Critical investigations on performance of ANN and wavelet fault classifiers

Purva Sharma and Akash Saxena

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Purva Sharma1 and Akash Saxena1*

Abstract: With increasing demands and competitive business environment, the structure of power system has become very complex. Moreover, power system is a dynamic framework due to faults and rapid load variations. Hence, the detection algorithms for faults are potential areas of research. To discuss this issue and to provide the solution methodology for detection of faults and further classification of those in a smart grid is a primary motivation of this manuscript. This paper presents application of supervised learning algorithms based on different neural network topologies for detection and classification of the faults in transmission lines in power system. Different wavelet transforms on different Multi Resolution Analysis levels are applied for detection of the potential features from the voltage waveforms of the Phasor Measurement Units (PMUs). These wavelet transforms are then applied to several neural networks classification engines to classify faults. Binary classification technique is used for definitions of faults. Different faults namely single line to ground, line to line, double line to ground and three phase symmetrical faults are designated as a binary digit. These definitions are employed to train the classification engine. Different plots of confusion and errors are plotted to establish a fair comparison between supervised learning algorithms.

ABOUT THE AUTHORS

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PUBLIC INTEREST STATEMENT

With the increase in population and competitive business environment, existing grids are operating at their operating limits. In recent years, fault classification algorithms have gained interest of researchers. Fault classification algorithms are hybrid applications of wavelet transforms and supervised learning engines. However, choice of mother wavelets, MRA levels and proper selection of neural topologies are major issues in the design of these algorithms. In view of these facts the manuscript presents a comprehensive study on different topologies of neural networks along with different wavelet transforms to build an efficient classification algorithm for a given transmission network. After reading this manuscript the reader can choose mother wavelets of wavelet transform and neural topologies to build a classification engine. The classification engine can be employed at various energy management centres to acquire the knowledge of faults in a transmission network.
1. Introduction

Contemporary power system incorporates many adequacies at generation, transmission and distribution ends, thus the modern power network is appraised as a complex interconnected grid. With the arising trends of consisting distributed generation sources (i.e. Wind, Solar and hybrid model) nearby load ends leads us to a reliable and diminished transmission loss networks. Synchronous power systems are related with serious issues of fault on high voltage transmission line, fault free system is unimaginable and it is practically and economically not possible. But the quick and genuine fault classification and detection technique is a significant demand in power transmission system for continuous power flow.

Several researchers proposed various methodology to overcome this issue. Table 1 shows the critical survey regarding these researches (Dalstein & Kulicke, 1995; Hippert, Pedreira, & Souza, 2001). In Dalstein & Kulicke (1995) digital signal processing concept for high speed protective relay is used to analyze its efficacy on parallel transmission line. A novel approach to distinguish the patterns of transmission line faults is integrated with PC-based system to examines data files from substation digital fault recorder (Kezunovic & Rikalo, 1996). In Chan, Edward, & Danish (2000) kohonen network is used to classify the faults after detection process. This approach is applicable for arbitrary dynamic system and can be model free or model based. Intelligent decision rules are created by the analysis of fault indicator using standard statistical hypothesis testing or by Artificial Neural Network. A fault classifier developed for optimal feature selection in wavelet and ann (Othman, Mahfouf, & Linkens, 2004). These are the generalized regression neural network (GRNN), the probabilistic neural network (PNN), and the adaptive network fuzzy inference system (ANFIS). Hilbert Huang transform is combined with the Support Vector Machine, complex space phasor, radial basis exact fit neural network to classify the faults. The authors evaluated the most promising results by using fuzzy inference system (FIS) from the current and voltage signals which are having precariousness in raw data form.

Following are the research objectives of the paper:

(1) To develop the data based on offline simulation studies for seven faults and pre-process the data with the help of wavelet transform.

(2) To design a classifier output definition with binary attributes for training the supervised learning module.

(3) To employ different statistical attributes of wavelet transforms of the voltage signals namely maximum, minimum, norm, mean and standard deviation values as input features of supervised learning module on different MRA levels (levels 3, 5 and 7).

(4) To simulate the circuit for different cases such as normal environment, noisy environment (SNR = 20 db) and noisier (SNR = 30 db), collect the data, calculate the different types of errors.

(5) To compare the performance of the different MRA levels of supervised learning based classifiers on the basis of different error indices and confusion matrix (confusion values and classification accuracy) for all three cases.
### Table 1. Critical literature review

| S. No. | Techniques | Benefits | Drawbacks |
|--------|------------|----------|-----------|
| 1      | Artificial neural network | Reliable and efficient up to 90%, useful for complex power transmission system, useful for large training data-set, robust | Conclusions are based on offline simulation data sets. Preparation of data sets and training of the same is a time consuming process |
|        | Digital signal processing simulation programme NETOMAC (Dalstein & Kulicke, 1995) |           |           |
|        | Combined supervised and unsupervised technique with ISODATA clustering algorithm (Kezunovic & Rikalo, 1996) |           |           |
|        | FFNN (Vazquez, Altuve, & Chacon, 1996; Vazquez, Chacon, & Altuve, 1996) |           |           |
|        | Fuzzy art neural network (Huisheng Wang & Keerthipala, 1998; Keerthipala, Wang, & TatWai, 2000; Vasilic & Kezunovic, 2005; Zhang & Kezunovic, 2005) |           |           |
|        | Inter-circuit and cross-country fault (Jain, Thoke, Patel, & Koley, 2010) |           |           |
|        | ANN based fault detector and classifier (Jain, Thoke, Patel, 2008, 2009; Jain, Thoke, Patel, & Madi, 2010; Yadav, 2012) |           |           |
|        | ANN with back propagation algorithm (BPN), RBFN, cascaded correlation |           |           |
|        | Feed-forward network (CFBPN) (Saravanan & Rathinam, 2012) |           |           |
| 2      | Combined technique of ANN and Wavelet transform | Waveform presentation is visualized, useful for non-stationary signals, wide functional form (Haar and Daubechies wavelet), useful for transient or discontinue signals, useful to detect the high frequency component from fault signals | High computational burden and high sampling rate |
|        | Kohonen network and MRA wavelet filter bank (Chowdhury & Aravena, 1998; Chowdhury & Wang, 1996) |           |           |
|        | Combined wavelet and ANN (Geethanjali & Priy, 2009; Kawady, Ibrahim, & Taaalab, 2008; Mahmoud, Jaidane-Saidane, & Hizaoui, 2008; Martin, Aguada, Medina, & Mu'noz, 2008) |           |           |
|        | DWT and back propagation (Pothisarn & Ngaopitakkul, 2009) |           |           |
|        | MRA three classifier GRNN, PNN, ANFIS (Othman & Amari, 2008; Othman, Mahfouf, & Linkens, 2004) |           |           |
|        | Combined wavelet and ANN with Levenberg–Marquardt algorithm (Kale et al., 2009; Yadav & Swetapadma, 2014; Yadav & Thoke, 2011) |           |           |
|        | Haar wavelet transform and ANN (Kumar, Koley, Yadav, & Thoke, 2014) |           |           |
| 3      | Combined technique of ANN and Fourier transform | Useful for stationary, pseudo-stationary signals, fast time response | Require periodicity all the time, only global frequency content retrieved, no satisfactory results for highly stationary, noisy and aperiodic signals |
|        | Comparison of Fourier and wavelet (Abdollahi & SeyediTabei, 2010), short time fourier transform (Samantaray & Dash, 2007) |           |           |
|        | Combined technique of Fourier filtering and fast detector (Chen & Liu, 2006) |           |           |
| 4      | Hilbert transform and combined techniques | Useful for stationary and non-stationary signals |           |
|        | Hybridisation of SVM and EMD with Hilbert Huang transform (Ramesh Babu & Jagan Mohan, 2015) |           |           |
|        | Signal processing method using complex space-phaser and Hilbert Huang transform (Bernadic & Leonowicz, 2011, 2012) |           |           |
|        | Combined technique with RBFNN and Hilbert Huang transform (Jayasree, Sam Harrison, & SreeRangaraja, 2011) |           |           |
|        | Combined technique of SVM and Hilbert Huang transform (Guo, Li, & Gao, 2013) |           |           |
The paper is organised as follows in series Section 2 is an explanation about classification engine. Section 3 is a brief introduction to Wavelet Transform and Multi Resolution Analysis and its applications are illustrated. Brief description about simulation model and its working are given in Section 4. Section 5 contains simulation result and discussion. The conclusion is presented with a future scope.

