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Transmission Line Fault Detection and Classification Using Discrete Wavelet Transform and Artificial Neural Network

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Abstract: Fault diagnosis is a major area of investigation for power system and intelligent system applications. When the fault occurs on the transmission lines, the current and voltage waveforms contain significant high frequency transient signals. This paper presents a Discrete Wavelet Transform and Artificial Neural Network approach to fault detection and classification in transmission line faults. The discrete wavelet transform is applied for decomposition of fault transients, because of its ability to extract information from the transient signal, simultaneously both in time and frequency domain. The data sets which are obtained from the Discrete Wavelet Transform are used for training and testing the Artificial Neural Network architecture. The feasibility of proposed algorithm is tested on transmission line using MATLAB software. The proposed algorithm is very simple and accurate in fault detection and classification. Simulation results shows that the proposed algorithm gives satisfactory results and will be very useful in the development of a power system protection scheme.

Key words: Discrete Wavelet Transform · Artificial Neural Network · Fault transient · Fault diagnosis · intelligent system · High frequency transient

INTRODUCTION

As years pass by, the world population has increased drastically. It has contributed to the increasing needs of electrical energy. Providing sufficient and uninterrupted power supply to the consumers is the main objective of a power system. Unfortunately, unavoidable faults could occur due to factors such as lightning, storm and other natural disasters which is uncontrollable by human beings. [1], any abnormal flow of current in a power system's components is called a fault in the power system. The transmission line fault is mainly classified into balanced and unbalanced fault. The balanced faults in transmission lines are three phase fault. Single phase to ground, double phase, double phase to ground fault are unbalanced in nature. The appropriate percentage of occurrence of various types of faults are given below.

- Single line to ground fault - 70-80%
- Line-to-Line to ground fault - 10 -17%
- Line-to- Line fault - 8-10%
- Three phase fault - 3 %

Hence, it is very important to have a well-coordinated protection system that detects any kind of abnormal flow of current in the power system, identifies the type of fault accurately and rapidly. There are various techniques have been used for fault detection and classification. Some of the techniques are Wavelet Transform [2-5], Fuzzy Logic [6, 7], Artificial Neural Network (ANN) [8], Support Vector Machines (SVM) [9, 10], WT and ANN [11, 12], WT and Fuzzy logic [13], combination of ANN and Fuzzy logic. Wavelet transform is commonly used to extract characteristic quantities, while ANN is used classify characteristic quantities. Characteristic quantity analysis of transmission line faults includes the decomposition coefficients and their energy, the maximum or minimum value of fault currents, such as wavelet coefficients of different phase currents, the maximum and minimum values of detailed coefficients at level 3 [14], the energy of current wavelet coefficients [15]. Although, the wavelet transform is very effective in detecting transient signals generated by the faults, it has one main challenge in using wavelet transform. [16], the main challenge is selecting the optimum mother wavelet for applications, if different

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mother wavelet are applied on the same signal, it may produces different results. According to [17], the db4, coiflet and b-spline were equally suitable in detecting power system transients. The [18] daubechies (dB) is the commonly used mother wavelet suitable for protection applications. ANN is the best approach have been quite successful in determining the correct fault type. One of the biggest drawbacks of applications that make use of artificial neural networks is that no well-defined guide exists to help us choose the ideal number of hidden layers to be used and the number of neurons per each hidden layer. Even though it has few drawbacks, it also has major advantage like high degree of robustness, ability to learn and capability to work with incomplete and unforeseen input data. Back Propagation, Radial Basis Functions [19], Multi-Layer Perceptron algorithm, Adaptive Resonance Theory (ART), Self-Organizing Maps (SOM) and Counter Propagation Networks (CPN) are few algorithms of neural networks. Among the various networks, Back propagation neural network is a kind of neural network, which is widely applied today owing to its effectiveness to solve almost all types of problems. Some other fast algorithms such as Levenberg-Marquardt [20], Quasi-Newton and conjugate gradients algorithms, gradient descent have been used to optimize the learning rules in BPN. Combination like WT & ANN is most commonly used for fault detection and classification purpose. According to [21], DWT based approach for fault detection not only detects the fault accurate and quick, it also reduces the volume of input data of the ANN without loss of information. This dramatically reduces the training time and increases the overall performance. The MATLAB / SIMULINK is used to generate the fault signals and verify the correctness of the algorithm. Since it provides interactive environment among toolboxes like Wavelet Transform [22], Neural Networks toolbox [23], Fuzzy interference system and Simulink, making programming and transfer of data between program modules simpler.

