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

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Abstract

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 aretested 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 that ANN 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 utilitiesat transmissions, 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 centre 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 centre.

In past various approaches are applied for fault identifications such as Neural Networks (NNs) [1]-[21], Fuzzy Neuro approaches [1], combined applications [3,4] and wavelet transforms [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. Fuzzy neuro technique was applied in [1]. The approach employed symmetrical components of currents and the numerical values of line currents as an input to the fuzzy neuro system. In [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. [9]. In this technique authors proposed a Fourier filtering to access the advantage of recursive computing and a decaying dc offset. Hilbert Haung transform was applied in [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. 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

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classification purpose. The ability of these approaches to transform signals in a time domain is inevitable and appreciable.

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

1. To investigate the system's health under different fault conditions by measuring the phase voltages.
2. To apply wavelet transforms to create an initial frame work for binary classifier on the basis of standard deviations in the phase voltages.
3. To prepare different supervised learning modules with the offline training dataset to classify different faults in a transmission network and derive the comparison between those supervised learning models.
4. To prepare a binary class with the help of offline datasets of faults and abnormal conditions.

The remaining paper organizes as follows in section 2; system description along with preliminaries of Wavelet transform is discussed. The details of ANN and Classifier architecture are given in section 3. Brief description of fault is given in section 4 and description of working model is given in section 5. Simulation results are given in section 6. Following to this discussions and conclusions are presented.

2. Wavelet Transform (WT)

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 [11], load forecasting [12], image processing [13], is a mathematical tool to disintegrate a signal into various frequency components. This is the way to study of 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 application like: Daubechies, Haar, Coiflet, Symlet etc. A WT is a precursor a utilitarian representation of a function in the time- frequency domain. In the series of applications, WT is applied for protection of power system, analysis of power system transients, detection and classification of power quality.

Wavelet is a function of $ø\varepsilon L^2$(R) with a zero average

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

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

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

Where φ(t) is known as mother wavelet and a, b are 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.

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

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 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. Figure 1 shows Wavelet MRA

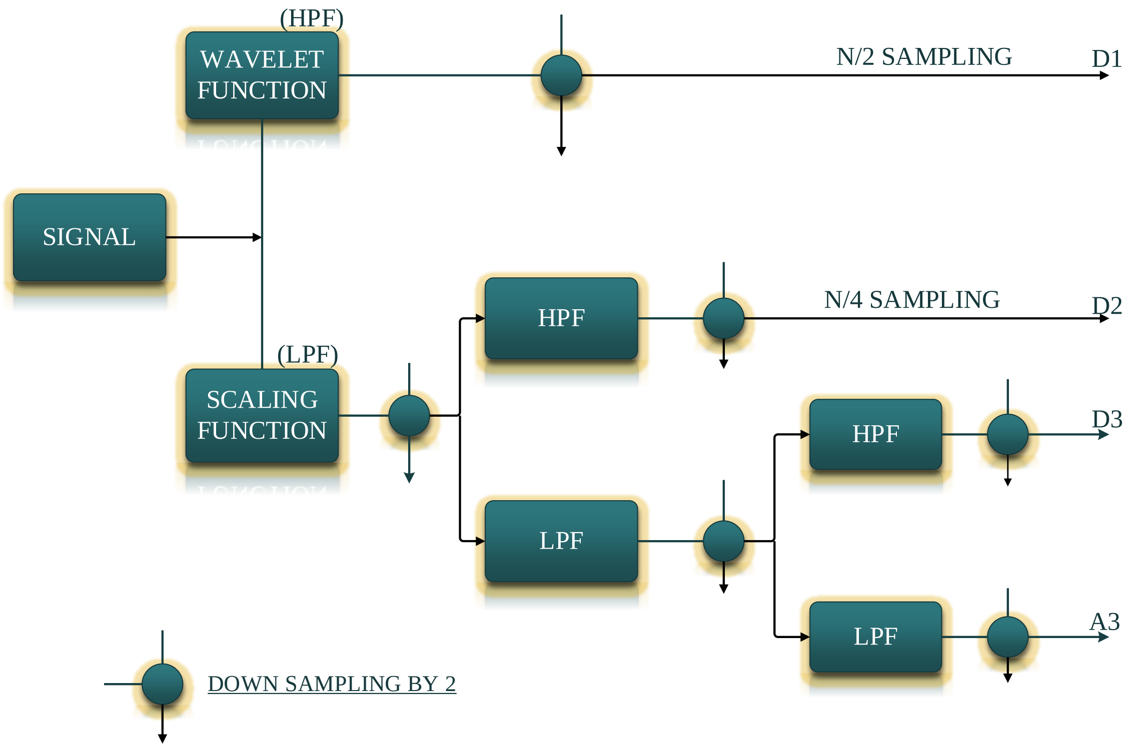


Figure 1. Wavelet MRA

3. Artificial Neural Network

Neural network has been deal 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 [14]. Neural Network works in large area like load forecasting [15-17], fault diagnosis/fault location [18], economic dispatch [19], security assessment [20], transient stability [21] etc. Figure 2 shows architecture of neural network