2. Fault classification engine
Neural network deals in a 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 (Hippert et al., 2001). Neural Network works in a large area like load forecasting (Charytoniuk & Chen, 2000; Rolim & Zur, 2003; Sinha, 2000), fault diagnosis/fault location (Lukomski & Wilkosz, 2003), economic dispatch (Kumarappan, Mohan, & Murugappa, 2002), security assessment in reference (Chan, Edward, & Danish, 2000), transient stability (Bahbah & Girgis, 2004) etc.

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

1. The system voltage is varied randomly in a close range to generate 3,500 samples of different contingencies in transmission network. Seven faults are simulated with the help of nonlinear simulation. The voltage at bus is measure with the help of Phasor Measurement Units (PMUs). After measurement of the voltage, wavelet transform of voltage is obtained.

2. Proper choice of mother wavelet to extract potential attributes from the voltage signals is a daunting task. Often the choice of mother wavelet is considered as a critical issue in the design of classification engine. Considering this fact, this manuscript presents a comprehensive study of the effect of all mother wavelets on the performance of classification.

3. 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 3,500 samples 70% data are used for training and remaining are used for validation and testing of the neural topologies. Figure 1 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 Section 4.
3. Wavelet transform

In recent years’ application of wavelet transform in real power system has been increased. This signal processing technique is used in power quality event classification (Chaturvedi, Sinha, & Malik, 2014), load forecasting (Baleavu, 2012), image processing (Vakil & Pavesic, 2003). Wavelet transform is a mathematical tool to disintegrate a signal into various frequency components. As it has been studied that Fourier analysis is 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 \( \omega \in L^2(\mathbb{R}) \) with a zero average

\[
\int_{-\infty}^{+\infty} \phi(t)dt = 0
\]

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

\[
CWT_{\phi} x(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \phi^* \left( \frac{t - b}{a} \right) dt
\]

where \( \phi(t) \) 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.

\[
DWT(m, n) = \int_{-\infty}^{+\infty} x(t) \varphi^*_{m,n} (t) dt
\]

where; \( \varphi_{m,n} (t) = a_0^{-m/2} \left( \frac{t - nb_0}{a_0^m} \right) \)

These parameters are \( a = a_0^m, b = nb_0a_0^n \)

where \( m, n \in \mathbb{Z}; m, n \) 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 MRA. Haar, Daubechies, Symlet and Coiflet wavelets are discussed in this paper. Haar wavelet is a very oldest
and simplest wavelet and very fast to transform. This is the sequentially ordered matrix contains vector matrix. On the mathematical basis this is the sequence of rescaled function (or) square shaped function. But discontinuity and differentiable phenomenon with resemblances of the step function is the drawback of this wavelet. It is poor energy compression for the signals and impertinent i.e. $H_r = H_r^*$ the (Antonini & Barlaud, 1992).

On the other hand, daubechies wavelet is used to determining the low pass filter $h$, or in an equal manner to the Fourier series. This wavelet is useful to understand the practical analysis of discrete wavelet in a concise manner (Singh & Singh, 2001). More application of wavelets have been observed by researchers in Tezcan, Puri, and Cheng (2008), Tezcan, Cheng, and Cheng (2016). Daubechies wavelet signal is outlined by the scaling function which is explained in terms of $\alpha$ and $\beta$ coefficients. For higher order wavelet $DbN$ is used where $N$ refers the order of daubechies wavelet and the number of disappearance moment.

$$\text{Floor} \left( \frac{n - 1}{2} \right) + N(n \rightarrow \text{length of } f(t)) \quad (4)$$

But the daubechies wavelet transform selects the minimum phase square root, so the energy centralizes virtually the starting point of support that is remark on its efficacy and consider as a drawback of this wavelet and it get overcome in the symlet transform which select every set of roots who has approximate symmetry with linear complex phase. Basically this wavelet having all properties as similar as daubechies but the tiny modification makes it better in performance when it applied on signal to improve the signals in signal to noise ratio (SNR).

Similarly, the coiflet wavelet is also having same properties at definite level, but the construction of coiflet was for a special task that is disappearance moment for wavelet $\phi(x)$ and scaling function $\theta(x)$. This wavelet function is enclosed in the wavelet transform scheme. From multi-resolution analysis it can be developed like scaling function having definite number of disappearance moment. Coiflet transform is having ability to consider time information and frequency in an inherent scheme.