The focus of this paper is to develop a novel technique for real-time fault detection, classification using discrete wavelet transform and artificial neural network. The fault condition are simulated in MATLAB (8.2) on the 220kV transmission line. The fault signals are decomposed up to fifth detail level using DWT to obtain feature extraction. The feature extracted by processing the discrete wavelet transform are maximum and minimum detail coefficient value of three phase current signal at level 4 and level 5. These feature are taken as input to the artificial neural network.

Description of Proposed Transmission Line Fault Analysis Method: The proposed algorithm is applied in two main steps. First step is fault detection and the last step is fault classification. A flow chart of the proposed algorithm is shown in Fig. 1. The fault detection process is done using DWT and fault classification process is done using ANN [24, 25].

Discrete Wavelet Transform: Wavelet transform possesses excellent features such as a little wave, little in the sense of being short duration with finite energy which integrates to zero. The foundation of the Discrete Wavelet Transform (DWT) go back to 1976 when Croiser, Esteben and Galand devised a technique to decompose discrete time signals. In DWT, a time- scale representation of a discrete signal is obtained using digital filtering technique. The signal needed to be analyzed is passed through different filter having different cutoff frequency at different scales. The DWT is computed by successive low pass (h) and high pass (g) filtering of discrete time-domain signal. This is called as MALLAT algorithm. In first decomposition level, signal is decomposed into D1 and A1, with the frequency band of D1 and A1 is $f_s/2$–$f_s/4$, $0 - f_s/4$. In the second decomposition, again the low pass filter, A1 is splitted into D2 and A2 with the frequency band of D2 is $f_s/4 - f_s/8$ and A2 is $0 - f_s/8$.

The wavelet coefficient energy can be calculated as shown below equation (1),

$$E_w = \sum_{k=1}^{N_w} [d_w(k)]^2 \tag{1}$$

where, d_w (k) is the k_{th} wavelet coefficient within the w^{th} window and N_w is the window length which is computed as, $N_w = N_s/2$, where N_s is the number of samples.

Fault Detection Using DWT: Discrete Wavelet Transform is found to be useful in analyzing transient phenomenon such as that associated with faults on the transmission lines. In this paper, DWT is used for fault detection purpose due to following reasons. It provides a fast, reliable, accurate fault analysis and it also easier to implement and it provides less computation time and resources required compared to the continuous wavelet transform.

Feature Extraction of Line Signals Using DWT: The three phase current signal of transmission line are taken as input and decomposed using discrete wavelet transform to obtain feature extraction.

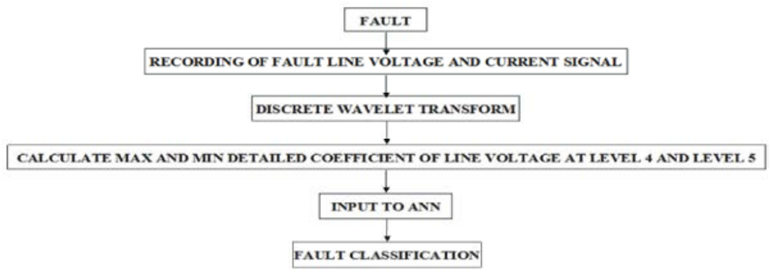


Fig. 1: Flow chart of the proposed approach for fault detection and classification

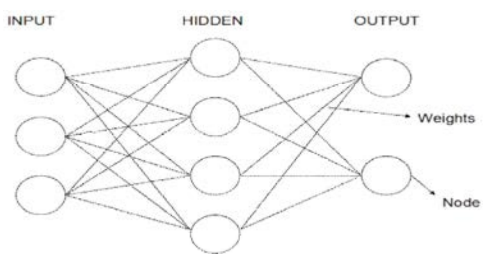


Fig. 2: ANN architecture

Wavelet Type used	:	One- Dimensional Discrete Wavelet Transform (DWT)
Family chosen	:	Daubechies
Filter used	:	DB6
Resolution level	:	5