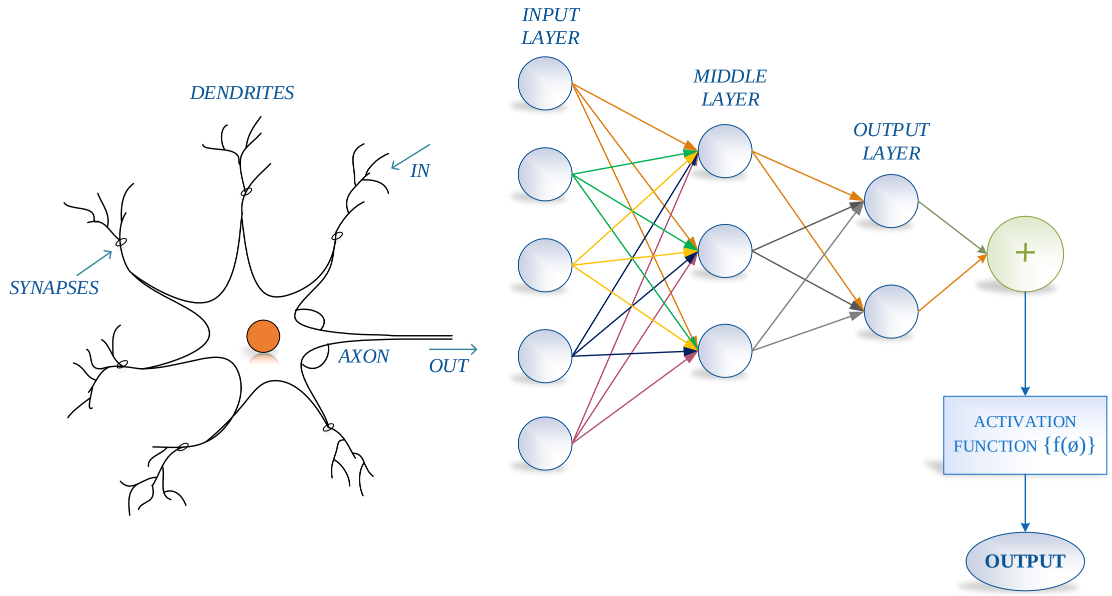
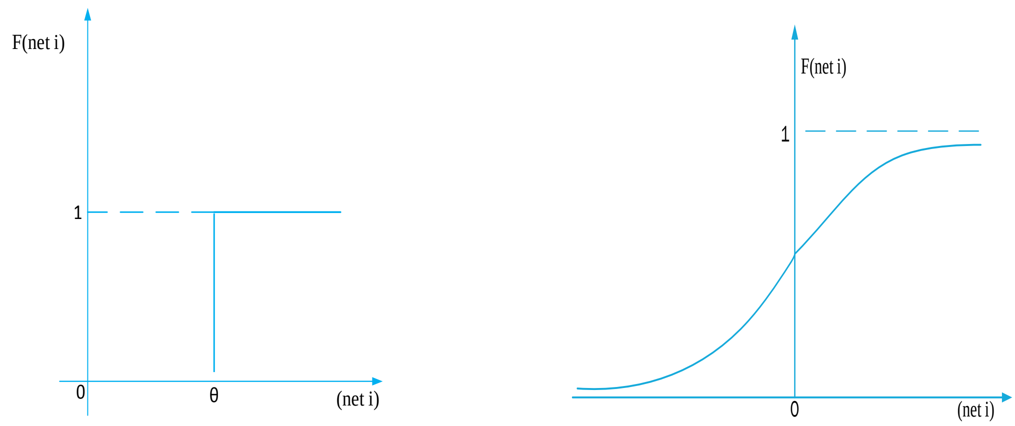


Figure 2. Architecture of neural network

The basic computational element (model neuron) is often called a node (or) unit. It receives input from some units, or perhaps from external sources. Each input has an associated weight W. which can be modified so as to model synaptic learning. The unit computes some function F of the weighted sum of its input.

$$y_i = f(net_i)$$
$$net_i = \sum_j W_{ij} X_i + b$$

Its output in turn case serves as input to other units. The weighted sum is called the unit input to unit I, often written net_i.
Where; the W_{ij} refers to the weight from unit j to unit i.
Above shown function is known as activation function. It consists of many type of function. Some are shown here i.e. hard limit (step) and sigmoid function. Figure 3 shows activation function.