4. System details and simulink implementation

To simulate various faults transmission network is modelled in MATLAB®2013 Simulink and Neural network tool box is utilized to design binary classifier. Circuit (Figure 2) contains 1 three phase voltage source with 25,000 V base voltage. V-I measurement is connected there. It can measure the voltages and currents in per unit values or in volts and amperes. 3-phase transmission line of 200 km is associated there, which is having 0.01273 resistance, 0.9337e-3 inductance and 12.74e-9 capacitance for per unit length. Along with transmission line, fault circuit is also there which is having 0.001 ohm fault resistance and 0.001 ohms ground resistance. To add or remove elements from the RL-branch is linked there. Containing $R = 10$ ohms and $L = 0.05$ H. Generated signals (voltage and current) are obtained at scope.

5. Simulation results

This section presents critical analysis of the performance of fault classifier. The fault classification engines have been tested for around 10,500 test fault cases including several faults i.e. LG, LLG, 3-phase fault in different environment conditions with varying voltages. Raw data is collected from simulation process. Five types of statistical attributes are calculated here i.e. standard deviation, maximum value, minimum value, mean value and normal value of the signals. Network is simulated for three cases i.e. in normal condition (without noise), noisy environment (SNR = 20 db), noisier environment (SNR = 30 db).

Artificial neural network topologies are trained by using collected raw data and binary classifier. Among all the results some cases are discussed below:

Case-1: When system is noise free
## Table 2. Performance of classifiers with different mother wavelets (Case 1)

| Network type | Wavelet type | MRA level | Errors and efficiency | Radial basis exact fit neural network (RBGFNN) |
|--------------|-------------|-----------|----------------------|-----------------------------------------------|
| Back propagation neural network (BPNN) | | | MSE | MAE | RMSE | SSE | SAE | CON. EFF (%) | MSE | MAE | RMSE | SSE | SAE | CON. EFF (%) |
| | HAAR | 7 | 0.0556 | 0.1111 | 0.2359 | 1.362 | 2.722 | 0.2871 | 71.3 | 5.7164e-16 | 7.6122e-09 | 2.3909e-08 | 1.4005e-11 | 1.8650e-04 | 0 | 100 |
| | | 1 | 0.0590 | 0.0981 | 0.2302 | 1.362 | 2.722 | 0.2871 | 71.3 | 6.7317e-08 | 6.7317e-08 | 2.5946e-04 | 0.0016 | 2.6394 | 0 | 100 |
| | | 3 | 0.0649 | 0.1307 | 0.2547 | 1.589 | 3.186 | 0.3594 | 64.1 | 0.0361 | 0.0929 | 0.1901 | 88.5115 | 2.275 | 0.1806 | 81.9 |
| | Daubechies mother wavelet | Db4 | 7 | 0.0452 | 0.0893 | 0.2125 | 1.106 | 2.187 | 0.2254 | 77.5 | 1.1916e-13 | 1.0773e-04 | 2.5946e-04 | 0.0016 | 2.6394 | 0 | 100 |
| | | | 5 | 0.0500 | 0.0758 | 0.2235 | 1.342 | 2.187 | 0.2446 | 75.5 | 6.1916e-13 | 1.0773e-04 | 2.5946e-04 | 0.0016 | 2.6394 | 0 | 100 |
| | | | 3 | 0.0670 | 0.0978 | 0.2580 | 1.678 | 3.186 | 0.3594 | 64.1 | 0.0361 | 0.0929 | 0.1901 | 88.5115 | 2.275 | 0.1806 | 81.9 |
| | Symlet mother wavelet | Sym3 | 7 | 0.0411 | 0.0821 | 0.2026 | 1.005 | 2.010 | 0.2020 | 79.8 | 8.1615e-10 | 9.6314e-06 | 2.5946e-04 | 0.0016 | 2.6394 | 0 | 100 |
| | | | 5 | 0.0467 | 0.0936 | 0.2160 | 1.143 | 2.293 | 0.2431 | 75.7 | 0.0022 | 0.0106 | 0.0467 | 75.7 | 0.0060 | 99.4 |
| | | | 3 | 0.0799 | 0.1045 | 0.2300 | 1.296 | 2.560 | 0.2851 | 71.5 | 0.0396 | 0.0966 | 0.1901 | 88.5115 | 2.275 | 0.1806 | 81.9 |
| | Coiflet mother wavelet | Coif4 | 7 | 0.1000 | 0.0178 | 0.1000 | 2.45187 | 4.354167 | 0.2974 | 70.3 | 6.4891e-07 | 6.3746e-05 | 6.8477e-04 | 0.0115 | 0.9003 | 0 | 100 |
| | | | 5 | 0.0250 | 0.0502 | 0.1580 | 611.5490 | 1.231 | 0.1317 | 86.8 | 9.0000 | 520.5365 | 0.0334 | 96.7 |
| | | | 3 | 0.0391 | 0.0811 | 0.1978 | 958.5230 | 1.986 | 0.2243 | 77.6 | 0.0353 | 0.0837 | 0.1878 | 864.1601 | 2.049 | 0.1929 | 80.7 |