The features extracted by processing discrete wavelet transform are maximum and minimum detail coefficient at five level decomposition levels (d1, d2, d3, d4, d5). The maximum and minimum detail coefficient of line current at level 4 and level 5 are used for the study. The maximum and minimum detail coefficient of line current at level 4 and level 5 are calculated for all different fault types such as Single Phase to Ground, Double Phase Fault, Double Phase to Ground Fault and Three Phase Fault using wavelet toolbox. The maximum and minimum detail coefficient of normal condition (pre-fault) values at level 4 and level 5 are taken as reference and compared with abnormal one's. If the maximum and minimum detail coefficient value of the signal exceeded that of a normal condition, a fault is detected. The feature obtained by processing the discrete wavelet transform are provided to neural network for fault classification purposes.

Artificial Neural Network: Artificial Neural Networks (ANN) are inspired by biological nervous systems and they were first introduced as early as 1960. ANN is made up of many computational processing elements called neurons or nodes. These nodes operate in parallel and are connected through topologies that are loosely modeled after biological neural system. ANN has three layers i.e. input layer, hidden layer and output layer. Patterns are presented to the network via input layer, which communicate to one or more hidden layer where the actual processing is done. The hidden layers then links to an output layer as shown in Fig. 2.

The number of input in a neural network is equal to the number of nodes in the input layer. Similarly, the number of outputs in neural network is equal to the number of nodes in the output layer. The number of hidden layers and number of nodes in the hidden layer are varying depending on its application. There are two distinctive network topology with regard to the way neurons are connected namely feed forward and feedback network. In the feed forward network, an outcrop in a layer is an input to the next layer. In the feedback network, an outcrop in a layer can be its own input to the previous layers. To get the intended output for the given inputs, the network weights need to adjust. The process of weights adjustment are called network learning / training. Learning process is the most important step when applying neural network. The learning techniques are classified into supervised learning and unsupervised learning. In supervised learning, each input signal is associated with the labelled output. In unsupervised learning, the outputs are not known in advance.

Fault Classification Using ANN: Once a fault has been detected, the next step is to identify the type of fault. Back propagation algorithm, a supervised learning is used as the network will be trained using the data created from the simulation model of transmission line. The maximum and minimum detail coefficient of all the three phases (A, B, C) at level 4 and level 5 are taken as input to neural network. The network designed here has six inputs and four outputs associated with the four fault categories. The outputs contain variables whose values are given as either 0 or 1 corresponding to the three phases and the ground (i.e, A, B, C and G) and can be generalized to represent all the fault categories.

Table 1: Truth table for fault classification

FAULT TYPE	A	B	C	G
A-G	1	0	0	1
B-G	0	1	0	1
C-G	0	0	1	1
A-B	1	1	0	0
B-C	0	1	1	0
A-C	1	0	1	0
AB-G	1	1	0	1
BC-G	0	1	1	1
AC-G	1	0	1	1
ABC	1	1	1	0

- Indicates fault condition
- Indicates non-fault condition

The proposed neural network should be able to accurately distinguish between the ten possible categories of faults. The desired truth table for fault classification is shown in Table 1.

RESULTS AND DISCUSSIONS

Description of Line Diagram of Test System: The system studied is composed of 220 KV transmission circuit with section lengths 200 km (section 1), 120 km (section 2) and 110 km (section 3), connected to sources at each end. The single line diagram of the line is shown in Fig. 3.

Short circuit capacity of the equivalent thevenin sources on each sides of the line is considered to be 1.25 GVA and X/R ratio is 10. Test system transmission line parameters are shown in Table 2.

The transient signals of three phase current are produced using the simulation model which are built using power block set of SIMULINK. The simulation results are obtained for all different fault conditions, but only shown here are Phase A to ground (single phase fault), Phase AB (double phase fault), AB-G (double phase to ground fault), Three Phase Faults and normal condition (pre fault) in Fig. 4. These results are stored in MATLAB workspace for future uses.

