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Fault Detection and Classification in Transmission Line using Wavelet Transform and ANN

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Abstract

In recent years, there is an increased interest in fault classification algorithms. The reason, behind this interest is the escalating power demand and multiple interconnections of utilities in grid. This paper presents an application of wavelet transforms to detect the faults and further to perform classification by supervised learning paradigm. Different architectures of ANN are tested with the statistical attributes of a wavelet transform of a voltage signal as input features and binary digits as outputs. The proposed supervised learning module is tested on a transmission network. It is observed the Layer Recurrent Neural Network (LRNN) architecture performs satisfactorily when it is compared with the simulation results. The transmission network is simulated on Matlab. The performance indices Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Sum Square Error (SSE) are used to determine the efficacy of the neural network.

Keywords*: wavelet transform, daubechies wavelet, artificial neural network, supervised leaning method, mean square error, mean absolute error, root mean square error, sum square error*

1. Introduction

Modern power network consists of many utilities at transmission, generation and distribution ends, hence the contemporary power system is considered as a complex interconnected grid. With the rising trends of incorporating distributed generation sources (solar, wind and Hybrid power system models) near load ends leads us to a reliable and reduced transmission loss networks. However, with these installations there is a question mark on the reliability of conventional protection schemes due to a significant increase in fault MVAs. Moreover, the presence of DGs near to load center invites the possibility of the island formation which further leads to stability issues. An accurate fault detection methodology is required to initiate the preventive action at control center. In past various approaches are applied for fault identifications such as Neural Networks (NNs) in refrences [1]-[23], Fuzzy Neuro approaches in reference [1], combined applications in reference [3,4] and wavelet transforms in reference [5-8]. Normally these approaches employ the symmetrical components of the current and voltages as input features of supervised learning model. However, the noise and surges in transmission lines are a major factor in the performance of these approaches. The approach employed symmetrical components of currents and the numerical values of line currents as an input to the fuzzy neuro system. In reference [2], author proposed a technique to detect shunt faults in double end double fed transmission lines. In this approach author compared the performance of modular and single ANN. Fast distance protection of transmission lines were proposed by Ching Shan Chen et.al. in reference [9]. In this technique authors proposed a Fourier filtering to access the advantage of recursive computing and a decaying dc offset. Hilbert Huang transform was applied in reference [10]. This approach was an attempt to inculcate signal processing in fault identification. The approach employed in this paper was based on the conversion of three phase voltages in the vector of absolute values of its complex space-phasor. In reference [8] A. Yadav et.al. presented a fault classification algorithms based on Linear Discriminant Analysis (LDA). Current signals of each phase along with the zero sequence components of the currents are used as the input features of the ANN. The signals are processed with DB4 wavelets. Recent years signal processing techniques are used for classification purpose. The ability of these approaches to transform signals in a time domain is inevitable and appreciable.

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In the view of above discussion following are the research objectives of the paper:

a. To investigate the system's health under different fault conditions by measuring the phase voltages.
b. To apply wavelet transforms to create an initial frame work for binary classifier on the basis of standard deviation, maximum, minimum, mean and norm value of the phase voltages.
c. To prepare different supervised learning modules with the offline training dataset to classify different faults in a transmission network and derive the comparison between supervised learning models.
d. To prepare a binary class with the help of offline datasets of faults and abnormal conditions.

The remaining part of the paper is organized in following sections as, section 2; system description along with preliminaries of Wavelet transform. The details of classification engine are given in section 3. Description of system parameters is given in section 4. Simulation results are given in section 5. Following to this discussions and conclusions are presented.

2. Wavelet Transform

In recent years application of wavelet transform in real power system applications is increased. This signal processing technique is used in power quality event classification in reference [11], load forecasting in reference [12], image processing in reference [13]. This technique is a mathematical tool to disintegrate a signal into various frequency components. This is the way to study transient signal to extract time and frequency information simultaneously.

