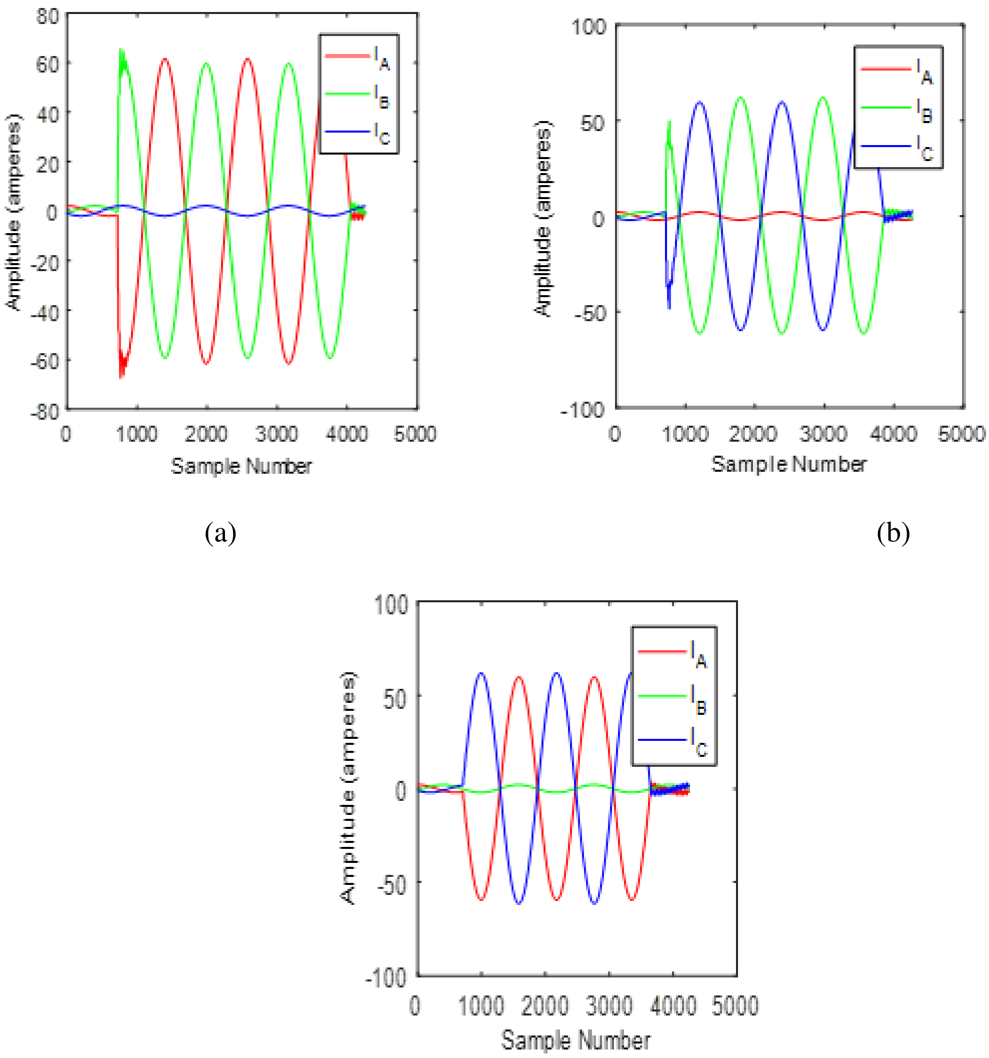


(a) (b)



(c)

Fig. 9: Measured fault current for 11KV system under (a) AG Fault (b) BG Fault (c) CG fault

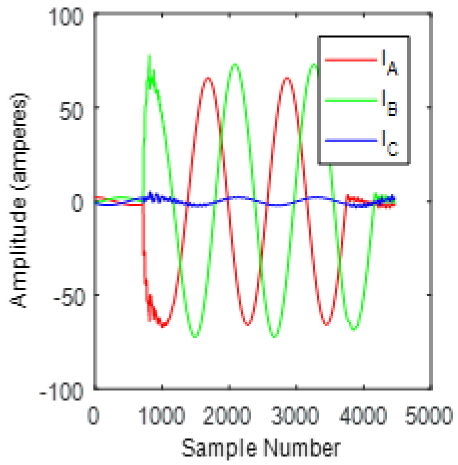


(a)