Performance of the Programmed Fault Signals: The fault detection and classification results of the proposed system are discussed below.

Fault Detection Simulation Results and Discussions: As discussed earlier in this section, the fault data is created using simulation model of transmission lines. These three phase current signal are decomposed up to fifth detail level using db6 mother wavelet to obtain feature extraction. The feature extracted by processing

Table 2: Test system transmission line parameters

Positive sequence resistance R1, Ω/km	0.01809
Zero sequence resistance R0, Ω/km	0.2188
Positive sequence Inductance L1, H/km	0.00092974
Zero sequence Inductance L0, H/km	0.0032829
Positive sequence Capacitance C1, F/km	1.2571e-008
Zero sequence Capacitance C0, F/km	7.8555e-009

Table 3: Max and Min Detail coefficient of current signal under different fault conditions

FAULT TYPE	PARAMETER	PHASE A	PHASE B	PHASE C
PRE-FAULT	D4 MAX	1.017	1.508	4.344
	D4 MIN	-0.191	-5.361	-1.373
	D5 MAX	0.994	7.720	3.724
	D5 MIN	-1.256	-4.071	-7.238
PHASE A-G	D4 MAX	104.80	1.508	4.344
	D4 MIN	-207.66	-5.361	-1.378
	D5 MAX	173.96	7.739	3.724
	D5 MIN	-157.31	3.724	-7.219
PHASE B-G	D4 MAX	1.017	23.882	4.344
	D4 MIN	-0.186	-27.808	-1.378
	D5 MAX	0.997	69.733	3.724
	D5 MIN	-1.256	-36.381	-7.219
PHASE C-G	D4 MAX	1.017	1.508	229.69
	D4 MIN	-0.186	-5.361	-117.01
	D5 MAX	0.997	7.765	193.69
	D5 MIN	-1.256	-4.110	-243.70
PHASE A-B	D4 MAX	106.11	142.88	4.344
	D4 MIN	-142.88	-106.11	-1.373
	D5 MAX	119.49	139.48	3.724
	D5 MIN	-139.47	-119.50	-7.238
PHASE B-C	D4 MAX	1.0176	158.12	224.37
	D4 MIN	-0.186	-224.37	-158.12
	D5 MAX	0.997	206.37	183.22
	D5 MIN	-1.256	-183.22	-206.37
PHASE A-C	D4 MAX	252.84	1.508	367.25
	D4 MIN	-367.25	-5.361	-252.84
	D5 MAX	325.88	7.720	322.69
	D5 MIN	-322.70	-4.071	-325.86
PHASE AB-G	D4 MAX	119.78	156.21	4.344
	D4 MIN	-188.30	-145.61	-1.373
	D5 MAX	137.05	193.54	3.724
	D5 MIN	-203.99	-154.28	-7.238
PHASE BC-G	D4 MAX	1.017	211.76	223.71
	D4 MIN	-0.191	-235.37	-170.39
	D5 MAX	0.997	238.95	225.62
	D5 MIN	-1.256	-148.81	-207.82
PHASE AC-G	D4 MAX	255.89	1.508	364.92
	D4 MIN	-369.58	-5.361	-249.79
	D5 MAX	328.08	7.833	344.80
	D5 MIN	-300.59	-4.166	-323.66
PHASE ABC	D4 MAX	237.51	48.001	339.42
	D4 MIN	-340.09	-54.33	-268.24
	D5 MAX	296.91	76.435	337.28
	D5 MIN	-308.12	-62.722	-354.83