Fourier analysis doesn't show its effectiveness in non-stationary signals because in this type of analysis time information gets lost. As we know that the sine waves in the Fourier transform the, mother wavelet is the basic block representation of a signal in WT. As we have studied that the Fourier analysis having fixed application like sine (or) cosine functions while mother wavelet is having several existing applications like: Daubechies, Haar, Coiflet, Symlet etc. A WT is a precursor a utilitarian representation of a function in the time- frequency domain. Wavelet is a function of ø εL^2(R) with a zero average

$$\int_{-\infty}^{+\infty} \varphi(t)dt=0 \quad (1)$$

Continuous Wavelet Transform of a signal x(t) is explained as

$$CWT_{\varphi}x(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty} x(t)\varphi^*\left(\frac{t-b}{a}\right)dt \quad (2)$$

Where φ(t) is known as mother wavelet and a, b is scaling (dilation and translational) parameters respectively which determines its oscillatory frequency length of wavelet and shifting position respectively. Wavelet coefficient leads to huge computational burden. Therefore, to overcome this problem researcher introduced DWT. Discrete Wavelet Transform uses some values called scale and position value based on powers of two known as dyadic dilations and translation.

$$\text{DWT (m, n)} = \int_{-\infty}^{+\infty} x(t)\varphi_{m,n}^*(t)dt \quad (3)$$

Where; $\varphi_{m,n}(t) = a_0^{-m/2}(\frac{(t-na_0^m b_0)}{a_0^m})$

These parameters are a = a_0^m , b = $nb_0a_0^m$

Where m, n Z; m, n represents frequency localization and time localization respectively. In general case $a_0 = 2, b_0 = 1$ which gives dyadic orthogonal WT and determines the basis of Multi Resolution Analysis (MRA). In this paper we are using Db4 mother wavelet to detect faults in 3-phase compensation circuit. Daubechies wavelet is frequently used wavelet. Wavelet function with various disappearance moments has been tested on Db4 for fault detection and other properties are like low amplitude of signals, fast response etc. Various faults are like LG, LLG, 3-phase faults calculated (or) analysed by using this methodology. Results show that the methodology is effective, reliable, fast and highly accurate. As shown in Figure 1.

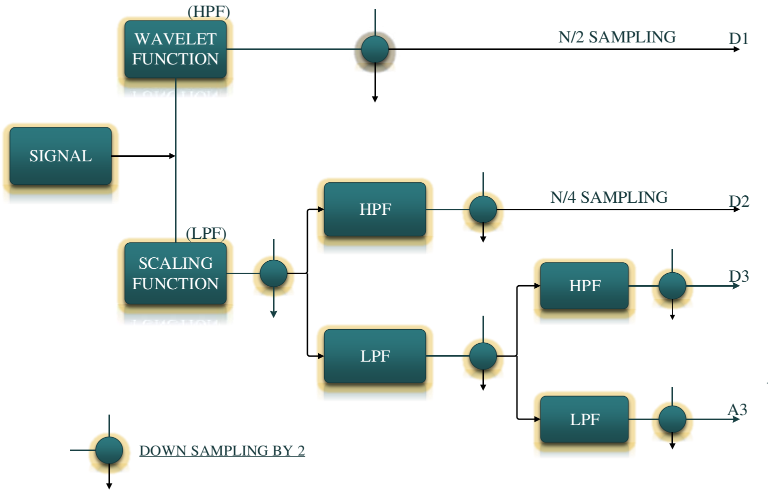


Figure 1. Wavelet MRA

3. Fault Classification Engine

Neural network deals in vast area of applications including: pattern classification, pattern recognition, optimization, prediction and automatic control. In malice of various structure and training paradigm, all NN applications are special cases of vector mapping in reference [14]. Neural Network works in large area like load forecasting in reference [15-17], fault diagnosis/fault location in reference [18], economic dispatch in reference [19], security assessment in reference [20], transient stability in reference [21] etc.