(a) Hard Limit /Step function (b) Sigmoid function

Figure 3. Activation function: (a) Hard limit (or) Step function, (b) Sigmoid function

Hard limit function (step function) is

$$F(net_i) = \begin{cases} 0 & net_i < \theta \\ 1 & net_i \geq \theta \end{cases}$$

Sigmoid function

$$F(net_i) = 1/\ 1+ e^{-net_i}$$

Every neural network consists of 3 layers i.e. input layer, hidden layer and output layer and these layers are formed by interconnected neurons.

To get deliberate output for the given input the network weights need to be modified. The operation of weights modification is called network learning/ training is done iteratively by presenting a set of input data and required output data. This learni8ng is called supervised learning.

Network training uses the (MSE) Mean Squared Error as the cost function which is explained as

$$E = \frac{1}{N}\sum_{n=1}^{N}(d_k(n) - y_k\ (n))^2 \tag{4}$$

Where; n= number of pattern in data set
$d_k(n)$, $y_k(n)$ = required output (k= output at layer k for n^{th})
The change in weight is as follows

$$W_k\,(t+1)= W_k(t) + \Delta W_k (5)$$

W_k = weight correction
Where weight correction is

$$\Delta W_k\,(n) = -\rho\frac{\delta E(n)}{\delta W_k}$$

Where; E(n) = immediate square error and $\rho = learningrate$,
Where; E (n) = ½ e_k^2 (n) = ½ (d_k(n) – y_k (n))2

4. Faults

Power system is a complex interconnected network which consists of generation, transmission and distribution utilities. Short circuit and other conditions occur in power system, called as fault. The essence of a fault is merely explained as any eccentric condition, which causes depletion in the basic insulation strength between phase conductors, phase conductor and earth or any earthed screens encompassing the conductors. Faults are cause of some conductor damage or insulation failure. It can be harmful to the whole power system. In transmission line faults occur by overvoltage due to lightning and switching surges or other external objects.

Power system faults may be classified as shunt fault and series fault. The most arising fault type of shunt fault is Single Line-to-Ground faults (SLG), which arise along the power lines. Line-to-Line-to-Ground (LLG) fault and 3-phase faults are consider as a most occurring and least occurring fault respectively. In this paper we are going to explain the detection and classification technique by using series compensation circuit. Figure 4 shows fault classifier processing.

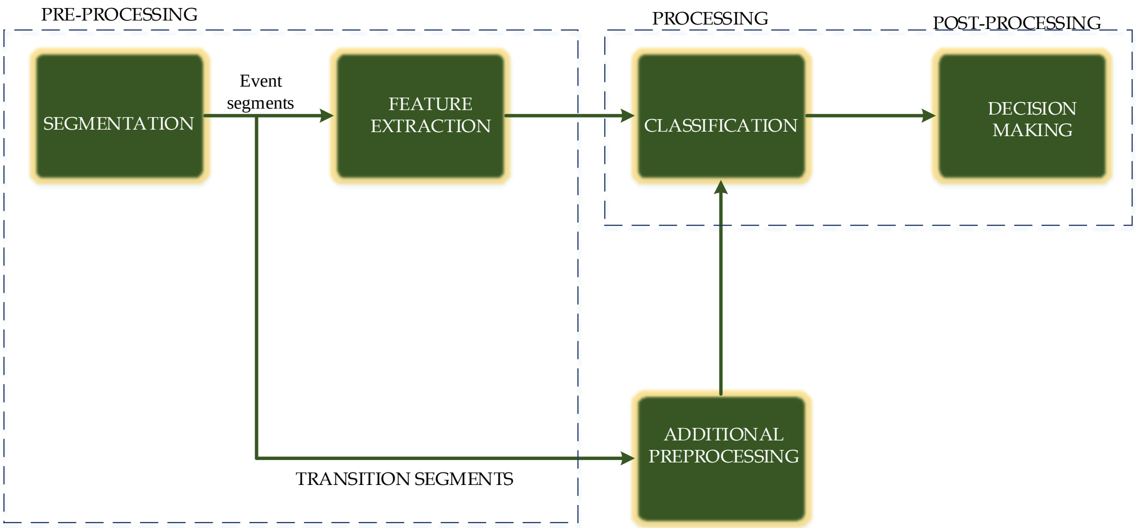


Figure 4. Fault classifier

5. Simulation Model and Result Discussion

This section presents the analysis of the performance of fault classifier. 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 containes 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 5 shows three-phase series compensated network.