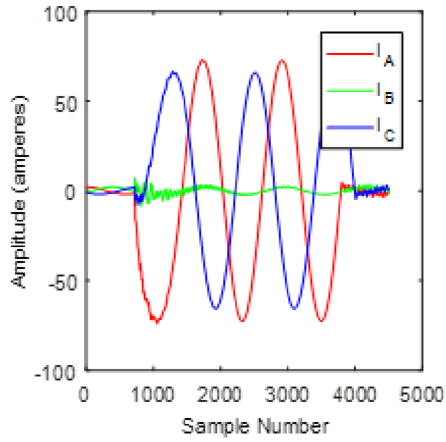
(b)

(c)

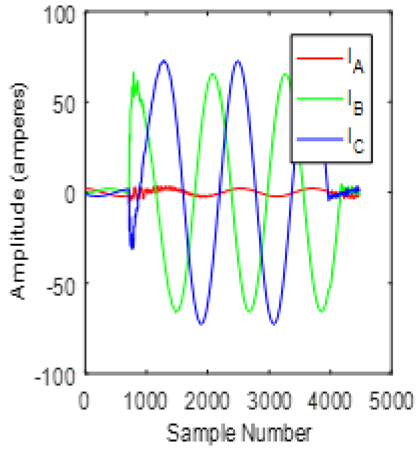
Fig. 10 Measured fault current for 11KV system under (a) AB Fault (b) BC Fault (c) CA fault



(a)



(b)



(c)

Fig. 11 Measured fault current for 11KV system under (a) ABG Fault (b) BCG Fault (c) ACG fault

4. SIMULATION RESULTS

The suggested fault classification algorithm is accomplished in a MATLAB/Simulink platform. The TL has a length of 100 KM fed with a source of 11KV from both end.

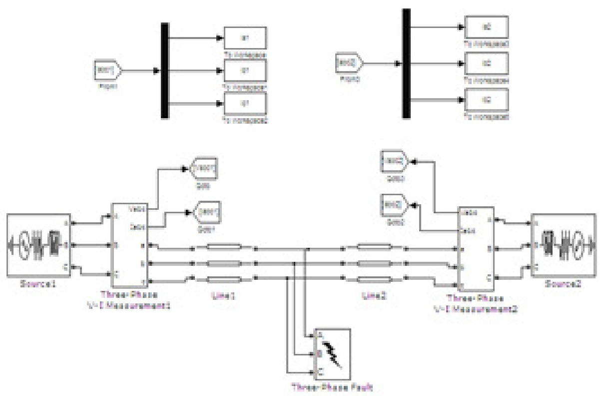


Fig 12 MATLAB/Simulink model for analysis

Fig. 9, 10 and 11 illustrates the simulated line currents for ground faults, line to line faults, and line to line ground faults respectively. The fault resistance was considered as 0.01Ω for obtaining the results for classification.

Table 4 Transmission line fault classification results using proposed algorithm

Fault Type	Number of Records	Number of Success Classification (AFC)	Number of Success Classification (ANNFC)
AG	10	10	10
BG	10	10	10
CG	10	10	10
AB	10	10	10
AC	10	10	10
BC	10	10	10
ABG	10	9	10
BCG	10	10	10
CAG	10	10	10
ABC	10	9	10
Total Samples	100	98	100

% Success Ratio with AFC = $\frac{98}{100} * 100 = 98\%$

It is observed that proposed algorithm provides nearly 100 % accuracy for AG, BG, CG, AB, AC, BC, ACG, BCG fault. Lowest accuracy obtained for ABG and ABC fault is 99%. As a result, it is seen that variation of performance accuracy is between 99% to 100% and overall accuracy of 98% was achieved for classification of fault using the AFC algorithm.

% Success Ratio with ANNFC = $\frac{100}{100} * 100 = 100\%$

It is observed that proposed algorithm provides nearly 100 % accuracy for AG, BG, CG, AB, AC, BC, ACG, BCG fault.