While designing the classification engine following parameters are kept in consideration.

a. The system voltage is varied randomly in a close range to generate 700 samples of different contingencies in transmission network. Seven faults are simulated with the help of nonlinear simulation. The voltage at bus B1 is measure with the help of Phasor Measurement Units (PMUs). After measurement of the voltage, wavelet transform of voltage is obtained.
b. Proper choice of mother wavelet to extract potential attributes from the voltage signals is a daunting task. It is empirical to judge that Db4 wavelet transform is the simplest form of wavelet transform and commonly used in approaches associated with fault classificationin reference [4]. Hence, in this work the Db4 transform is taken.

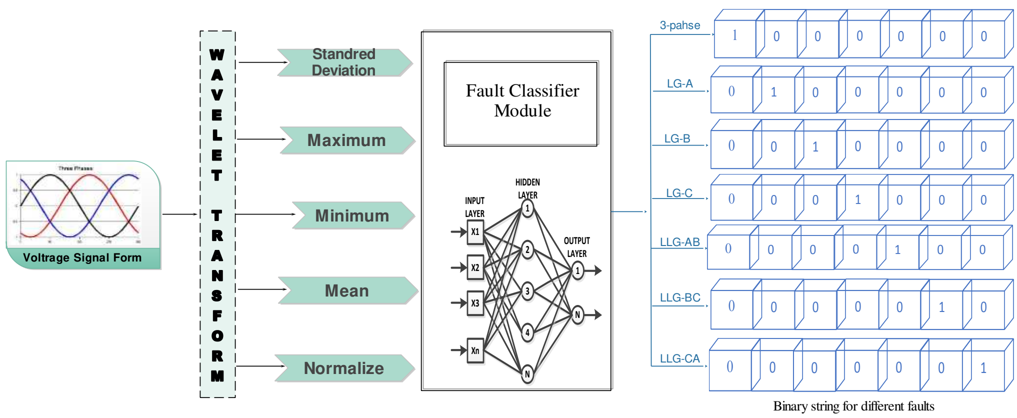


Figure 2. Classification Engine

c. Detailed and approximation coefficients are obtained from the transform. Mean, standard deviation, norm, maximum and minimum values of detailed coefficients are taken as potential input features for construction of the classification engine. Figure 2 shows the basic structure of the classification engine. Out of 700 samples 70 % data are used for training and remaining is used for validation and testing of the neural topologies. Figure 3 shows set of input features for all seven contingencies. It is observed that a significant amount of change in statistical attributes of detailed coefficients is observed for different contingencies. This fact set the frame work for development of the classification engine. The system details are given in preceding section.

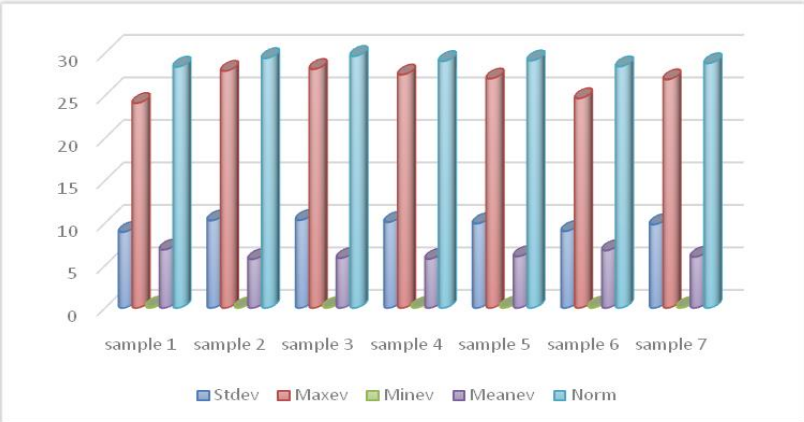


Figure 3. Input features for Different Contingency Conditions

4. System Parameters

To simulate various faults transmission network is modelled in Matlab Simulink and Neural network tool box is utilized to design binary classifier. This system has 6 generating units of 350 MVA, 13.8 KV at one end and 30,000 MVA and 735 KV generating unit at other end. These two generators are combined with a transmission network having two nonlinear and two linear loads. Two reactive loads are there having capacity of 330MVAR lagging load and 100MW and 250 MW active load. This system contains 6 transforming units of 350 MVA, 13.8/735KV (having two windings) at one end and 300MVA, 735/230KV (having three windings) transforming unit at another end.

