

Automatic Classification of Power Quality disturbances Using S-transform and MLP neural network

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Abstract: The paper presents an S-Transform based multilayer perceptron neural network (MLP) classifier for the identification of power quality (PQ) disturbances. The proposed method is used to extract the three input features (Standard deviation, peak value and variances) from the distorted voltage waveforms simulated using parametric equations. The features extracted through S-transform are trained by a MLP neural network for the automatic classification of PQ disturbances. MLP neural classifier has been implemented and tested for nine types of power quality disturbances. The results clearly show that the proposed method has the ability to identify and characterize PQ disturbances. The performance of the proposed technique is compared with the kalman based MLP neural network.

Keywords: Power quality, Power quality disturbances, S-transform, Neural classifier, MLP neural network.

Nomenclature

$h(t)$	–	Real signal
$S(t, f)$	–	Stransform
f	–	frequency
t	–	time
$WT(t, f)$	–	Continous wavelet transform
$e^{j2\pi f\tau}$	–	Phase factor
τ	–	time variable
d^τ	–	differential time variable
W^*	–	Complex conjugate of wavelet transform
$W(v, f)$	–	Time frequency resolution of wavelet transform

1. INTRODUCTION

In the recent years, power quality has become an important issue in the electric power system. There are various types of power quality issues in the transmission and distribution lines such as sag, swell, interruption, harmonics, sag with harmonics, swell with harmonics, flicker and notches. In order to improve power quality, the sources and causes of such disturbances must be known before the appropriate mitigating actions can be taken. The various types of power quality disturbances were detected and classified using wavelet transform analysis as illustrated in [1]. The time and frequency of multi resolution wavelet has been presented in [2] to analyze the electromagnetic

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power system transients. Analysis of the power quality transient signals using wavelet transform has been illustrated in [3].

The short time Fourier transforms (STFT) based power frequency harmonic analyzer has been discussed in [4] for the non stationary signals. The windowed FFT which is the time windowed version of discrete Fourier transform has been applied for power quality analysis to classify a variety of disturbances in [5]. Wavelet transform along with multi-resolution signal decomposition for the classification of power quality disturbances in [6]. A combination of Fourier and wavelet transform along with fuzzy expert system has been presented in [7] for the automatic monitoring and analysis of power quality disturbances.

Wavelet multi resolution analysis based neural network classifier is presented in [8] for the detection and extraction of power quality disturbances. An automated online power quality disturbances classification using wavelet based pattern recognition technique has been illustrated in [9]. Discrete STFT along with wavelet transform for the analysis of power quality disturbances in [10]. The detection, localization and classification of power quality disturbances are based on S-transform and compared with wavelet multi resolution analysis has been presented in [11]. Multi resolution S-transform along with fuzzy system was discussed for the classification of power quality classification in [12].

A two dimensional representation of analyzing the various types of power quality disturbances using DWT decomposition technique has been implemented in [13]. A combination of DSP hardware system along with kalman filter for the real time detection and analysis of the power quality disturbances has been illustrated in [14]. The classification of the power quality disturbances in both single and multiple natures using S-transform and Pattern recognition techniques has been implemented in [15]. The S-transform extract important information from a disturbance signal and trained by PNN to determine the type of disturbance that caused power quality (PQ) problem to occur has been presented in [16].

An S-transform based fuzzy and Particle swarm optimization has been presented in [17] and this combines to identify the time series PQ disturbance data and also classified it. A rule based technique along with S-transform has been discussed in [18] which diagnosis the Power quality disturbance in the time-frequency nature. Probabilistic neural network method based on optimal feature selection for power quality event classification has been illustrated in [19]. The windowed Hilbert huang transform (HHT) used to analyze the non-stationary signal in power quality analysis has been discussed in [20]. An S-transform based MLP neural network classifier for analysis of power quality disturbances in which the features are extracted using S-transform and disturbances are classified using an MLP based neural network is presented in this paper.

2. PROPOSED METHOD

The proposed method has two stages namely

- i. Feature extraction using S-transform
- ii. Classification stage using MLP neural network

S-transform is used for extracting features such as peak value, variances and standard deviation. MLP neural network is used for classifying the power quality disturbances. A set of parametric equations generate the disturbance waveforms.

2.1. Feature Extraction Stage using S-transform

The S-transform is a generalization of the Short-time Fourier transform (STFT) and an extension of the continuous wavelet transforms (CWT). The S-transform will perform multi-resolution analysis (MRA) on a time varying power signal, as its window width varies inversely with the frequency. The main function of the S-transform is a Gaussian modulation cosinusoid. The output of the S-transform is an $N \times M$ matrix called the S-matrix whose rows pertain to the frequency and columns to time.

A spectrogram or sonogram is a visual representation of the spectrum of frequencies. Spectrograms are usually created in one of two ways. They are approximated as a filter bank that results from a series of band pass filters, or calculated from the time signal using the short-time Fourier transform (STFT). These two methods actually form two different Time-Frequency Distributions, but are equivalent under some conditions. S-transform using spectrogram analysis provides better visual analyze of the signal.

The S-transform of a signal is defined as

$$S(t, f) = \int_{-\infty}^{\infty} h(\tau)w^*(\tau - t, f), e^{-j2\pi f\tau} d\tau \quad (1)$$

Where

$$S(t, f) = \frac{|f|}{a\sqrt{2\pi}}, e^{-t^2/2a^2} \quad (2)$$

The integration of S-transform over time results in the Fourier spectrum is given as

$$H(f) = \int_{-\infty}^{\infty} S(t, f) dt \quad (3)$$

For the gaussian window $\int_{-\infty}^{\infty} S(t, f) dt = 1$ (4)

The original signal can be obtained from S-transform as

$$h(t) = \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} S(\tau, f) d\tau \right\} e^{j2\pi f\tau} df \quad (5)$$

The S-transform is also represent as the amplitude and phase correction of the continuous wavelet transform

$$S(t, f) = \frac{\sqrt{f}}{2\pi\alpha} e^{j2\pi f\tau}, WT(t, f) \quad (6)$$

Wavelet transform is given as $WT(t, f) = \frac{\sqrt{|f|}}{\alpha}, e^{-t^2 f^2 / 2\alpha^2}, e^{j2\pi f\tau}$ (7)

The S-transform is now expressed in time frequency resolution as

$$S(t, f) = \int_{-\infty}^{\infty} H(v, f)w^*(v, f), e^{j2\pi v\tau} dv \quad (8)$$

$$w(v, f) = e^{-2\pi^2\alpha^2 v^2 / t^2} \quad (9)$$

2.2 Multi-Layer Perceptron (MLP) Neural Network

A multilayer perceptron neural network is a feed-forward artificial neural network that has an input layer, output layer and one or more hidden layers. A MLP based neural network consists of multiple layers of nodes in which each layer connected to the next one fully in a directed graph.