(Continued)
| Wavelet type         | MRA level | Network type | Errors and efficiency | Elman back propagation neural network (EBPNN) Errors and efficiency |
|----------------------|-----------|--------------|-----------------------|---------------------------------------------------------------|
|                      |           | Layer recurrent neural network (LRNN) |                      |                                                                 |
|                      |           | MSE | MAE | RMSE | SSE | SAE | CON. | EFF (%) | MSE  | MAE | RMSE | SSE | SAE | CON. | EFF (%) |
| Daubechies Mother Wavelet |          |     |     |      |     |     |      |         |      |     |      |     |     |      |         |
| Db4                  | 7         | 0.0469 | 0.0927 | 0.2166 | 1.149 | 2.271 | 0.2209 | 77.9 | 0.0481 | 0.0959 | 0.2193 | 1.178 | 2.348 | 0.2391 | 76.1 |
|                      | 5         | 0.0499 | 0.0789 | 0.2234 | 1.222 | 1.933 | 0.2766 | 72.3 | 0.0396 | 0.0779 | 0.1990 | 970.0427 | 1,909 | 0.2043 | 79.6 |
|                      | 3         | 0.0341 | 0.0663 | 0.1845 | 834.2541 | 1,625 | 0.1683 | 83.2 | 0.0428 | 0.0824 | 0.2070 | 1,049 | 2,018 | 0.2203 | 78.0 |
|                      |           |     |     |      |     |     |      |         |      |     |      |     |     |      |         |
| Db8                  | 7         | 0.0449 | 0.0887 | 0.2119 | 1.100 | 2.172 | 0.2160 | 78.4 | 0.0450 | 0.0903 | 0.2122 | 1.103 | 2.211 | 0.2200 | 78.0 |
|                      | 5         | 0.0348 | 0.0694 | 0.1866 | 852.8114 | 1,701 | 0.1740 | 82.6 | 0.0349 | 0.0688 | 0.1868 | 855.1099 | 1,684 | 0.1694 | 83.1 |
|                      | 3         | 0.0192 | 0.0387 | 0.1386 | 470.5908 | 94.2243 | 0.0997 | 90.0 | 0.0191 | 0.0376 | 0.1381 | 467.5673 | 921.8981 | 0.0989 | 90.1 |
|                      |           |     |     |      |     |     |      |         |      |     |      |     |     |      |         |
| Symlet mother wavelet |          |     |     |      |     |     |      |         |      |     |      |     |     |      |         |
| Sym3                 | 7         | 0.0431 | 0.0859 | 0.2077 | 1.057 | 2.105 | 0.2126 | 80.4 | 0.0395 | 0.0759 | 0.1987 | 967.7836 | 1,860 | 0.1960 | 80.4 |
|                      | 5         | 0.0456 | 0.0929 | 0.2156 | 1.139 | 2.275 | 0.2386 | 76.1 | 0.0457 | 0.0886 | 0.2139 | 1.120 | 2.170 | 0.2349 | 76.5 |
|                      | 3         | 0.0493 | 0.0953 | 0.22119 | 1.206 | 2.335 | 0.2683 | 73.2 | 0.0538 | 0.1074 | 0.2319 | 1.317 | 2.631 | 0.2877 | 71.2 |
|                      |           |     |     |      |     |     |      |         |      |     |      |     |     |      |         |
| Sym6                 | 7         | 0.0244 | 0.0496 | 0.1562 | 597.8954 | 1,214 | 0.1083 | 89.2 | 0.0219 | 0.0414 | 0.1481 | 537.1563 | 1,013 | 0.0980 | 90.2 |
|                      | 5         | 0.0340 | 0.0679 | 0.1845 | 834.0320 | 1,664 | 0.1711 | 82.9 | 0.0345 | 0.0665 | 0.1856 | 844.4013 | 1,628 | 0.1723 | 82.8 |
|                      | 3         | 0.0486 | 0.0983 | 0.2206 | 1,191 | 2,407 | 0.2717 | 72.8 | 0.0483 | 0.0970 | 0.2197 | 1,183 | 2,376 | 0.2609 | 73.9 |
|                      |           |     |     |      |     |     |      |         |      |     |      |     |     |      |         |
| Coiflet Mother Wavelet |          |     |     |      |     |     |      |         |      |     |      |     |     |      |         |
| Coif4                | 7         | 0.0101 | 0.0187 | 0.1003 | 246.2914 | 457.3996 | 0.0420 | 95.8 | 0.0104 | 0.0199 | 0.1020 | 255.0814 | 488.6255 | 0.0440 | 95.6 |
|                      | 5         | 0.0254 | 0.0510 | 0.1594 | 622.472 | 1,250 | 0.1334 | 86.7 | 0.0247 | 0.0495 | 0.1570 | 604.1191 | 1,213 | 0.1274 | 82.3 |
|                      | 3         | 0.0591 | 0.0983 | 0.2431 | 1,447 | 2,408 | 0.3634 | 63.7 | 0.0393 | 0.0814 | 0.1982 | 962.0993 | 1,994 | 0.2266 | 77.3 |
| Wavelet type               | MRA level | MSE  | MAE  | RMSE | SSE  | SAE  | CON. | EFF (%) | MSE  | MAE  | RMSE | SSE  | SAE  | CON. | EFF (%) |
|---------------------------|-----------|------|------|------|------|------|------|---------|------|------|------|------|------|------|---------|
| HAAR                      | 7         | 0.0665 | 0.1329 | 0.2578 | 3.255 | 0.3786 | 62.1 | 1.1175e-15 | 1.6928e-08 | 3.3429e-08 | 2.737e-11 | 4.1474e-04 | 0 | 100 |
|                           | 5         | 0.0587 | 0.1146 | 0.2423 | 2.808 | 0.3262 | 67.7 | 3.8509e-05 | 6.7329e-04 | 0.0662 | 0.9435 | 16.4955 | 0.0060 | 99.4 |
|                           | 3         | 0.0653 | 0.1325 | 0.2555 | 3.245 | 0.3729 | 62.7 | 0.0505 | 0.1182 | 0.2248 | 1237 | 2.896 | 0.2709 | 72.9 |
| Daubechies mother wavelet | Db4       | 7         | 0.0584 | 0.1152 | 0.2417 | 1.431 | 2.822 | 0.3246 | 67.5 | 5.2700e-12 | 8.5912e-07 | 2.2956e-06 | 1.2911e-07 | 0.0210 | 0 |
|                           | 5         | 0.0525 | 0.1067 | 0.2291 | 1.286 | 2.615 | 0.2994 | 70.1 | 0.0031 | 0.016 | 0.0553 | 74.9788 | 409.6397 | 0.0077 | 99.2 |
|                           | 3         | 0.0618 | 0.1254 | 0.2486 | 1.513 | 3.072 | 0.3597 | 64.0 | 0.0498 | 0.1143 | 0.2231 | 1219 | 2.799 | 0.2677 | 73.2 |
|                           | Db8       | 7         | 0.0636 | 0.1306 | 0.2522 | 1.558 | 3.199 | 0.3514 | 64.9 | 4.3898e-08 | 8.8707e-05 | 2.0952e-04 | 0.0011 | 2.1733 | 0 |
|                           | 5         | 0.0480 | 0.0969 | 0.2191 | 1.175 | 2.373 | 0.2874 | 71.3 | 0.0147 | 0.0484 | 0.1211 | 359.3125 | 1185 | 0.0634 | 93.7 |
|                           | 3         | 0.0592 | 0.1205 | 0.2432 | 1.449 | 2.951 | 0.3537 | 64.6 | 0.0522 | 0.1165 | 0.2285 | 1279 | 2.855 | 0.3054 | 69.5 |
| Symlet mother wavelet     | Sym3      | 7         | 0.0536 | 0.1077 | 0.2316 | 1.314 | 2.638 | 0.3063 | 69.4 | 4.6147e-10 | 7.7178e-06 | 2.1482e-05 | 1.1306e-05 | 0.1891 | 0 |
|                           | 5         | 0.0560 | 0.1154 | 0.2365 | 1.370 | 2.827 | 0.3243 | 67.6 | 0.0097 | 0.0346 | 0.0983 | 236.9719 | 847.1716 | 0.0420 | 95.8 |
|                           | 3         | 0.0634 | 0.1271 | 0.2518 | 1.553 | 3.113 | 0.3831 | 61.7 | 0.0558 | 0.1253 | 0.2362 | 1367 | 3.069 | 0.3246 | 67.5 |
|                           | Sym6      | 7         | 0.0396 | 0.0793 | 0.1989 | 0.9399 | 1.943 | 2.303 | 77.0 | 3.9327e-04 | 0.0013 | 0.0198 | 9.6351 | 31.8926 | 0.0014 | 99.9 |
|                           | 5         | 0.0460 | 0.0928 | 0.2146 | 1.128 | 2.272 | 0.2720 | 72.8 | 0.0152 | 0.0494 | 0.1232 | 371.6664 | 1209 | 0.0631 | 93.7 |
|                           | 3         | 0.0598 | 0.1232 | 0.2445 | 1.464 | 3.018 | 0.3634 | 63.7 | 0.0533 | 0.1181 | 0.2309 | 1305 | 2.893 | 0.3134 | 68.7 |
| Coiflet mother wavelet    | Coif4     | 7         | 0.0289 | 0.0578 | 0.1700 | 0.7023 | 1.415 | 0.1763 | 82.4 | 0.0023 | 0.0080 | 0.0475 | 55.3184 | 195.2733 | 0.0089 | 99.1 |
|                           | 5         | 0.0453 | 0.0935 | 0.2129 | 1.110 | 2.290 | 0.2620 | 73.8 | 0.0191 | 0.0595 | 0.1380 | 466.8156 | 1456 | 0.1380 | 91.6 |
|                           | 3         | 0.0547 | 0.1124 | 0.2338 | 1.339 | 2.752 | 0.3289 | 67.1 | 0.0509 | 0.1103 | 0.2257 | 1248 | 2.702 | 0.3046 | 69.5 |