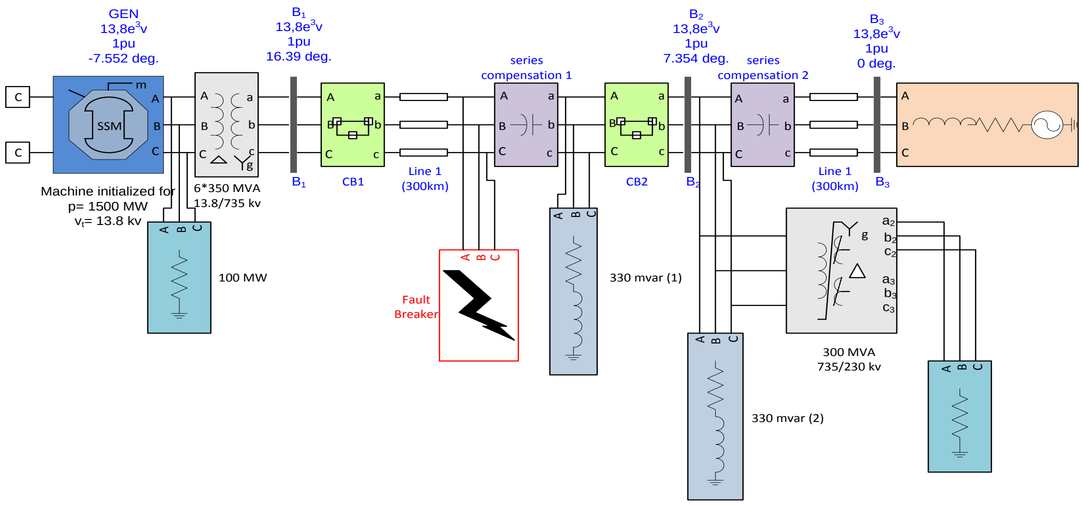


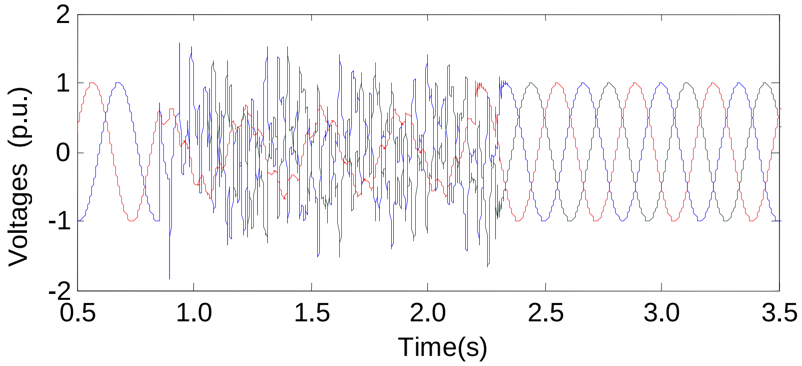
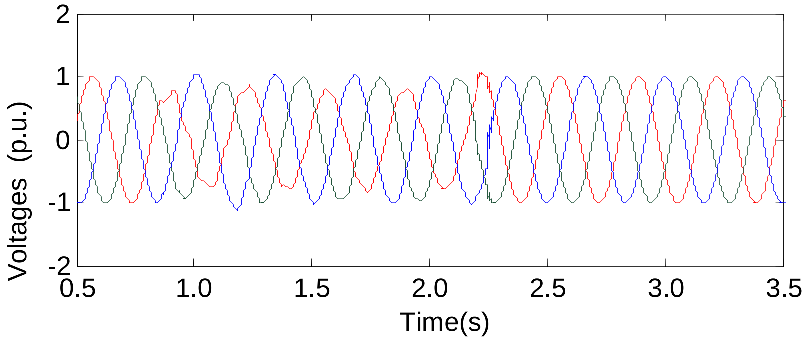
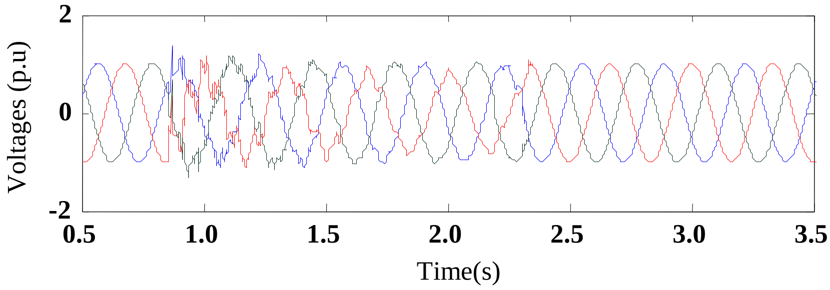
Figure 5. Three-phase series compensated network