Except for the input nodes, each node is a neuron with a nonlinear activation function. MLP based neural network utilizes a supervised learning technique called back propagation for training the network. MLP based neural network architecture diagram is shown as in the figure 1.

Further, MLP networks have redundant networking and are very robust, providing a mathematical flexibility. The training parameters and the structure of the MLP used in this work are shown in Table 1.

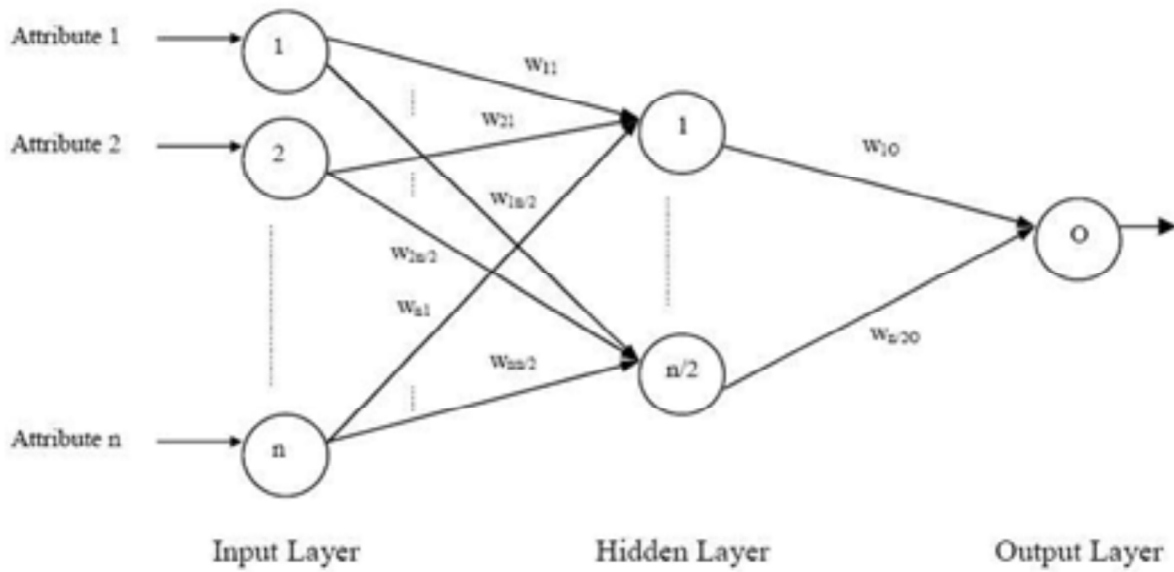


Figure 1: Architecture of MLP Neural Network

Table 1
MLP architecture and training parameters

Architecture	
The number of layers	3
The number of neuron on the layers	Input: 13, hidden: 10, output: 9
The initial weights and biases	Random
Activation functions	Tangent sigmoid
Training parameters	
Learning rule	Back-propagation
Learning rate	0.75
Mean-squared error	1E'08

2.3. Back propagation learning algorithm

BP has two phases:

- Forward pass phase: Computes the ‘functional signal’ and feed forward propagation of input pattern signals through network.
- Backward pass phase: Computes the ‘error signal’ and propagates the error backwards through network starting at output units (The error is the difference between actual and desired output values).

3. CLASSIFICATION STAGE

In this stage, features extracted through the S-transform are applied as inputs to the multi-layer perception based neural network in order to classify the disturbances. MLP networks are very useful for the classification of those input signals which cannot be defined mathematically.

3.1. Flowchart of the Proposed Method

The flowchart for the Classification of Power Quality disturbances is shown in below.

It has three different blocks.

- Block-(a) – Features extraction such as standard deviation, peak value and variances
- Block-(b) – Detection and classification of the power quality disturbances