(Continued)
| Wavelet type          | MRA level | MSE   | MAE   | RMSE  | SSE   | SAE    | EFF (%) | MSE   | MAE   | RMSE  | SSE   | SAE    | EFF (%) |
|-----------------------|-----------|-------|-------|-------|-------|--------|---------|-------|-------|-------|-------|--------|---------|
| HAAR                  | 7         | 0.0652| 0.1297| 0.2554| 1.597 | 3.177  | 0.3623  | 63.8  | 0.0661| 0.1325| 0.2570| 1.618  | 3.247   | 0.3691  | 63.1   |
|                       | 5         | 0.0604| 0.1186| 0.2459| 1.481 | 2.905  | 0.3303  | 67.0  | 0.0583| 0.1154| 0.2414| 1.427  | 2.827   | 0.3251  | 67.5   |
|                       | 3         | 0.0730| 0.1245| 0.2702| 1.788 | 3.050  | 0.4017  | 59.8  | 0.0670| 0.1342| 0.2587| 1.640  | 3.288   | 0.3906  | 60.9   |
| Daubechies mother wavelet | Db4      | 7     | 0.0584| 0.1149| 0.2416| 1.429 | 2.815  | 0.3220  | 67.8  | 0.0603| 0.1209| 0.2455| 1.476  | 2.961   | 0.3311  | 66.9   |
|                       |           | 5     | 0.0636| 0.1078| 0.2523| 1.559 | 2.641  | 0.3389  | 66.1  | 0.0520| 0.1042| 0.2280| 1.274  | 2.553   | 0.2954  | 70.5   |
|                       |           | 3     | 0.0631| 0.1299| 0.2513| 1.546 | 3.182  | 0.3694  | 63.1  | 0.0648| 0.1351| 0.2546| 1.588  | 3.310   | 0.3814  | 61.9   |
|                       | Db8       | 7     | 0.0592| 0.1172| 0.2432| 1.449 | 2.870  | 0.3220  | 67.8  | 0.0602| 0.1173| 0.2454| 1.475  | 2.874   | 0.3309  | 66.9   |
|                       |           | 5     | 0.0465| 0.0932| 0.2156| 1.139 | 2.283  | 0.2769  | 72.3  | 0.0482| 0.0976| 0.2195| 1.180  | 2.392   | 0.2874  | 71.3   |
|                       |           | 3     | 0.0592| 0.1206| 0.2433| 1.450 | 2.954  | 0.3529  | 64.7  | 0.0579| 0.1185| 0.2406| 1.418  | 2.902   | 0.3406  | 65.9   |
| Symlet mother wavelet | Sym3      | 7     | 0.0555| 0.1123| 0.2357| 1.360 | 2.750  | 0.3106  | 68.9  | 0.0644| 0.1106| 0.2537| 1.576  | 2.710   | 0.3191  | 68.1   |
|                       |           | 5     | 0.0545| 0.1090| 0.2333| 1.334 | 2.670  | 0.3229  | 67.7  | 0.0539| 0.1077| 0.2312| 1.320  | 2.637   | 0.3183  | 68.2   |
|                       |           | 3     | 0.0635| 0.1263| 0.2519| 1.554 | 3.095  | 0.3806  | 61.9  | 0.0664| 0.1308| 0.2538| 1.578  | 3.040   | 0.3823  | 61.8   |
|                       | Sym6      | 7     | 0.0396| 0.0800| 0.1990| 9.704234| 1.960  | 0.2291  | 77.1  | 0.0412| 0.0832| 0.2029| 1.008  | 2.039   | 0.2380  | 76.2   |
|                       |           | 5     | 0.0459| 0.0919| 0.2141| 1.123 | 2.251  | 0.2729  | 72.7  | 0.0461| 0.0932| 0.2148| 1.130  | 2.284   | 0.2729  | 72.7   |
|                       |           | 3     | 0.0591| 0.1196| 0.2431| 1.447 | 2.930  | 0.3549  | 64.5  | 0.0585| 0.1177| 0.2418| 1.433  | 2.884   | 0.3463  | 65.4   |
| Coflet mother wavelet | Coif4     | 7     | 0.0284| 0.0578| 0.1684| 695.0077| 1.416  | 0.1751  | 82.5  | 0.0285| 0.0573| 0.1690| 699.3419| 1.404   | 0.1731  | 82.7   |
|                       |           | 5     | 0.0442| 0.0906| 0.2103| 1.083 | 2.219  | 0.2626  | 73.7  | 0.0436| 0.0882| 0.2088| 1.067  | 2.161   | 0.2603  | 74.0   |
|                       |           | 3     | 0.0750| 0.1332| 0.2740| 1.838 | 3.262  | 0.4703  | 53.0  | 0.0539| 0.1084| 0.2321| 1.320  | 2.655   | 0.3229  | 67.7   |
| Network type               | Back propagation neural network (BPNN) | Elman back propagation neural network (EBPNN) |
|---------------------------|---------------------------------------|---------------------------------------------|
|                           | MSE | MAE | SSE | SAE | CON. EFF (%) | MSE | MAE | SSE | SAE | CON. EFF (%) |
|                           |     |     |     |     |             |     |     |     |     |             |
|                           | 7   | 0.0668 | 0.1358 | 0.2585 | 1.637 | 3.126 | 0.3377 | 6.2 | 7.0550e-10 | 8.2515e-07 | 2.6570e-06 | 1.7391e-07 | 0.0020 | 0.0000 | 100 |
|                           | 5   | 0.0598 | 0.1289 | 0.2427 | 1.590 | 3.043 | 0.4166 | 5.3 | 8.785e-04 | 0.0225 | 0.1216 | 0.2522 | 1.0176e-06 | 3.8158e-05 | 1.5778e-05 | 0.7072 | 97.7 |
|                           | 3   | 0.0541 | 0.1165 | 0.2368 | 1.556 | 2.940 | 0.3833 | 4.9 | 3.445e-10 | 6.750e-05 | 1.8551e-05 | 4.4116e-06 | 4.1650 | 5.3862e-06 | 0.0011 | 0.0010 | 99.7 |
|                           | 5   | 0.0461 | 0.0937 | 0.2148 | 1.086 | 2.225 | 0.2633 | 3.1 | 1.038e-04 | 0.0049 | 0.0249 | 0.0734 | 3.2264e-06 | 2.2364e-05 | 0.0012 | 1.0586 | 100 |
|                           | 3   | 0.0403 | 0.0793 | 0.1934 | 0.947 | 1.924 | 0.2058 | 3.2 | 4.956e-04 | 4.320e-05 | 0.3274e-05 | 0.0099 | 0.0099 | 0.0099 | 0.0099 | 0.0099 | 0.0099 | 0.0099 | 0.0099 |