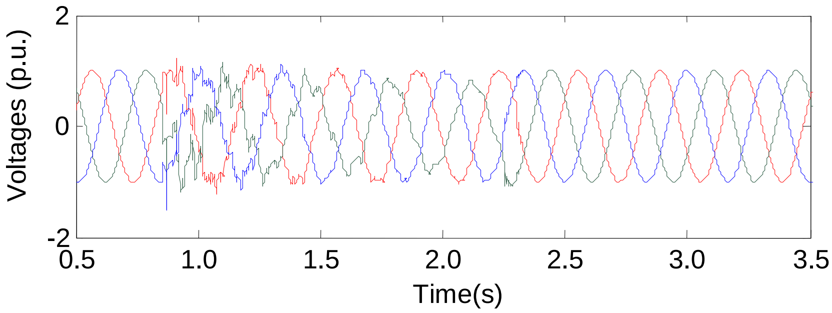
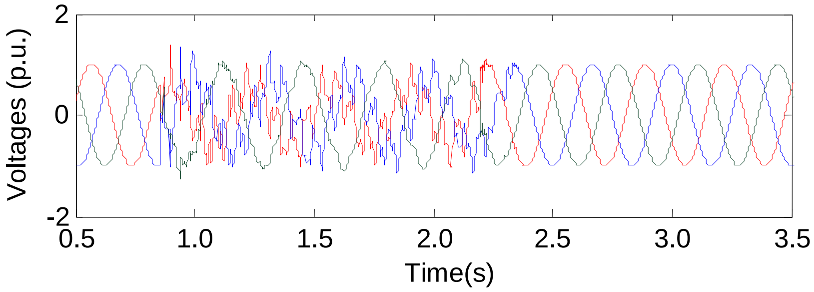
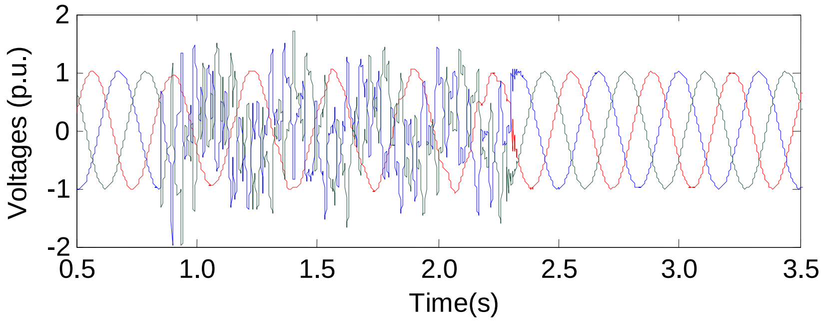
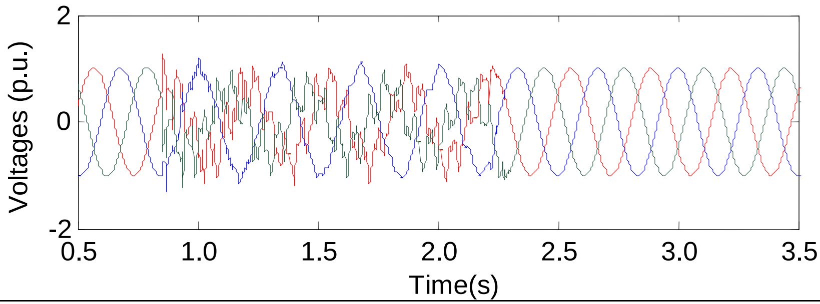
After carefully observing the waveforms it is empirical to see that different fault has different effect on the system performance. From here it is concluded that in a large transmission system supervised learning based algorithm is required to classify the faults so that an effective preventive action 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 2. For voltage measurement, a unit is installed at point B.

Table 1. Fault classification with binary strings

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

Table 2. 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	Double line to ground (LLG) fault
6.		BC-phase	
7.		CA-phase	

There are 700 patterns of above mentioned faults are created by varying the system voltages. The wavelet transforms of system voltages are calculated. Standard deviation of detailed energy coefficient is utilized as efficient feature to map the outputs in Table 3. Out of these 700 patterns 70% patterns are utilized for training remaining 15-15 % patterns are utilized for testing and validation purposes. Error indices are defined in [22].

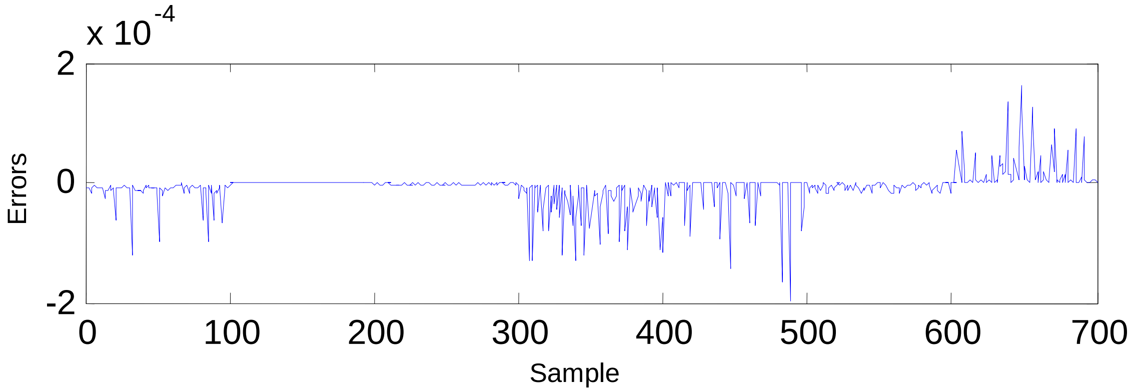
Table 3. Network errors

Error Indice	FFNN	Elman BPP	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