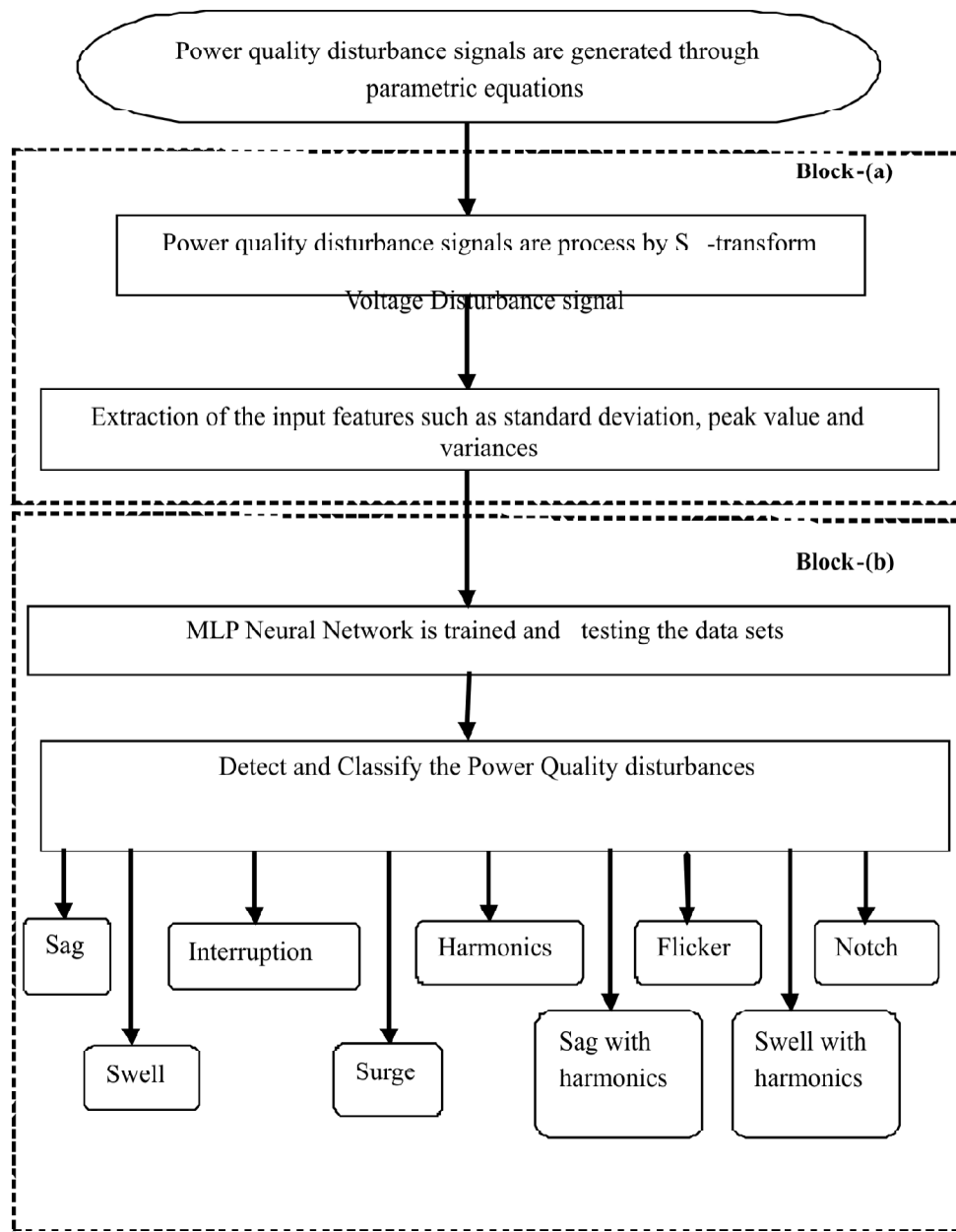


Figure 2: Flowchart for the Classification of Power Quality disturbances

4. SIMULATION AND TEST RESULTS

Training and Test data for various classes of disturbances using a set of parametric equations and this method of data generation offers the advantages such as a wide range of parameters can be generated in a controlled manner. signals closer to real situation can be simulated. 100 cases of each class with different parameters were generated for training and another 100 cases were generated for testing. The feature extraction of these signals has been done by S-transform. Total size of the training data set is 3×900 , where 3 represents the number of features extracted for each type of disturbance and 900 represents the total number of samples at the rate of 100 samples for each one of the 9 disturbances. These input signals, when applied to the MLP neural network to get accurate classified disturbances. The various types of power quality disturbances are presented to highlight the suitability of the application of the proposed method.

Pure sine wave is the normal voltage signal of at frequency 50 Hz and its waveform is as shown in the figure 3(a). The time frequency analysis of S-transform and spectrogram representation of the pure sine wave are shown in the figures 3(b) and 3(c). The standard deviation, peak value and the variances of the pure sine wave are shown in the figures 3(d) and 3(f).

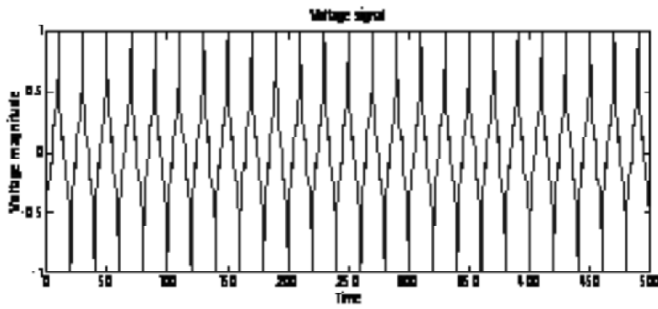


Figure 3(a)

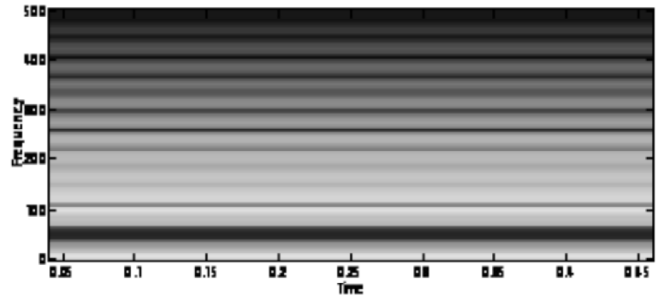


Figure 3(b)



Figure 3(c)

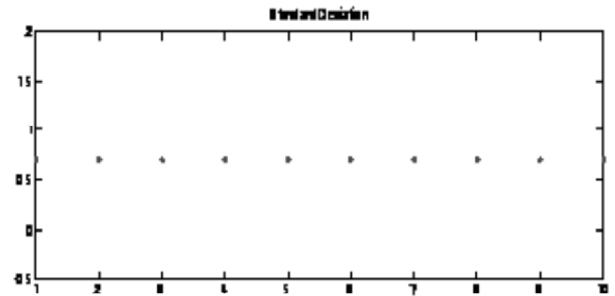


Figure 3(d)

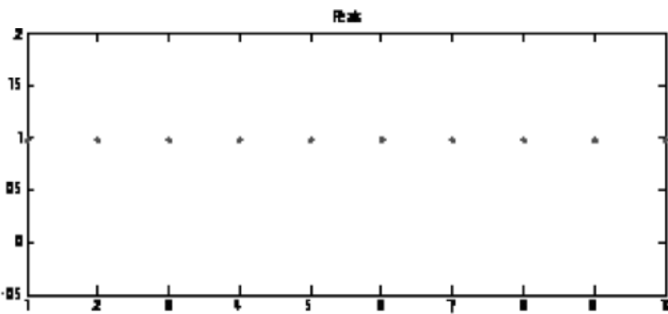


Figure 3(e)

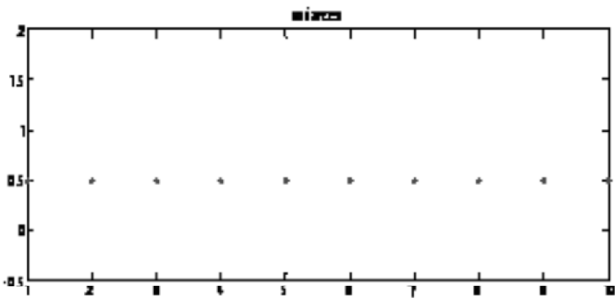


Figure 3(f)

Voltage sag (or) **voltage dips** causes the decrease of system voltage and its waveform is as shown in the figure 4(a). The time frequency analysis of S-transform and spectrogram representation of the voltage sag are shown in the figures 4(b) and 4(c). The standard deviation, peak value and the variances of the voltage sag are shown in the figures 4(d) and 4(f).