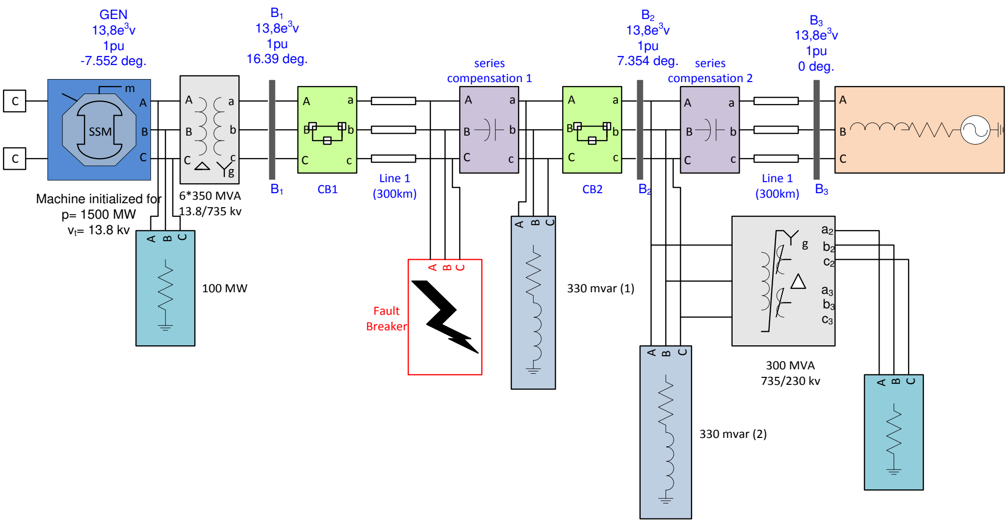


Figure 4. Three-phase Series Compensated Network

5. Simulation Results

This section presents the analysis of the performance of fault classifier. After carefully observing the waveforms it is empirical to see that different fault has different effect on the system performance. From here it is concluded that in a large transmission system supervised learning based algorithm is required to classify the faults so that an effective preventive action can be initiated at substation. These simulation results are also useful in designing protective schemes of this transmission network. Table 1 shows different fault events with their equivalent binary representation. These seven faults are simulated with the 5 cycle transition time. Fault resistance has considered as 0.001 ohms. To judge the effects of different faults on the system voltages different faults are simulated and the results in terms of voltage at B1 are shown in table 3. For voltage measurement, a unit is installed at point B.

Table 1. Fault Cassification with Binary Strings

Type of Fault	Phase`	Binary Equivalent
LG	A	0001
	B	0010
	C	0011
Double line to Ground	A-B	0100
	B-C	0101
	C-A	0110
Three Phase Fault	A-B-C	0111
Normal Condition		1000