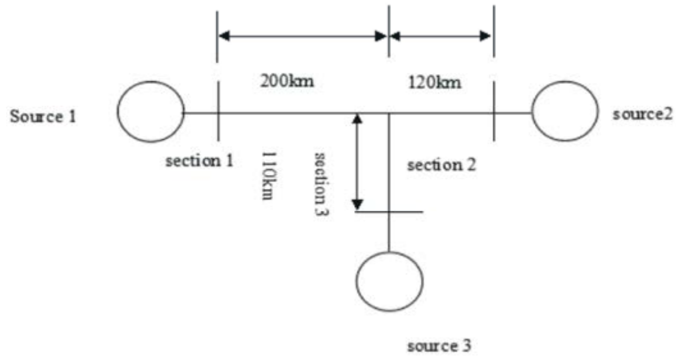


Fig. 3: Simulated Power System Model

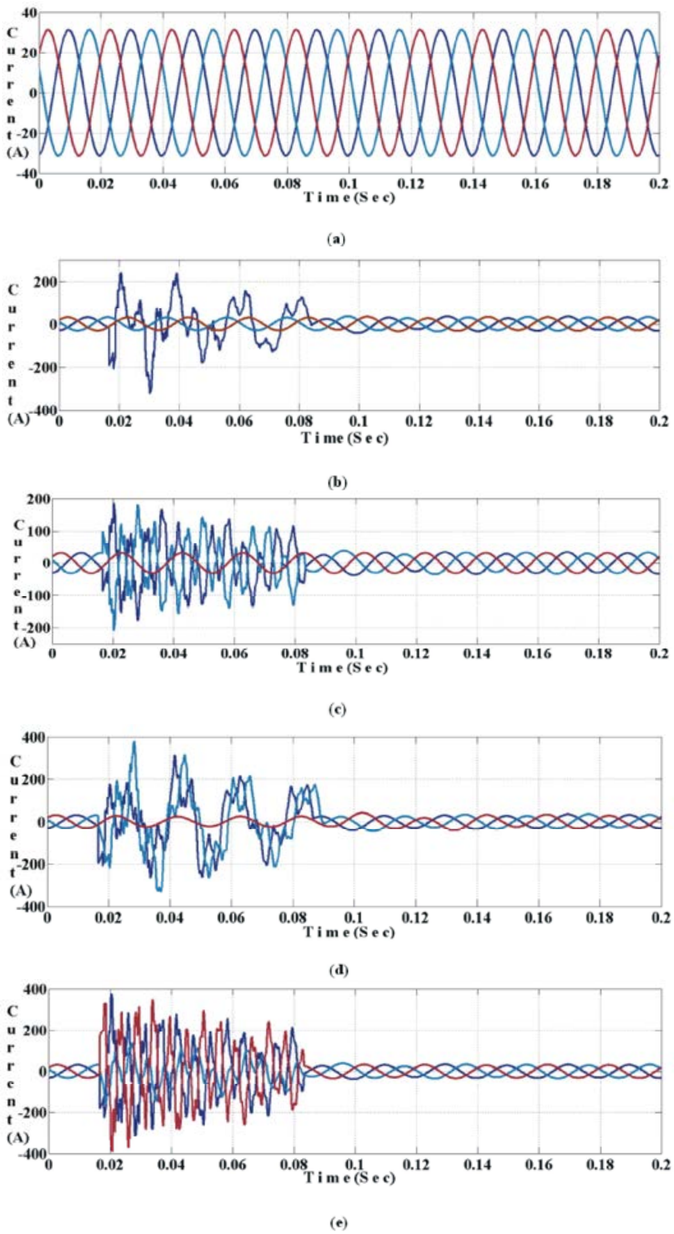


Fig. 4: Simulated Result for (a) Normal Condition, (b) Phase A to Ground, (c) Phase A to B, (d) Phase AB to Ground, (e) Phase ABC

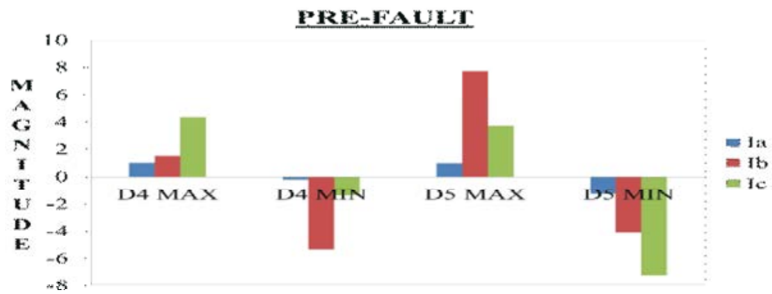
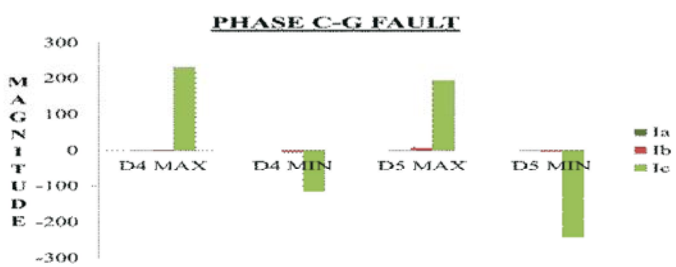