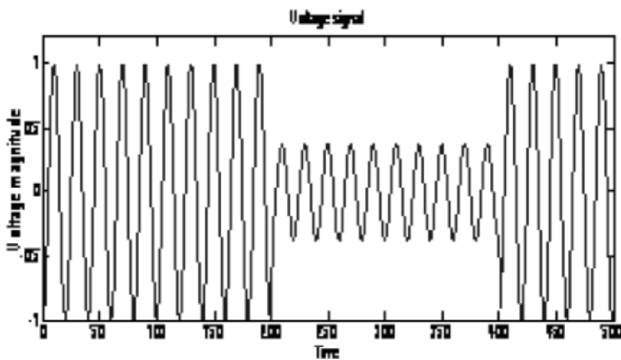


Figure 4(a)

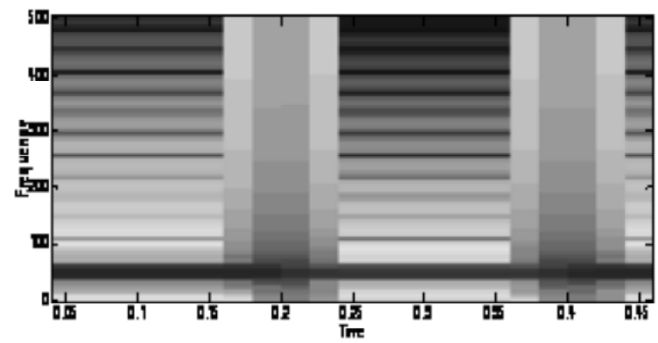


Figure 4(b)



Figure 4(c)

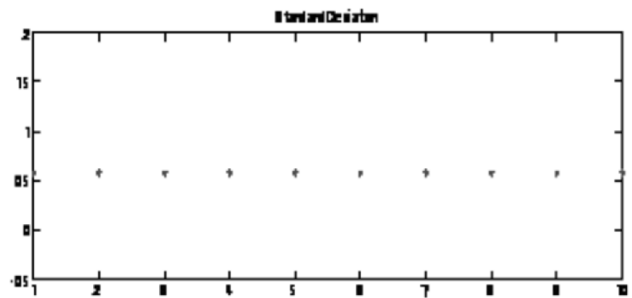


Figure 4(d)

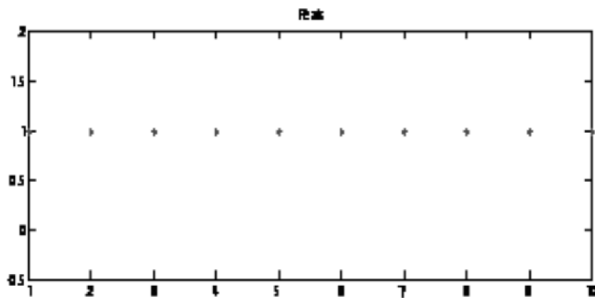


Figure 4(e)

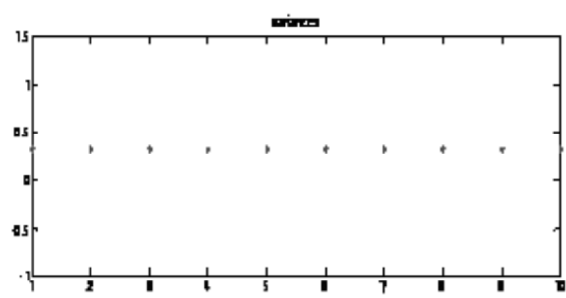


Figure 4(f)

Voltage swell causes the rise of system voltage and its waveform is as shown in the figure 5(a). The time frequency analysis of S-transform representation and spectrogram of the voltage swell are shown in the figures 5(b) and 5(c). The standard deviation, peak value and the variances of the voltage swell are shown in the figures 5(d) and 5(f).

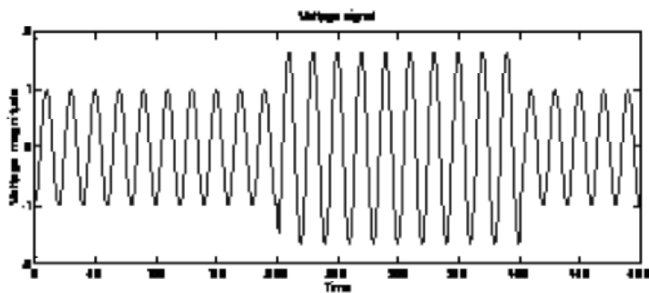


Figure 5(a)

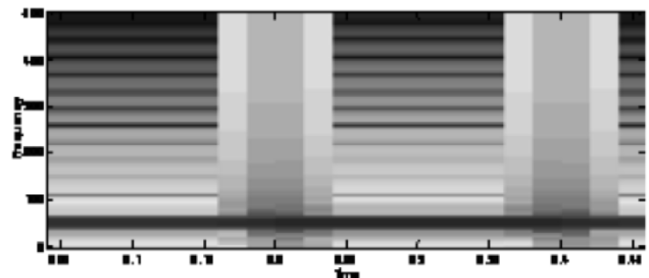


Figure 5(b)



Figure 5(c)

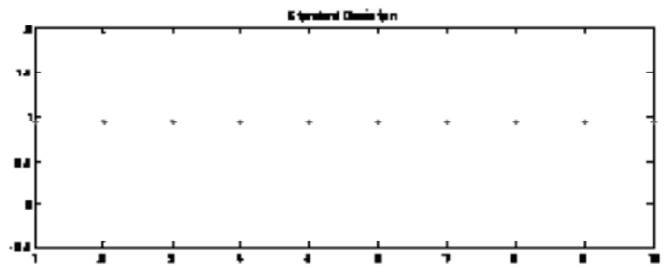


Figure 5(d)

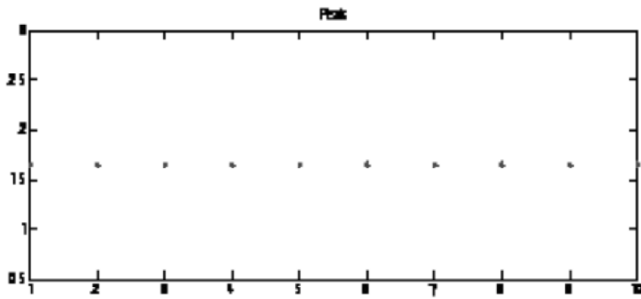


Figure 5(e)

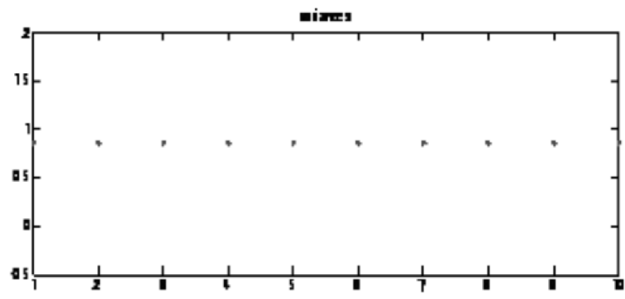


Figure 5(f)

Outages may be seen as a loss of voltage on the system for the short duration and its waveform is as shown in the figure 6(a). The time frequency analyses of S-transform representation spectrogram and of the voltage swell are shown in the figures 6(b) and 6(c). The standard deviation, peak value and the variances of the voltage swell are shown in the figures 6(d) and 6(f).