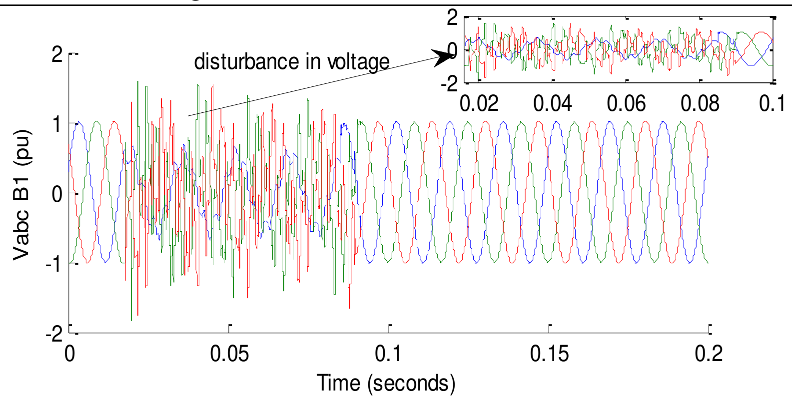
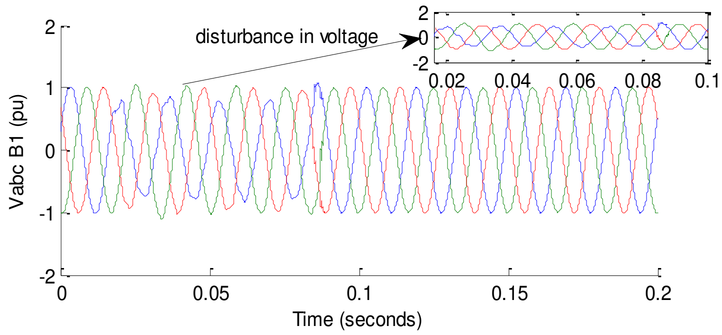
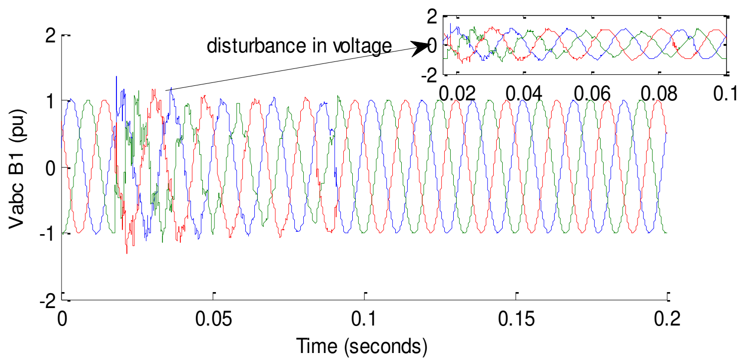
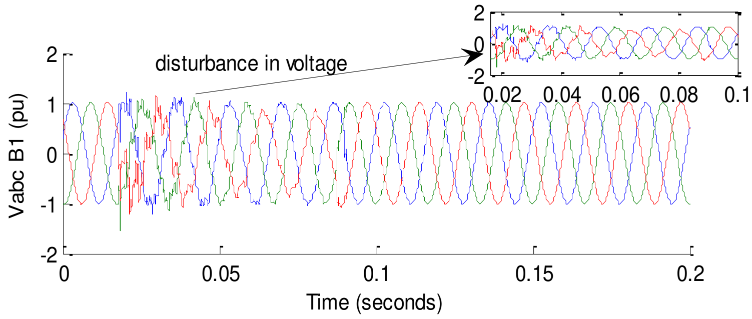
700 patterns of above mentioned faults are created by varying the system voltages. The wavelet transforms of system voltages are calculated. Standard deviation, maximum, minimum, mean and normalize value of detailed energy coefficient is utilized as efficient feature to map the outputs in table 1. Out of these 700 patterns 70% patterns are utilized for training remaining 15-15 % patterns are utilized for testing and validation purposes different architectures of neural network namely Feed Forward Neural Network (FFNN), Back Propagation Neural Network(BPNN), Layer Recurrent Neural Network(LRNN) and Radial Basis Function Neural Network(RBFNN).