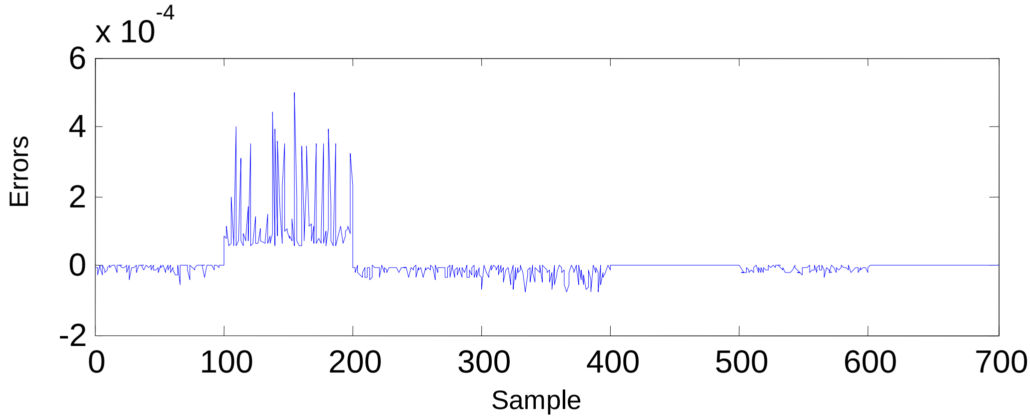
The error plots for these faults are shown in Figure 6. Different error indices are calculated to validate the efficacy of the neural networks for determining the faults. It is observed that the values of these indices are very low and that advocates the efficacy of the proposed supervised learning model.

Above shown Table 2 is the brief description of voltage and timephenomenon with each other during fault condition in system. Various tye of faults occur in syetm that is single line to ground, double line to ground to line and 3-phase fault where collect data from signal bus B1, signal busB2 and Signal cS1 shows the different voltages on different time.

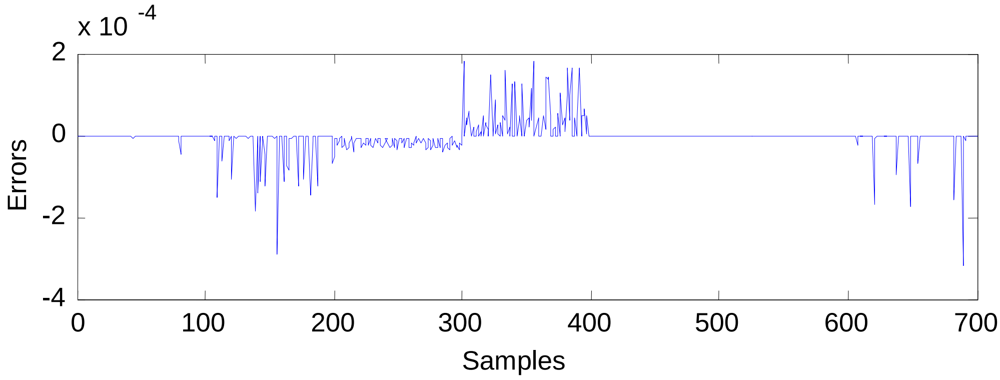
By the help of different supervised learning modules classification of the faults can obtain by offline trained data. A comparison based on different error indices is incorporated in Figure 6. Error plots indicate the events wrongly identified by Layer Recurrent Neural Network. Error plots for 3-phase, LG fault and LLG fault shown below which ploted between samples and detected error of the system:



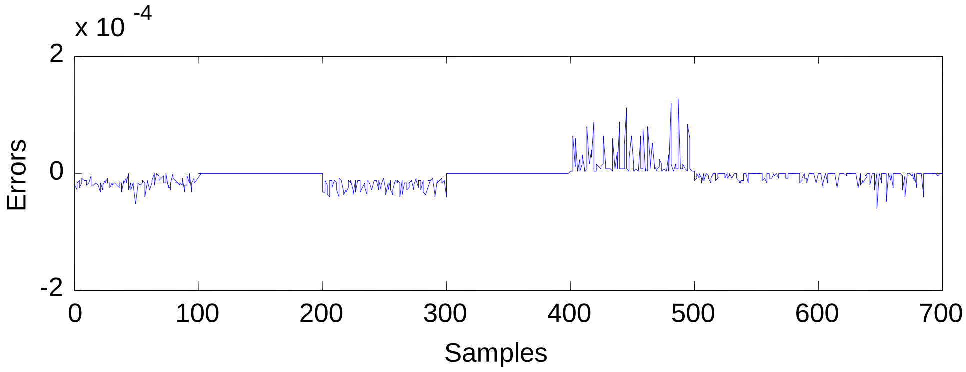
(a) Error plot for 3-phase fault



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



(c) Error plot for AB-phase (LLG) fault



(d) Error plot for BC-phase (LLG) fault

Figure 6. Error plots for faults

It is observed that when different neural topologies are employed for fault classification in a transmission network, the efficacies of these different apparoches are different for solving the classification problems. From Figures 7 and 8 it is concluded that LRNN exhibits better results as compared with other topologies of neural networks. Average values for the indices are also fall in low range for LRNN.