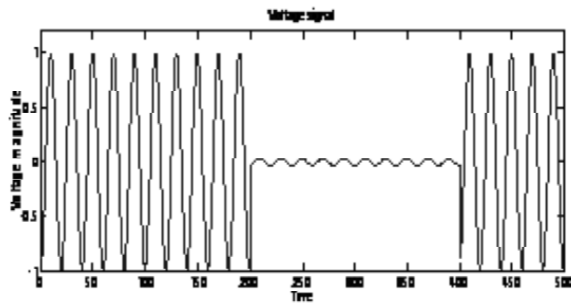


Figure 6(a)

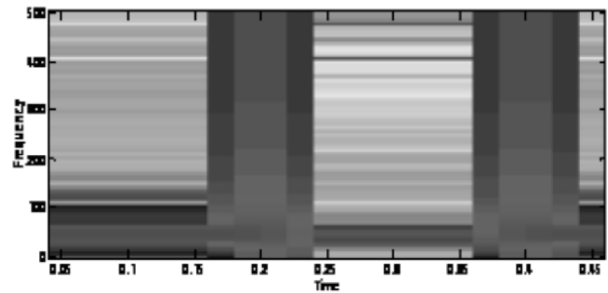


Figure 6(b)



Figure 6(c)

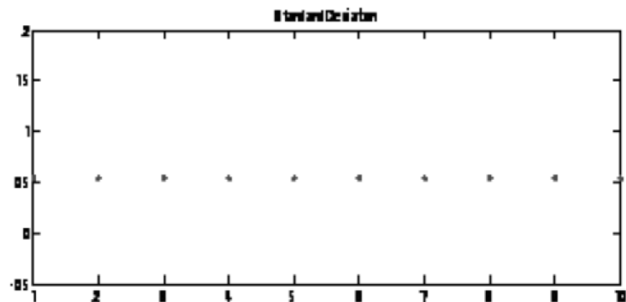


Figure 6(d)

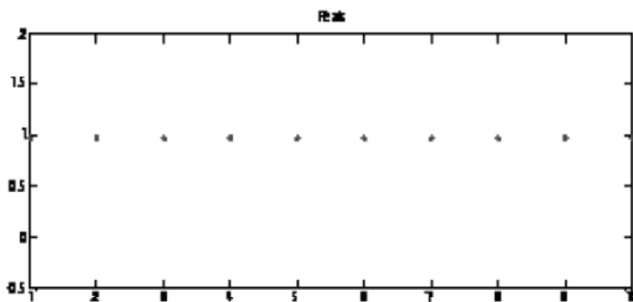


Figure 6(e)

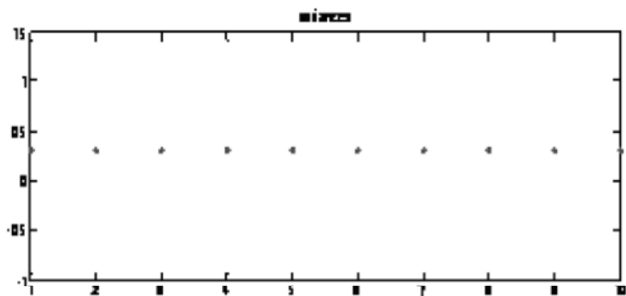


Figure 6(f)

Harmonics are generated by the connection of non linear load to the system duration and its waveform is as shown in the figure 7(a). The time frequency analysis of S-transform representation and spectrogram of the harmonics are shown in the figures 7(b) and 7(c). The standard deviation, peak value and variances of harmonics are shown in the figures 7(d) and 7(f).

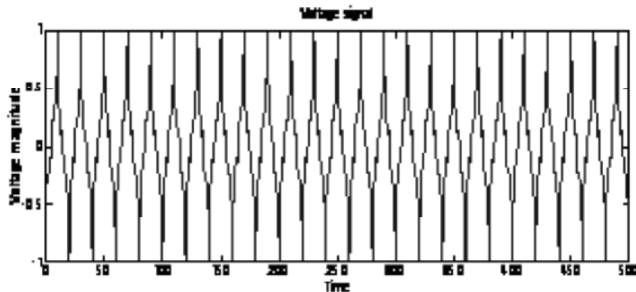


Figure 7(a)

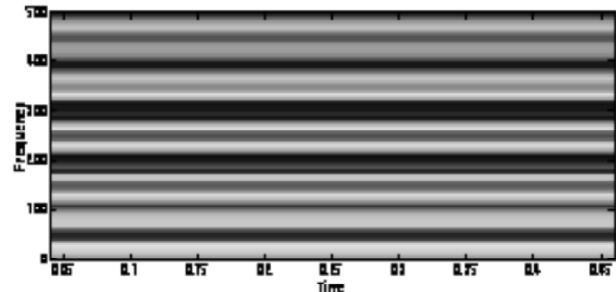


Figure 7(b)



Figure 7(c)

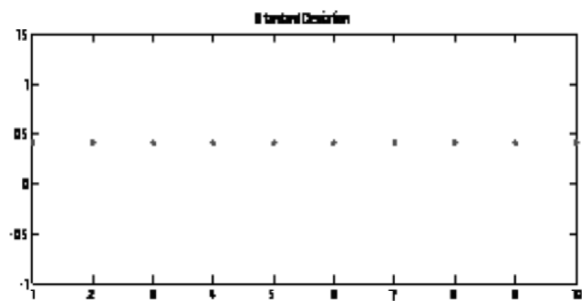


Figure 7(d)

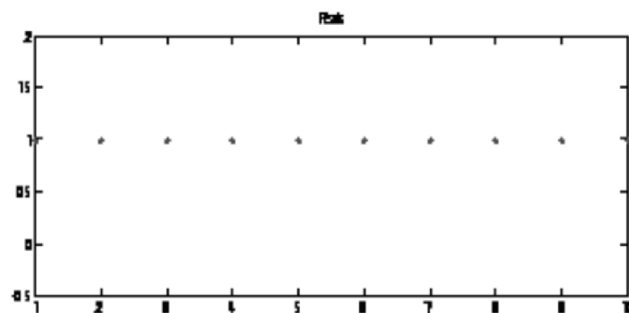


Figure 7(e)

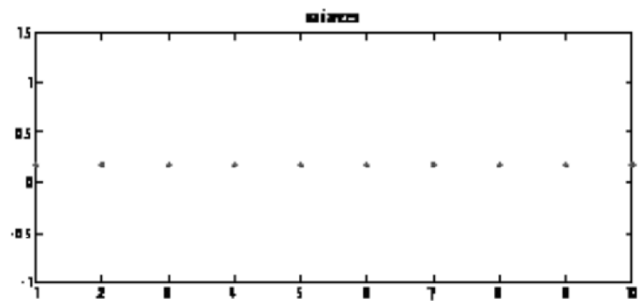


Figure 7(f)