Fig. 5: Maximum and minimum detail coefficient of level 4 and level 5 in case of pre-fault condition

(a)

(b)

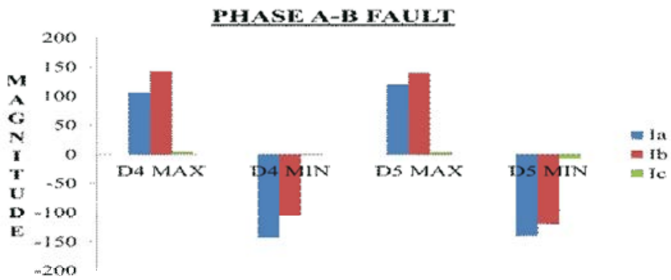


(c)

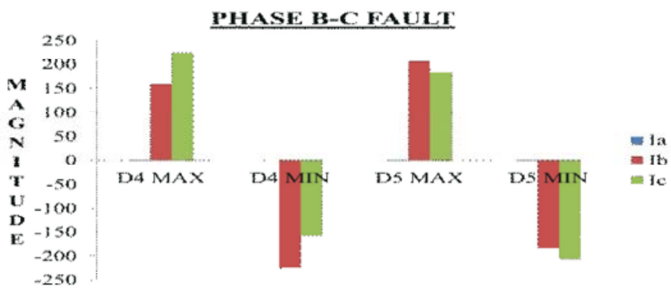
Fig. 6 Maximum and minimum detail coefficient of level 4 and level 5 in case of (a) A-G, (b) B-G, (c) C-G fault condition

DWT are maximum and minimum detail coefficient of three phase current signal at level 4 and level 5 which are used for fault detection and classification. The maximum and minimum detail coefficient of normal condition (pre fault) values at level 4 and level 5 are taken as reference and compared with abnormal one's. If the maximum and minimum detail coefficient value of the signal exceeded that of a normal condition, a fault is detected. The maximum and minimum detail coefficient of all different fault types are shown in Table 3 and Fig. 5, Fig. 6, Fig. 7, Fig. 8, Fig. 9.

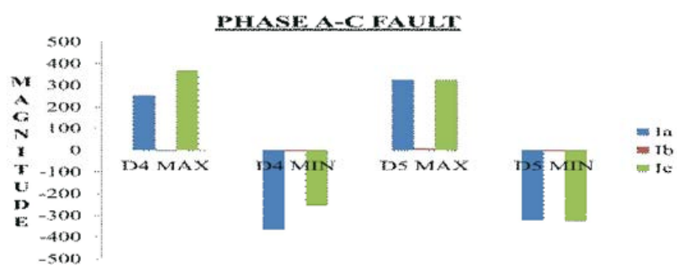
Fault Classification Simulation Results and Discussions: With the help of fault detection process, absence and presence of faults are known. However the discrimination of fault is not possible just with the help of DWT transformed signal. In this proposed system, ANN is used for fault classification purpose. The feature obtained by processing DWT are provided as an input to ANN. The features used for fault classification are maximum and minimum detail coefficient of three phase current signal of d4 and d5.



(a)



(b)



(c)

Fig. 7 Maximum and minimum detail coefficient of level 4 and level 5 in case of (a) A-B, (b) B-C, (c) A-C fault condition.