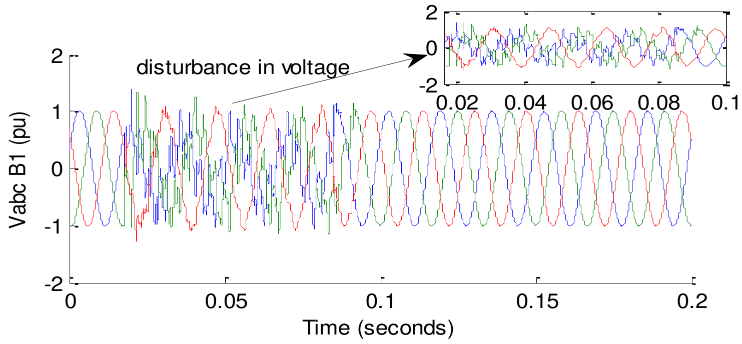
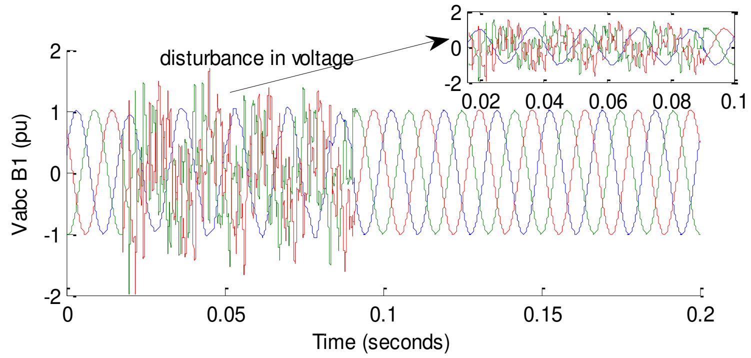
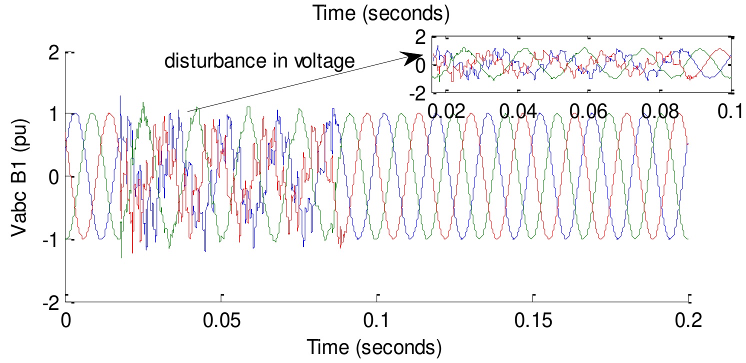
Table 2. Network Errors

Error Indice	FFNN	Elman BPNN	LRNN	RBFNN
MSE	1.81E-09	2.40E-09	1.40E-09	8.89E-09
MAE	9.27E-06	1.01E-05	1.06E-05	3.97E-05
RMSE	4.25E-05	4.90E-05	3.74E-05	9.43E-05
SSE	8.86E-06	1.17E-05	6.87E-06	4.36E-05

The error plots for these faults are shown in figure 5. Different error indices are calculated to validate the efficacy of the neural networks for determining the faults. It is observed that the values of these indices are very low and that advocates the efficacy of the proposed supervised learning model.

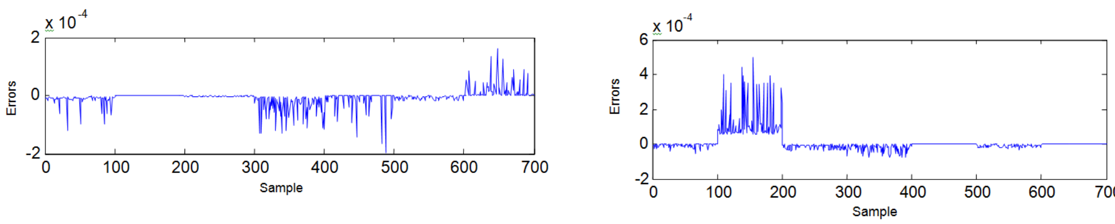
Table 3:- Time- Voltage Waveform for All Seven Faults

S.No	Voltage-Time waveform	Type of fault
1.		3-phase fault
2.		A-phase
3.		B-phase Single line to ground (LG) fault
4.		C-phase