Sag with harmonics is caused by the presence of a nonlinear load and its waveform is as shown in the figure 8(a). The time frequency analysis of S-transform representation and spectrogram of the harmonics are shown in

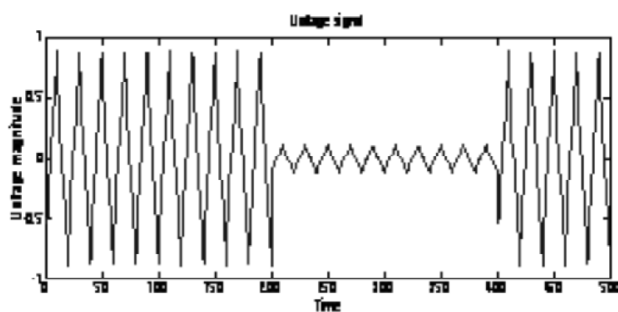


Figure 8(a)

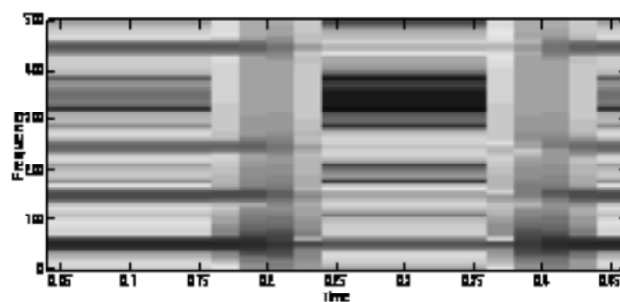


Figure 8(b)



Figure 8(c)

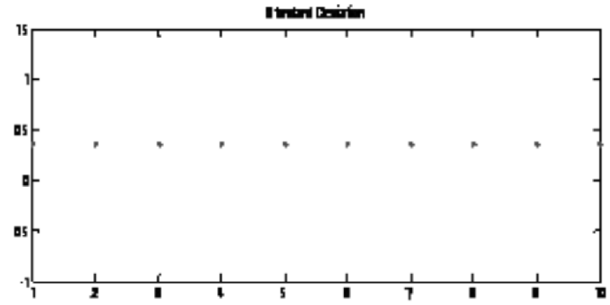


Figure 8(d)

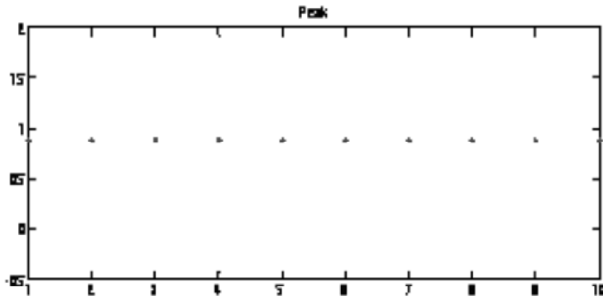


Figure 8(e)

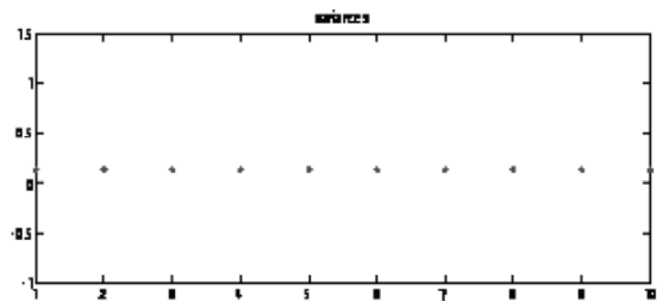


Figure 8(f)

the figures 8(b) and 8(c). The standard deviation, peak value and the variances of the harmonics are shown in the figures 8(d) and 8(f).

Swell with harmonics is caused by the presence of nonlinear load and its waveform is as shown in the figure 9(a). The time frequency analysis of S-transform representation spectrogram and of the swell with harmonics is shown in the figures 9(b) and 9(c). The standard deviation, peak value and the variances of the swell with harmonics are shown in the figures 9(d) and 9(f).

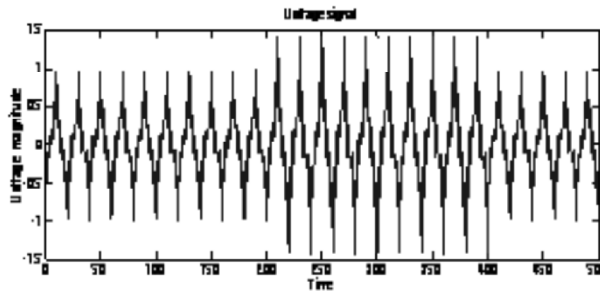


Figure 9(a)

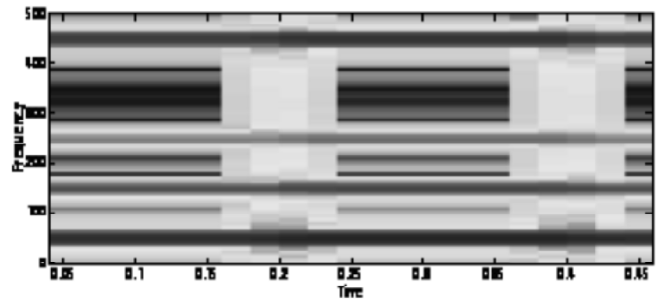


Figure 9(b)



Figure 9(c)

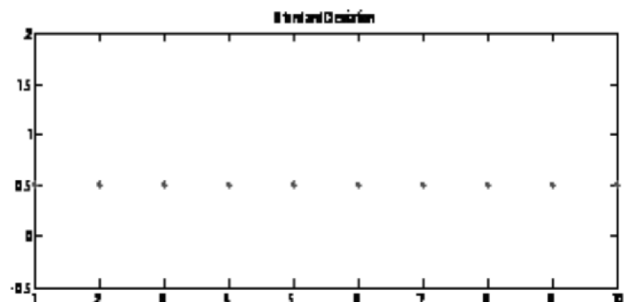


Figure 9(d)

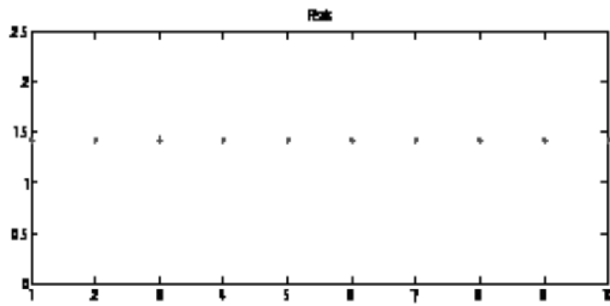


Figure 9(e)