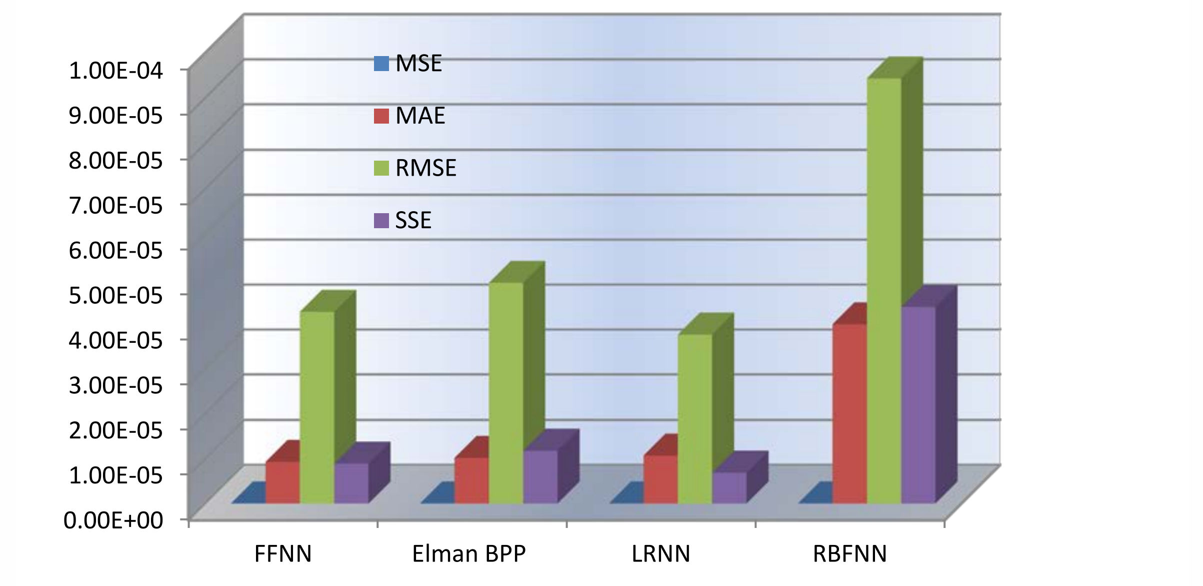


Figure 7. Analysis of error indices for different network topologies

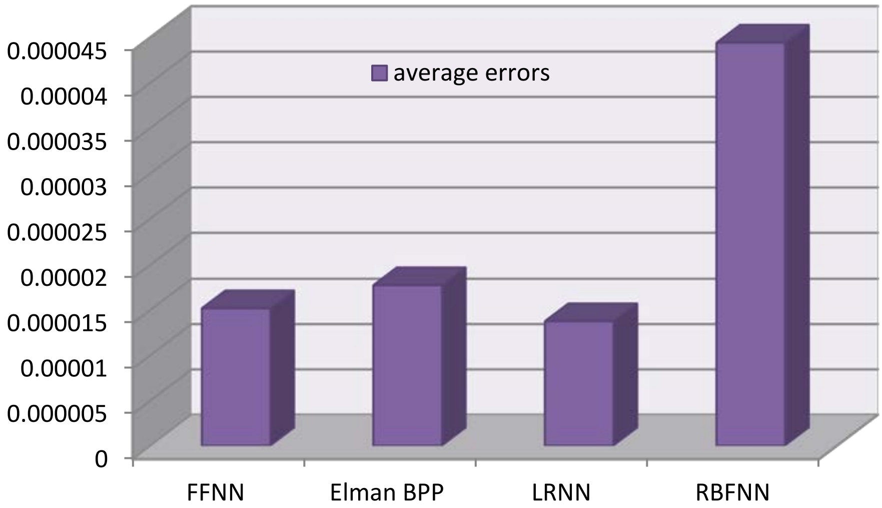


Figure 8. Analysis of average values of error indices for different network topologies

Figure 8 shows the error plots of neural network in the determination of different faults in transmission network. It is concluded that proposed neural network shows better classification efficiency to identify faulty conditions in power system.