(Continued)
| Wavelet type             | MRA level | MSE  | MAE  | RMSE | SSE  | SAE  | CON. | EFF [%] | MSE  | MAE  | RMSE | SSE  | SAE  | CON. | EFF [%] |
|-------------------------|-----------|------|------|------|------|------|------|--------|------|------|------|------|------|------|--------|
| Daubechies mother wavelet |           |      |      |      |      |      |      |        |      |      |      |      |      |      |        |
| Db4                     | 7         | 0.0662 | 0.1115 | 0.2573 | 1.621 | 2.732 | 0.3209 | 67.9  | 0.0599 | 0.1219 | 0.2447 | 1.466 | 2.987 | 0.3300 | 67.0   |
|                         | 5         | 0.0498 | 0.1005 | 0.2322 | 1.220 | 2.461 | 0.2874 | 71.3  | 0.0510 | 0.1057 | 0.2259 | 1.250 | 2.590 | 0.2983 | 70.2   |
|                         | 3         | 0.0618 | 0.1259 | 0.2487 | 1.514 | 3.085 | 0.3634 | 63.7  | 0.0400 | 0.1186 | 0.2450 | 1.470 | 2.906 | 0.3583 | 64.2   |
| Db8                     | 7         | 0.0582 | 0.1157 | 0.2412 | 1.425 | 2.834 | 0.3223 | 67.8  | 0.0602 | 0.1211 | 0.2453 | 1.474 | 2.966 | 0.3369 | 66.3   |
|                         | 5         | 0.0249 | 0.0492 | 0.1577 | 0.609 | 0.0015 | 1.206 | 0.1303 | 87.0  | 0.0260 | 0.0510 | 0.1612 | 636.9590 | 1.250 | 0.1311 | 86.9   |
|                         | 3         | 0.0590 | 0.1205 | 0.2428 | 1.444 | 2.952 | 0.3480 | 65.2  | 0.0569 | 0.1138 | 0.2385 | 1.393 | 2.788 | 0.3343 | 66.6   |
| Symlet mother wavelet   |           |      |      |      |      |      |      |        |      |      |      |      |      |      |        |
| Sym3                    | 7         | 0.0525 | 0.1046 | 0.2291 | 1.286 | 2.562 | 0.2963 | 70.4  | 0.0539 | 0.1105 | 0.2322 | 1.320 | 2.707 | 0.3091 | 69.1   |
|                         | 5         | 0.0550 | 0.1113 | 0.2346 | 1.348 | 2.726 | 0.3146 | 68.5  | 0.0549 | 0.1099 | 0.2342 | 1.344 | 2.693 | 0.3174 | 68.3   |
|                         | 3         | 0.0624 | 0.1255 | 0.2499 | 1.529 | 3.075 | 0.3803 | 62.0  | 0.0621 | 0.1227 | 0.2491 | 1.520 | 3.005 | 0.3746 | 62.5   |
| Sym6                    | 7         | 0.0369 | 0.0736 | 0.1922 | 0.905 | 2.173 | 0.2146 | 78.5  | 0.0368 | 0.0757 | 0.1919 | 902.3676 | 1.854 | 0.2169 | 78.3   |
|                         | 5         | 0.0657 | 0.1112 | 0.2564 | 1.610 | 2.723 | 0.4109 | 58.9  | 0.0455 | 0.0920 | 0.2133 | 1.115 | 2.253 | 0.2657 | 73.4   |
|                         | 3         | 0.0594 | 0.1211 | 0.2438 | 1.456 | 2.967 | 0.3611 | 63.9  | 0.0588 | 0.1190 | 0.2424 | 1.439 | 2.914 | 0.3603 | 64.0   |
| Coiflet mother wavelet  |           |      |      |      |      |      |      |        |      |      |      |      |      |      |        |
| Coif4                   | 7         | 0.0275 | 0.0566 | 0.1659 | 0.674 | 4.066 | 1.387 | 0.1711 | 82.9  | 0.0275 | 0.056 | 0.1659 | 674.4338 | 1.377 | 0.1689 | 83.1   |
|                         | 5         | 0.0449 | 0.0912 | 0.2119 | 1.100 | 2.235 | 0.2717 | 72.8  | 0.0444 | 0.0905 | 0.2108 | 1.088 | 2.218 | 0.2674 | 73.3   |
|                         | 3         | 0.0566 | 0.1181 | 0.2378 | 1.385 | 2.893 | 0.3420 | 63.8  | 0.0549 | 0.1100 | 0.2343 | 1.345 | 2.693 | 0.3397 | 66.0   |