5. CONCLUSIONS

This paper presents the development of algorithm for classification of power system transmission line faults which is deterministic in nature and easy to implement. The proposed ANNFC is trained using discrete sets of data achieved from wavelet analysis taking Db8 as mother wavelet and addition of fifth level detail coefficients of fault transients both for relay terminal and far end terminal for fault classification. The feed forward neural network along with back propagation algorithm is used and a detailed analysis with two hidden layer, one input and one output layer has been performed in order to validate the choice of neural network. The performance of the ANNFC is compared with AFC and results have shown that the proposed technique gives satisfactory results.

REFERENCES

[1] E.E. Ngu and K. Ramar, "A combined impedance and travelling wave based fault location method for multi-terminal transmission lines, " Int. Journal of Electric Power and Energy Systems, vol. 33, issue. 10, pp. 1767-1775, 2011.

[2] "IEEE guide for determining fault location on AC transmission and distribution lines", IEEE Power Engineering Society Pub., New York, IEEE Std C 37.114, 2005.

[3] M. Oleskovicz, D. V. Coury, and R. K. Aggarwal, "A complete scheme for fault detection, classification and location in transmission lines using neural networks," in

Proc. Inst. Elect. Eng., 7th Int. Conf. Developments in Power System Protection, Amsterdam, The Netherlands, Apr. 2001, pp. 335–338.

[4] Z. Q. Bo, F. Jiang, Z. Chen, X. Z. Dong, G. Weller and M.A. Redfern, “Transient based protection for power transmission systems.” IEEE Power Engineering Society Winter Meeting, Vol. 3, 2000. pp. 1832 – 1837.

[5] C. H. Kim and R. Aggarwal, “Wavelet transforms in power systems: Part. 1 General introduction to the wavelet transform,” IEEE Power Engineering Journal, April 2000, pp. 81-87.

[6] Sruti. V.S, Bobin K Mathew, “Classification of Transmission Line Faults Using Discrete Wavelet Transform,” International Journal of Emerging Science and Engineering (IJESE), ISSN: 2319–6378, Volume-1, Issue-10, August 2013.

[7] S. A. Shaaban and prof. Takashi Hiyama, “ Transmission line faults classification using wavelet transform,” international middle east power systems conference, cairo university, Egypt, December 19-21, 2010.

[8] Avagaddi Prasad, J. Belwin Edward, “Application of Wavelet Technique for Fault Classification in Transmission Systems,” 2nd International Conference on Intelligent Computing, Communication & Convergence, 2016, pp 335-338

[9] Mousam Choudhary and Dr. Amrita Ganguly’ “Transmission line fault classification using discrete wavelet transform,” IEEE ICEPE, June 2015.

[10] Eisa Bashier M. Tayeb Orner AI Aziz AlRhirn, “Transmission Line Faults Detection, Classification and Location using Artificial Neural Network,” International Conference & Utility Exhibition on Power and Energy Systems 2011

[11] M. Jamil, S. K. Sharma, and R. Singh, “Fault detection and classification in electrical power transmission system using artificial neural network,” Springer plus, vol. 4, no. 1, p. 334, Dec. 2015.

[12] Farhana Fayaz, Abubakar Isa, H.K Verma, Soma Deb, “Improved ANN-Based Algorithm for Detection and Classification of Faults on Transmission Lines” India International Conference on Information Processing 12-14 Aug. 2016

[13] Ashish Maheshwari and Dr. Sanjeev Kumar Sharma, “Improved Wavelet Based Algorithm for Classification of Fault on Transmission Lines” IEEE Conference (ICITE-2018) Osmania University, Hyderabad, India, During 11-13 April 2018.

[14] Ashish Maheshwari and Dr. Sanjeev Kumar Sharma, “Classification of fault identification techniques in power system transmission lines,” International journal of emerging technology and innovative research, Jaunary 2018, vol. 5, Issue 1, pp. 89 – 98.

[15] Anamika Jain, V.S. Kale and A.S. Thoke, “Application of artificial neural networks to transmission line faulty phase selection and fault distance location,” *Proceedings of the IASTED International conference “Energy and Power System”,* Chiang Mai, Thailand, Mar. 29-31, 2006, pp. 262-267.

[16] Dr. I. Daubechies, "Ten Lectures on Wavelets", Society for Industrial and Applied Mathematics, Philadelphia, Pa, 1992.