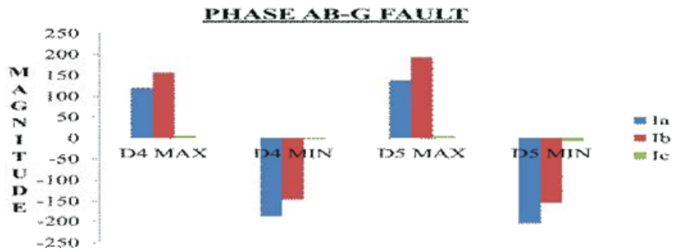
Training of the Neural Network: A feed forward back propagation neural network with 1 hidden layers is used for fault classification purpose. Input layer consists of six neurons which takes the maximum and minimum detail coefficient of three phases of the transmission line. The number of neurons in hidden layer is fixed with 10 neurons. Output layer has four neuron, output indicates fault type. This neural network structure is trained using back propagation training algorithm for the training data of transmission line model. The data using for training data division is done randomly, training algorithm used is Scaled conjugate Gradient algorithm. Performance function used is cross entropy. The different training parameter encountered during the training process is gradient, cross entropy and validation check. These training parameter plots are shown in Fig. 10. For better training purpose, cross entropy value should decrease when the training process continues, validation check gives us maximum number of fails in the Neural Network training process.

Performance Plot: The training data (maximum and minimum detail coefficient of three phases), when fed for training the neural network, is divided into three parts. The data samples are divided into train, test and validation sets randomly by the program, in the ratio 0.7:0.15:0.15.

The performance plot of proposed system is shown below in Fig. 11.

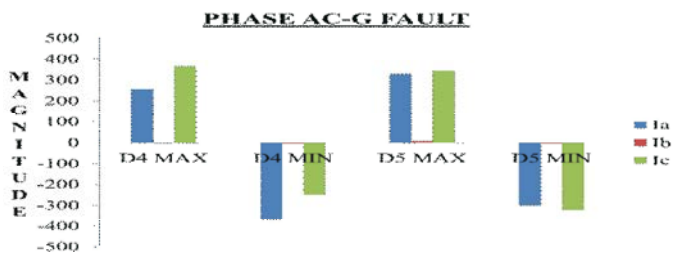
The above Performance results are reasonable because of the following considerations:

- The final mean-square error is small.
- The test set error and the validation set error has similar characteristics.



(a)

(b)



(c)

Fig. 8: Maximum and minimum detail coefficient of level 4 and level 5 in case of (a) AB-G, (b) BC-G, (c) AC-G

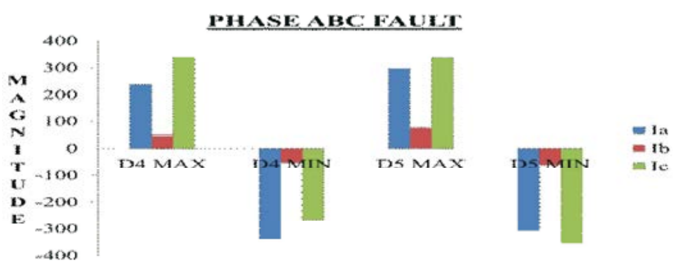


Fig. 9: Maximum and minimum detail coefficient of level 4 and level 5 in case of ABC fault condition