Table 4. (Continued)
The presented topologies are tested for different faults in noise free environment. The data is obtained from simulation process. Presented topologies are namely backpropagation neural network, radial basis exact fit neural network, layer recurrent neural network and elman backpropagation neural network. Voltage signals are decomposed by different wavelets i.e. Haar wavelet, daubechies (Db4, Db8) wavelet, symlet (Sym3, Sym6) wavelet, coiflet (Coif4) wavelet, on various MRA levels. As
presented in Table 2 six types of wavelets are discussed on above mentioned four neural networks at different MRA levels.

To judge the performance of the classifier various error indices (i.e. mean square error, mean absolute error, root mean square error, sum square error and sum absolute error) are calculated. It is observed that, in BPNN Haar wavelet MRA level-5 shows best efficiency. For the same network Db4 and Db8 shows its effectiveness on MRA level-3. In case of symlet transform MRA level-7 shows best results. Similarly, coiflet transform at MRA level-3 gives good results. Different observations are shown in Table 2.

Radial basis exact fit neural network is the efficient network which exhibits its effectiveness on MRA level-7 for all 6 wavelets. It is noted that LRNN performance is comparable with BPNN. Elman Back propagation neural network is giving effectual results for Haar wavelet on MRA level-7, for db4 and Db8 on MRA level-5 and 3 respectively and for Sym3, Sym6 and Coif4 on MRA level-7. On the basis of above discussion, it is concluded that in the noise free system Radial Basis Exact Fit Neural Network shows efficient results (Figure 3) for Db8 wavelet (Figure 4) on MRA level-7 (Figure 5).
Case-2: when environment is noisy (SNR = 20 db)

All above mentioned neural networks are tested for identification of different faults in noisy environment (SNR = 20 db). It is observed that, in Back propagation neural network Haar wavelet MRA level-7 exhibits best efficiency. For the same network topology Db4 and Db8 shows its efficacy on MRA level-5. In case of symlet transform for both Sym3 and Sym6, MRA level-7 gives best results. Similarly, coiflet transform at MRA level-7 gives good results. Observations pertaining different MRA levels, neural topologies and wavelets are shown in Table 3. RBEFNN is the efficient method which exhibits its effectiveness on MRA level-7 for all 6 wavelets. LRNN with Haar wavelet gives best results at MRA level-5, daubechies transform shows effectiveness at different levels i.e. Db4 at MRA level-7, Db8 at MRA level-5 and symlet, coiflet wavelet show good performance at MRA level-7. EBPNN gives effectual results for Haar wavelet, Db4, Db8 and Sym3 exhibits efficacious results at MRA level-5 while Sym6 and Coif4 on MRA level-7. On the basis of above discussion, it is concluded that in the noisy environment RBEFNN shows efficient results (Figure 6) for Haar wavelet (Figure 7) on MRA level-7 (Figure 8).

Case-3: when environment is noisier(SNR = 30 db)

The intended techniques are tested for different faults in noisier environment on Signal to Noise Ratio(SNR = 30 db). This noise level is capable to alter the values of phase voltage and line currents.
All experimental results are shown in Table 4. It is observed that with the presence of noise the performance of all neural networks except RBEFNN affected and a significant decrement in the classification efficiency of BPNN, LRNN and EBPNN is observed. Figure 9 shows this comparison. RBEFNN gives best results with Haar wavelet as shown in Figure 10. Figure 11 shows the classification efficiency of RBEFNN at different MRA levels. On the basis of above discussion, it is concluded that in the noisier environment RBEFNN shows efficient results (Figure 9) for Haar wavelet (Figure 10) on MRA level-7 (Figure 11).

From this analysis it can be judged that RBEFNN is a best suitable topology for designing a classifier for transmission line protection system. Haar wavelet gives satisfactory response in noisy environment for almost all topologies.

5.1. Performance analysis
Performance of any classifier can be judged through the value of confusion in classification. Due to space limitations a few confusion diagrams of the experimental work have been incorporated as supplementary material. It is observed that in the presence of noise in voltage signals the classification efficiency of different classification engines comes down drastically. However, the RBEFNN topology along with Haar wavelet on MRA level 5 and 7, Db4 on MRA level 5 and 7, Db8 on MRA level 5 and 7 and Sym 3 on MRA level 5 and 7 Sym 6 and Coif4 on MRA level 7 gave classification efficiency above 95%. The classification accuracy found low for this topology with (67.0%) for Sym3 at MRA level 3, Sym6 MRA level 3 (67.4%) and Coif4 MRA Level 3 (68.2%). It is also observed that Haar wavelet is suitable for this sort of classification as the classification efficiency in noisy condition (Case 3) for BPNN is 62.2%, 66.2 at MRA level 7 and level 5, for RBEFNN for MRA level 7 100%, for LRNN is 62.0% at MRA level 5, for EBPNN is 66.8 at MRA level 5. For extreme conditions the MRA level 7 can be
chosen along with Haar mother wavelet and RBEFNN to get more efficiency. Following section presents the conclusion of this work.

6. Conclusion

In this work authors address the problem of selection of mother wavelets and ANN topologies for designing the classifier for faults. Seven major faults are considered for a transmission network. Following are the major conclusions derived from this work.

(1) **Performance of classifier in noisy environment:** It is observed that Haar Mother Wavelet is suitable for fault classification under noisy environment. However, Db8 wavelet gives best results when the system is noise free. It is observed that with the increase in noise the classification efficiency reduces.

(2) **Performance of neural topologies:** From the results it can be observed that RBEFNN is the most favourable topologies under all three cases for classification. However, Back propagation network gives poor results.

(3) **MRA levels:** It is observed that 7th MRA decomposition level is best for classification under all three cases.

The same observations on different systems including renewable energy sources lay in the future scope.

**Supplementary material**

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**References**

Abdollahi, A., & Seyyedtabaii, S. (2010). Comparison of fourier & wavelet transform methods for transmission line fault classification. Proceedings of the 4th International Power Engineering and Optimization Conference (PEOCO ’10) (pp. 579–584), Shah Alam.