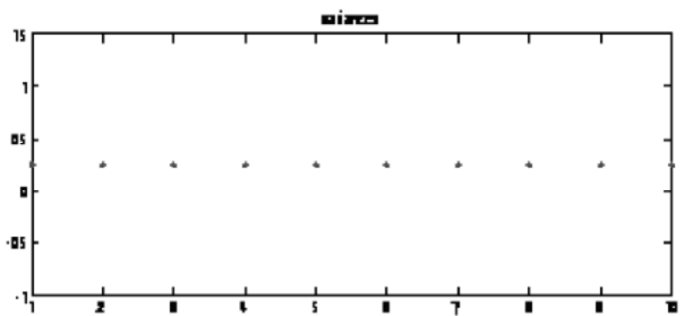


Figure 9(f)

Flicker is caused by the continuous and rapid variation of the system load and its waveform is as shown in the figure 10(a). The time frequency analysis of S-transform representation spectrogram and of the flicker is shown in the figures 10(b) and 10(c). The standard deviation, peak value and the variances of the flicker are shown in the figures 10(d) and 10(f).

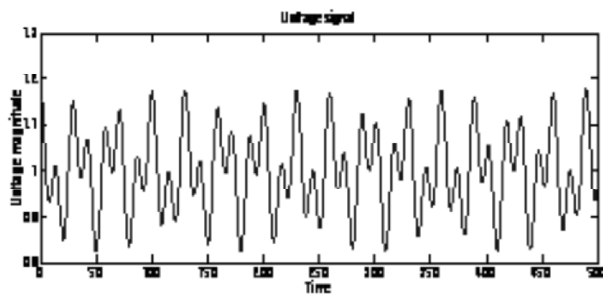


Figure 10(a)

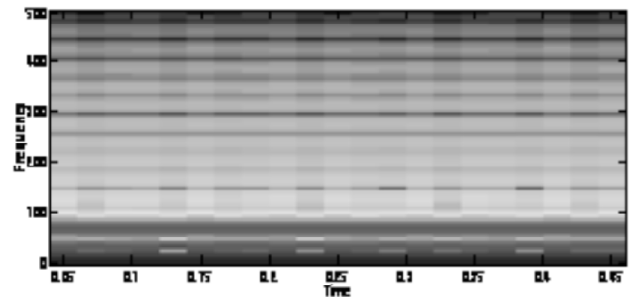


Figure 10(b)



Figure 10(c)

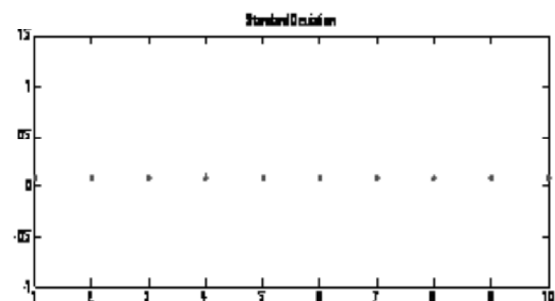


Figure 10(d)

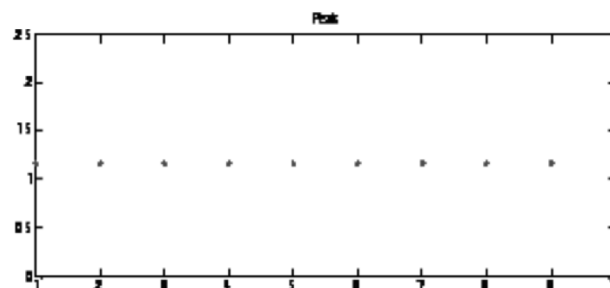


Figure 10(e)

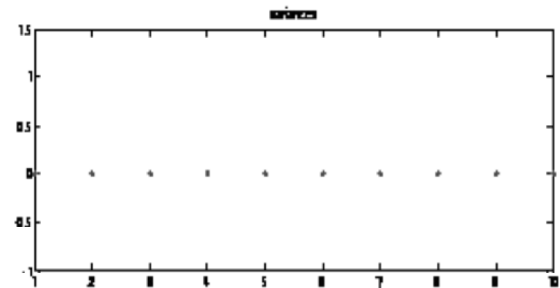


Figure 10(f)

Notch is a disturbance of the nominal power voltage waveform lasting for less than half a cycle. The disturbance is initially of opposite polarity and hence it is to be subtracted from the waveform and shown in the figure 11(a). The time frequency analysis of S-transform representation spectrogram and of the notch is shown in the figures 11(b) and 11(c). The standard deviation, peak value and variances of notch are shown in the figure 11(d) and 11(f).

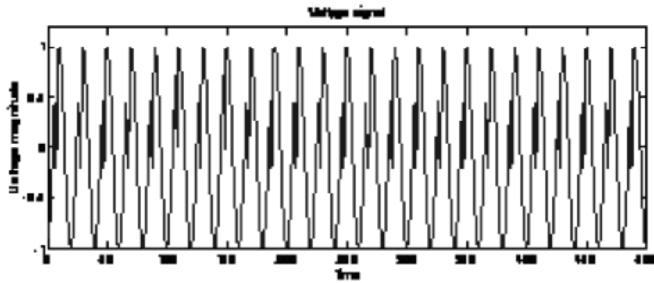


Figure 11(a)

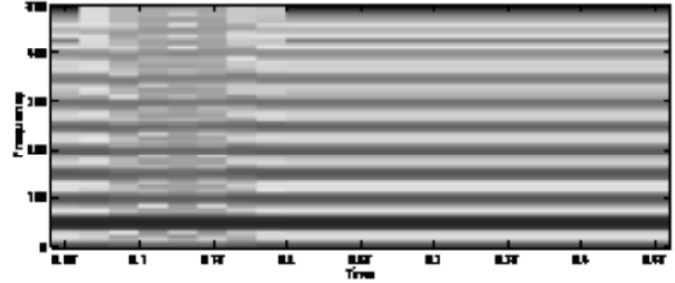


Figure 11(b)



Figure 11(c)

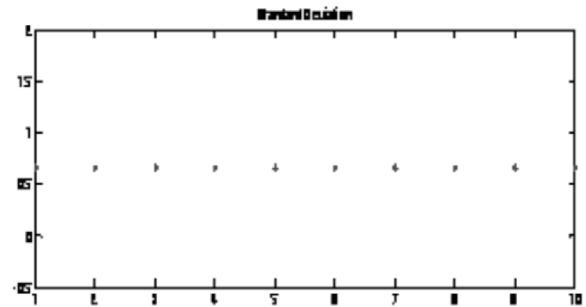


Figure 11(d)