6. Conclusion

This paper presents a combined approach of Wavelet(DB4) and Artificial Neural Network to classify the single line and double line faults for protection of transmission line.The performance of presented method is declared encorporating 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 metioned above encorporating variations in various fault parameters. Presented method shows promosing results in all those fault conditions and the efficiency of this method is high for fault detection and classification. According to thesimulation 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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References

[1] H Wang, WWL Keerthipala. "Fuzzy-neuro approach to fault classification for transmission line protection". *IEEE Transactionson Power Delivery*. 1998; 13(4): 1093–1104.
[2] A Jain, AS Thoke, RN Patel. "Classification of single line to ground faults on double circuit transmission line using ANN". *International Journal of Computer and Electrical Engineering*. 2009; 1(2): 197–203.
[3] M Geethanjali, KS Priya. "Combined wavelet transforms and neural network (WNN) based fault detection and classification in transmission lines". in *Proceedings of the InternationalConference on Control,Automation, Communication and EnergyConservation (INCACEC '09)*. 2009:1–7.
[4] M Patel, RN Patel. "Fault Detection and Classification on a Transmission Line using Wavelet Multi Resolution Analysis and Neural Network". in Journal of *International Journal of Computer Applications (0975 – 8887).* 2012; 27(22): 27-33.
[5] J Chen, RK Aggarwal. "A new approach to EHV transmission line fault classification and fault detection based on the wavelet transform and artificial intelligence". in *Proceedings ofthe IEEE Power and Energy Society General Meeting*. 2012: 1–8.

[6] MF Othman, M Mahfouf, DA Linkens. “Transmission lines fault detection, classification and location using an intelligent power system stabiliser”. in *Proceedings of the IEEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies (DRPT ’04)*. 2004; 1: 360–365.

[7] MF Othman, HA Amari. “Online fault detection for power system using wavelet and PNN”. in *Proceedings of the IEEE 2nd International Power and Energy Conference (PECon’08)*. 2008: 1644–1648.

[8] A Yadav, A Swetapadma. “A novel transmission line relaying scheme for fault detection and classification using wavelet transform and linear discriminant analysis”. in *proceeding Ain Shams Engineering Journal.* 2014; 6: 199-209.

[9] CS Chen, CW Liu. “Application of Combined Adaptive Fourier Filtering Technique and Fault Detector to Fast Distance Protection”. in *proceeding of the IEEE transaction of power delivery*. 2006; 21(2): 619-626.

[10] A Bernadic, Z Leonowicz. “Fault location in power networks with mixed feeders using the complex space-phasor and Hilbert–Huang transform”. in proceeding *ELSEVIER*. 2012: 208-219.

[11] DK Chaturvedi, AP Sinha, OP Malik. “Short term load forecasting using fuzzy logic and wavelet transform integrated generalized neural network”. *Electrical Power and Energy System-ELSEVIER*. 2014; 67: 230-237.

[12] D Baleavu. “Advanced in wavelet theory and their applications in engineering, physics and technical”. ISBN: 978-953-51-0494-0. 2012.

[13] MT Vakil, N Pavesic. “A Fast Simplified Fuzzy ARTMAP Network”. *Kluwer Academic Publisher*. 2003: 273-316.

[14] HS Hippert, CE Pedreira, RC Souza. “Neural Networks for Short-Term Load Forecasting: A Review and Evaluation”. *IEEE Trans. onPower System*. 2001; 16(1): 44-53.

[15] W Charytoniuk, MS Chen. “Neural Network Design for Short-Term Load Forecasting”. *IEEE International Conference of Deregulation of Power System Technologies*. 2000: 554-551.

[16] AK Sinha. “Short Term Load Forecasting Using Artificial Neural Networks”. *IEEE Trans. On Power System Distribution*. 2000: 548-553.

[17] G Rolim, JG Zurn. “Interpretation of Remote Backup Protection for Fault Section Estimation by a Fuzzy Exper System”. *IEEE PowerTechConference*. 2003: 312-315.

[18] R Lukomski, K Wilkosz. “Power System Topology Verification Using Artificial Neural Network Utilization of Measurement Data”. *IEEEPowerTech Conference*. 2003: 180-186.

[19] N Kumarappan, MR Mohan, S Murugappa. “ANN Approach to Combined Economic and Emission Dispatch for Large-Scale System”. *IEEE Power Distribution system*. 2002: 323-327.

[20] KW Chan, AR Edward, AR Danish. “On-Line Dynamic Security Contingency Screening Using Artificial Neural Network”. *IEEE Trans.Power Distribution System*. 2000: 367-372.

[21] AG Bahbah, AA Girgis. “New Method for Generator's Angles and Angular Velocities Prediction for Transient Stability Assessment of Multi Machine Power Systems Using Recurrent Neural Network”. *IEEE Trans. of Power System*. 2004; 19: 1015-1022.

[22] Nikita Mittal, Akash Saxena. “Layer recurrent neural network power system load forecasting”. *Telecomonika Indonesian journal of electrical engineering*. 2015; 16(3).