Antonini, M., & Barlaud, M. (1992). Image coding using wavelet transform. IEEE Transaction on Image Processing, 1, 205–220.

Bernadic, A., & Leonowicz, Z. (2011). Power line fault location using the Complex Space-Phasor and Hilbert-Huang Transform. PrzeglądElektrotechniczny (Electrical Review), ISSN 0033-2097, R. 87 NR.

Bernadic, A., & Leonowicz, Z. (2012). Fault location in power networks with mixed feeders using the complex space-phasor and Hilbert-Huang transform. Electrical Power and Energy Systems, ELSEVIER, 42, 208–219.

Bohbah, A. G., & Girgis, A. A. (2004). New method for generators’ angles and angular velocities prediction for transient stability assessment of multimachine power systems using recurrent artificial neural network. IEEE Transactions on Power Systems, 19, 1015–1022. http://dx.doi.org/10.1109/TPWRS.2004.826765

Baleou, D. (2012). Advanced in wavelet theory and their applications in engineering, physics and technical. Intech, Numerical Analysis and Scientific Computing. ISBN: 978-953-51-0494-0.

Chan, K. W., Edward, A. R., & Danish, A. R. (2000). On-line dynamic security contingency screening using artificial neural network. IEEE Transaction on Power Distribution System, 147, 367–372. ISSN: 1350-2360.

Chaturvedi, D. K., Sinha, A. P., & Malik, O. P. (2014). Short term load forecasting using fuzzy logic and wavelet transform integrated generalized neural network. International Journal of Electrical Power and Energy System, 67, 230–237.

Charytoniuk, W., & Chen, M. S. (2000). Neural network design for short-term load forecasting. IEEE International Conference of Deregulation of Electric utility Deregulation and Restructuring and Power Technologies (DRPT) (pp. 554-561). London.

Chen, C.-S., & Liu, C.-W. (2006). Application of Combined Adaptive Fourier Filtering Technique and Fault Detector to Fast Distance Protection. IEEE Transactions on Power Delivery, 21, 619–626. http://dx.doi.org/10.1109/TPWRD.2005.858808

Chowdhury, F. N., & Aravena, J. L. (1998). A modular methodology for fast fault detection and classification in power systems. IEEE Transactions on Control Systems Technology, 6, 623–634. http://dx.doi.org/10.1109/87.709497

Chowdhury, B. H., & Wang, K. (1996). Fault classification using Kohonen feature mapping. In Proceedings of the International Conference on Intelligent Systems Applications to Power Systems (ISAP ’96) (pp. 194–198). Orlando, FL. http://dx.doi.org/10.1109/ISAP.1996.501067

Dalstein, T., & Kulicke, B. (1995). Neural network approach to fault classification for high speed protective relaying. IEEE Transactions on Power Delivery, 10, 1002–1011. http://dx.doi.org/10.1109/61.400828
Guo, Y., Li, C., Li, Y., & Gao, S. (2013). Research on the power system fault classification based on HHT and SVM using wide-area information. *Energy and Power Engineering, 5*, 138–142. http://dx.doi.org/10.4236/epe.2013.548026

Jain, A., Thoke, A. S., & Patel, R. N. (2008). Fault classification of double circuit transmission line using artificial neural network. *International Journal of Electrical Systems and Science and Engineering, 1*, 750–755.

Jain, A., Thoke, A. S., & Patel, R. N. (2009). Classification of single line to ground faults on double circuit transmission line using ANN. *International Journal of Computer and Electrical Engineering, 1*, 197–203. http://dx.doi.org/10.7763/IJCEE.2009V1.30

Jain, A., Thoke, A. S., Patel, R. N., & Koley, E. (2010). Intercircuit and cross country fault detection and classification using Artificial Neural Network. *Proceeding of the annual IEEE India Conference: Green Energy computing and communication (INDICON’ 10) (pp. 1–6)*, Kolkata.

Jain, A., Thoke, A. S., Patel, R. N., & Modi, P. K. (2010). Classification and location of single line to ground faults in double circuit transmission lines using artificial neural networks. *International Journal of Power and Energy Conversion, 2*, 109–125. http://dx.doi.org/10.1504/IJPEC.2010.037041

Jayasree, T., Sam Harrison, D., & SreeRangaraja, T. (2011). Automated classification of power quality disturbances using hilbert huang transform and RBF networks. *International Journal of Soft Computing and Engineering (IJSCCE), 1*(5), ISSN: 2213-2307.

Kole, V. S., Bhide, S. R., & Bedekar, P. P. (2009). Faulted phase selection on double circuit transmission line using wavelet transformand neural network. *Proceedings of the International Conference on Power Systems (ICPS ’09) (pp. 1–6)*, Kharagpur.

Kowady, T. A., Ibrahim, A. E., & Taalab, A. M. (2008). A gabor transform-based Universal fault detector for transmission lines. *Proceedings of the 12th International Middle East Power System Conference (MEPCON ’08)* (pp. 265–269). http://dx.doi.org/10.1504/IJPEC.2010.037041

Keerthipala, W. W. L. (1998). Fuzzy-neuro approach to fault classification for transmission line protection. *IEEE Transactions on Power Delivery, 13*, 1093–1104. http://dx.doi.org/10.1109/61.714467

Jain, A., Thoke, A. S., & Patel, R. N. (2008). Fault classification of double circuit transmission line using artificial neural network. *International Journal of Electrical Systems and Science and Engineering, 1*, 750–755.
Yadav, A. (2012). Comparison of single and modular ANN based fault detector and classifier for double circuit transmission lines. *International Journal of Engineering, Science and Technology*, 4, 122–136.

Yadav, A., & Svetapadma, A. (2014). Improved first zone reach setting of artificial neural network-based directional relay for protection of double circuit transmission lines. *IET Generation, Transmission and Distribution*, 8, 373–388. [http://dx.doi.org/10.1049/iet-gtd.2013.0239](http://dx.doi.org/10.1049/iet-gtd.2013.0239)

Yadav, A., & Thoke, A. S. (2011). Transmission line fault distance and direction estimation using artificial neural network. *International Journal of Engineering, Science and Technology*, 3, 110–121.

Zhang, N., & Kexunovic, M. (2005). Coordinating fuzzy ART neural networks to improve transmission line fault detection and classification. In *Proceedings of the IEEE Power Engineering Society General Meeting* (Vol. 1, pp. 734–740). San Francisco, CA: IEEE.