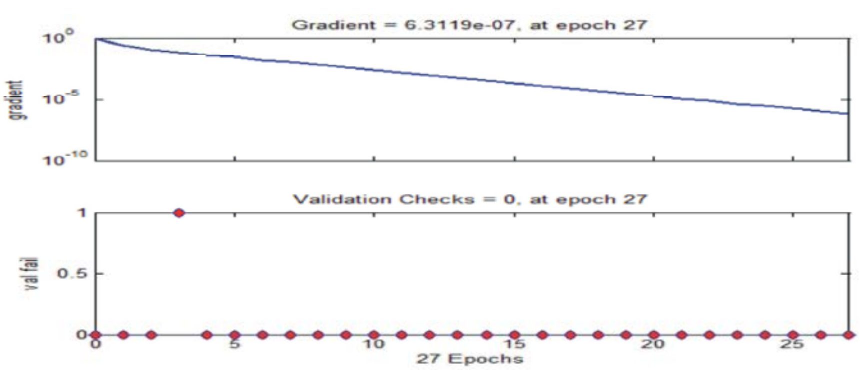


Fig. 10: Training Parameter Plot

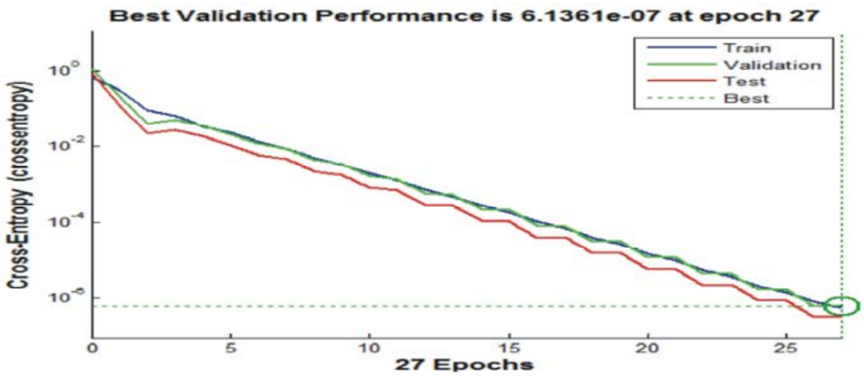


Fig. 11: Performance Plot

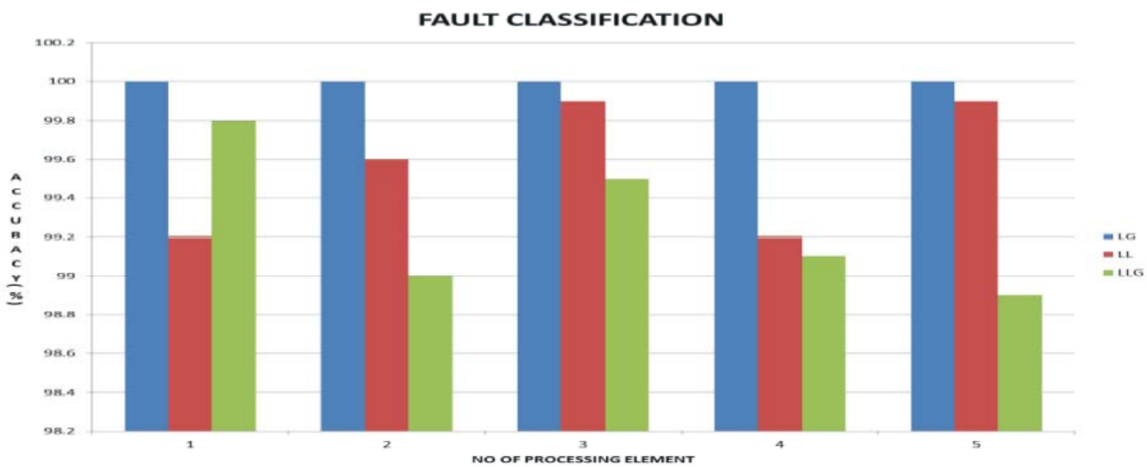


Fig. 12: Accuracy of fault classification

s The fault classification accuracy for proposed system is shown in Fig. 12.

CONCLUSION

The proposed paper uses an DWT-ANN techniques for fault detection and classification. Various transmission line fault are simulated in MATLAB 8.2. The three phase current signal of transmission line are decomposed up to fifth detail level using DWT to obtain feature extraction. The feature extracted by processing the discrete wavelet transform are maximum and minimum detail coefficient value of d4 and d5, which are used for fault detection and classification. The proper selection of db6 as mother wavelet has played a significant role of extracting the useful information for fault detection and classification. A feed-forward BP-ANN structure using scaled conjugate gradient algorithm is presented for fault classification. ANN is the best approach for determining the correct fault type in transmission line fault classification. The proposed paper provides approximately 90.60 percent accurate classification. Further work will be the investigation of fuzzy logic for more complicated transmission line protection. The proposed model can also be extended to other power system protection problems such as finding fault location. The proposed scheme is easily comprehensible, deterministic and feasible for aquatically implementation.

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