5.		AB-phase	
6.		BC-phase	Double line to ground (LLG) fault
7.		CA-phase	

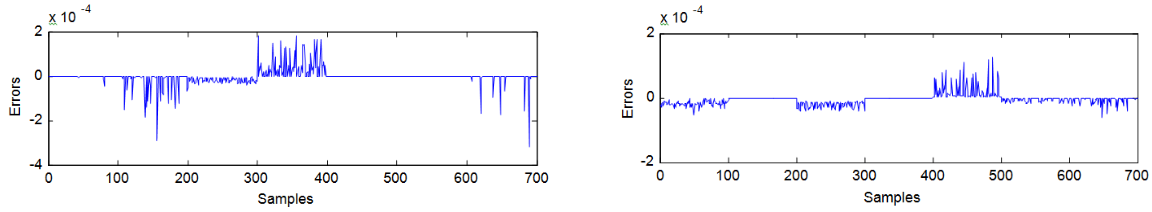
Above shown table 3 is the brief description of voltage and time phenomenon with each other during fault condition in system. Various types of faults occur in system that is single line to ground, double line to ground and 3-phase faults. where collected data from signal bus B1, signal busB2 and Signal cS1 shows the different voltages on different time.

By the help of different supervised learning modules classification of the faults can be obtained by offline trained data. A comparison based on different error indices is incorporated in figure 6. Error plots indicate the events wrongly identified by LRNN. Error plots for 3-phase, LG fault and LLG fault are shown below (Figure 5) which have been plotted between samples and detected error of the system.



(a) Error Plot for 3-Phase Fault

(b) Error plot for B-phase (LG) Fault



(a) Error Plot for AB-Phase (LLG) Fault (d) Error Plot for BC-phase (LLG) Fault

Figure 5. Error Plots for Different Faults

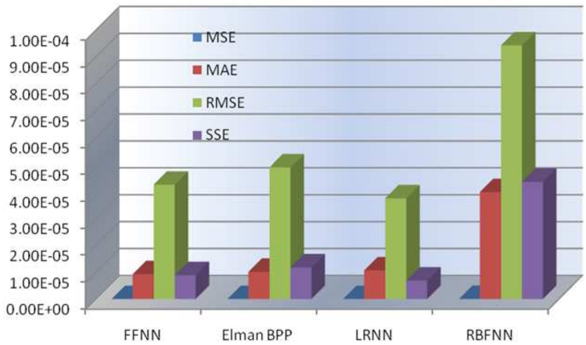


Figure.6 Analysis of Error Indices for Different Network Topologies

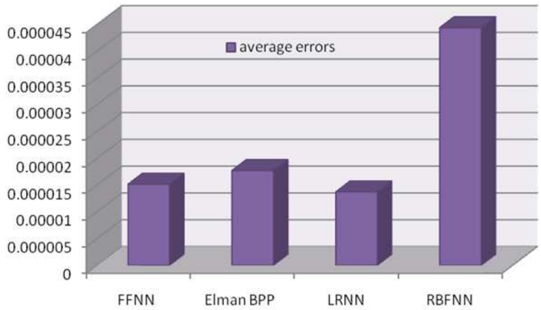


Figure.7 Analysis of average Values of Error Indices for Different Network Topologies

Figure 5 shows the error plots of LRNN in the determination of different faults in transmission network. Figure 6 shows the analysis of error indices for different network topologies. Which shows that MSE, MAE, RMSE, SSE of LRNN network is less in the comparison of other networks. It is concluded that LRNN shows better classification efficiency to identify faulty conditions in power system. Figure 7 shows the average values of errors in fault condition.

5. Conclusion

This paper presents a combined approach of Wavelet (DB4) and Artificial Neural Network to classify the single line, double line and 3-phase faults for protection of transmission line. The performance of presented method is declared incorporating the effect of various parameters like fault type, fault location, fault resistance and variation in power flow angle. Inputs given to the neural are approximate and detailed coefficient of wavelet transform. Once the neural network has been trained, it is tested for various fault condition as mentioned above incorporating variations in various fault parameters. Presented method shows promising results in all those fault conditions and the efficiency of this method is high for fault detection and classification. According to the simulation results presented method classify the faults within very less time which is the benefit of this method over other previous proposed approaches.

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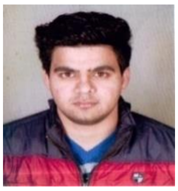

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