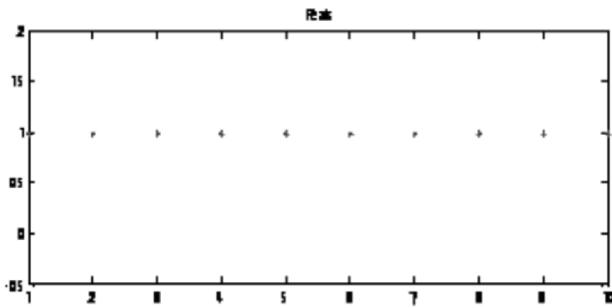


Figure 11(e)

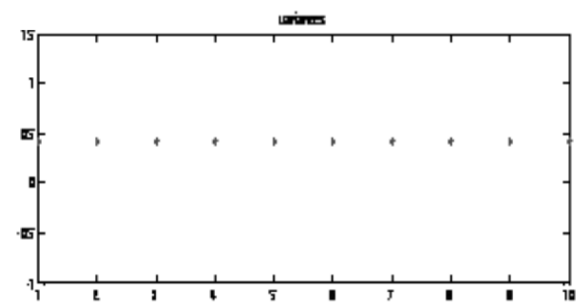


Figure 11(f)

Table 3
Classification accuracy

Sno	PQ Disturbances	Percentage of Accuracy		
		Input Features	Kalman filter based MLP neural network	S-transform based MLP neural network
1	Voltage Sag	100	98	96
2	Voltage Swell	100	98	100
3	Outages	100	92	98
4	Harmonics	100	90	98
5	Sag with Harmonics	100	90	100
6	Swell with Harmonics	100	100	97
7	Flicker	100	100	100
8	Notch	100	98	100
	Overall accuracy		95.75	98.63

5. CONCLUSION

In this paper, a new technique to detect and classify the various types of Power quality disturbances using S-transform and MLP neural network. The Power quality disturbance waveforms were generated through parametric equations. By using S-Transform the input features such as standard deviation, peak value and variances were extracted and MLP based neural network has been applied for classifying the various PQ disturbances. The classification accuracy has been validated by comparing the results obtained by the proposed technique against kalman based neural classifiers and it has been concluded that the proposed method performs better than those technique. The proposed technique enables the accurate classification of all nine types of PQ disturbances. Simulation results demonstrate that the performance and accuracy of the S-transform. Neural Network is a versatile classifier that can be trained for any input combination and its application makes the suggested technique particularly suitable for classification of disturbances of varying nature. The results show that the proposed technique performs very well in detection and classification of PQ disturbances.

References

- [1] Surya Santoso, Edward J. Powers, and W. Mack Grady, "Electric power quality disturbances detection using wavelet transform analysis", IEEE Transaction, 1994.
- [2] David C. Robertson Octavia I. Camps, Jeffrey S. Mayer, William B. Gish, "Wavelet and electromagnetic power system transients", IEEE Transaction on power delivery, Vol. 11, April 1996.
- [3] G.T. Heydt, A.W. Galli, "Transient power quality problem analyzed using wavelets", IEEE Transaction on power delivery, Vol. 12, April 1997.
- [4] Paul S. Wright, "Short time Fourier transforms and wigner-ville distributions applied to the calibration of power frequency harmonic analyzers", IEEE Transaction on instrumentation and measurement, Vol. 48, no.2, April 1999.
- [5] G.T. Heydt, P.S. Fjeld, C.C. Liu, D. Pierce, L. Tu, G. Hensley, "Applications of the windowed FFT to Electric Power quality assessment", IEEE Transaction on power delivery, oct 1999.
- [6] A.M. Gaouda, M.R. Sultan, A. Y. Chinkani and M.M.A. Salama, "Power quality detection and classification using wavelet-multiresolution signal decomposition" IEEE Transaction on power delivery, Vol. 14, no.4, October 1999.
- [7] Mladen Kezunovic, "Advanced assessment of the power quality events", IEEE Transaction, 2000.
- [8] Surya Santoso, Edward J. Powers, W. Mack Grady, and Antony C. Parsons, "Power quality disturbance waveform recognition using wavelet based neural classifier-part 1: theoretical foundation", IEEE Transaction on power delivery, Vol. 15, no.1, January 2000.
- [9] A.M. Gaouda, S.H. Kanoun and M.M.A. Salama, "On-line disturbance classification using nearest neighbor rule", Electric power systems research, 2001.
- [10] Francisco Jurado, Jose´ R. Saenz, "Comparison between discrete STFT and wavelets for the analysis of power quality events", Electric power systems research, 2002.
- [11] P.K Dash, G.Panda and B. K. Panigrahi, "Power quality analysis using S-transform", IEEE Transaction on power delivery, Vol. 18, no.2, April 2003.
- [12] M. V. Chilukuri and P. K. Dash, "Multi resolution S-transform-based fuzzy recognition system for power quality events", IEEE Transaction on power delivery, Vol. 19, no.1, January 2004.
- [13] Dogan gokhan ece, and Omer nezih gerek, "Power quality event detection using joint 2-D-wavelet subspaces", IEEE Transaction on instrumentation and measurement, Vol. 53, no.4, August 2004.
- [14] Julio Barros and Enrique Perez, "Automatic detection and analysis of voltage events in power systems", IEEE Transaction on instrumentation and measurement, Vol. 55, no.5, October 2006.
- [15] Fengzhan Zhao, Rengang Yang, "Power quality disturbance recognition using S-transform", IEEE transaction on power delivery, Vol. 22, no.2, April 2007.
- [16] Ameen M. Gargoom, Nesimi Ertugrul, and Wen. L. Soong, "Automatic Classification and Characterization of Power Quality Events", IEEE Transaction on power delivery, oct 2008.
- [17] H.S. Behera, P.K. Dash, B. Biswal, "Power quality time series data mining using S-transform and fuzzy expert system", Applied soft computing, 2010.
- [18] M. Faisal, A. Mohamed, H. Shareef, A. Hussain, "Power quality diagnosis using time frequency analysis and rule based techniques", 2011.

- [19] Chun-Yao Lee, Yi-Xing Shen, "Optimal Feature Selection for Power-Quality Disturbances Classification", IEEE Transaction on power delivery, oct 2011.
- [20] Mohammad Jasa Afroni, Danny Sutanto and David Stirling, "Analysis of Nonstationary Power-Quality waveforms using iterative Hilbert Huang transform and SAX algorithm", IEEE Transaction on power delivery, Oct 2013.

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