Intelligent Power Quality Monitoring by using S-Transform and Neural Network

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***Abstract*: -** In this paper a method in intelligent monitoring of the power quality events is presented. The main objectives are the identification and classification of these events. A method for classification is used based on the combination of S-transform and neural networks. The S-transform, which is based on the wavelet transform with a phase correction, provides frequency dependent resolutions that simultaneously localize the real and imaginary spectra. Neural network configurations are trained with features from the S-transform for recognizing the waveform class. The whole method is tested over a variety of power network disturbance signals and their combinations which are created by EMTP simulations in a 34 bus IEEE standard network. The classification accuracy for these events is given and shows that proposed method is doing well in detecting and classifying these types of disturbances.

***Key-Words:* -** detection and classification of power quality events, S-transform, neural networks

1 Introduction

During last decade, the increasing use of equipment sensitive to power system disturbances and their related economic aspects, have created power quality monitoring a common practice for utilities. Utilities try to meet the demands of their customers by monitoring the power quality to prove that the quality of the offered power is within the specified standards. A reliable identification of the disturbances enables the utilities to locate the source of the problems that might occur. Other important aspect of power quality monitoring is the collection of information regarding the performance of the power system.

To monitor electrical power quality disturbance, short time discrete Fourier transform (STFT) is most often used. This transform has been successfully used for stationary signals where properties of signals do not evolve in time. For nonstationary signals, the STFT does not track the signal dynamics properly due to the limitations of a fixed window width. Thus, STFT cannot be used successfully to analyze transient signals comprising both high- and low-frequency components.

On the other hand, wavelet analysis provides a unified framework for monitoring power quality problems and has been used in power quality analysis [1]-[3]. The wavelet transform (WT), like the Short Time Fourier Transform (STFT), provides an understandable transient signal representation corresponding to a time-frequency plane. This plane gives time and frequency information relating to the analyzed signal. Unlike STFT, the length of the smoothing window of the WT depends on the frequency analyzed: long windows are used at low frequencies, and short windows at high frequencies [3]. Therefore, the WT leads to relatively accurate frequency resolution and poor time location at low frequency. The WT also provides accurate time location and bad frequency resolution at high frequency. This characteristic is appropriate for real signals such as voltage sags and transient overvoltages. Time-frequency planes are also meaningful signatures of each kind of disturbances providing time and frequency characteristics.

For pattern classification of a nonstationary time series like power quality disturbance signals, multiresolution analysis of the discrete wavelet transform (DWT) cannot yield easily distinguishable features and exact spectral contents and needs multiple neural networks resulting in high computational overhead [4]. The S-transform, on the other hand, produces a time-frequency representation of a time series. Furthermore, the S-transform can be derived from the continuous wavelet transform (CWT) choosing a specific mother wavelet and multiplying a phase correction factor [4], [5].

In this paper a method for automatically detecting and classifying various types of power quality events is presented. The method is based on S-transform analysis and neural networks. The various power quality disturbance signals such as voltage sag, swell, interruption, impulsive, surge, notch, harmonics, voltage flicker and combination of these events has been considered for the S-transform analysis. These signals have been created by EMTP simulations in a 34 bus IEEE standard network.

2 Basic Principles of Monitoring

The S-Transform (ST) is an extension to the Gabor transform and WT and falls within the broad range of multiresolution spectral analysis, used with a translatable and scalable Gaussian window, where the standard deviation is an inverse function of the frequency, thus reducing the dimension of the transform. With the introduction of a dilation parameter, the localizing Gaussian function g(t) is defined as: [3]

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{t^2}{\sigma^2}} \quad (1)$$

Where σ is the standard deviation. The Multiresolution ST is defined by

$$S^*(f,\tau,\sigma) = \int_{-\infty}^{\infty} h(t) \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(t-\tau)^2}{2\sigma^2}} e^{-i2\pi ft} dt \quad (2)$$

The ST performs multiresolution analysis on the signal, because the width of its window varies inversely with the frequency. This gives high time resolution at high frequencies and high frequency resolutions at low frequencies. The width of the window has been chosen to be proportional to the period of the cosinusoid being localized as follow:

$$\sigma(f) = \frac{1}{|f|} \quad (3)$$

Therefore the ST may be written as:

$$S(f,\tau) = \frac{|f|}{\sqrt{2\pi}} \int_{-\infty}^{\infty} h(t) e^{\frac{-(t-\tau)^2 f^2}{2}} e^{-i2\pi ft} dt \quad (4)$$

It is clear that the zero frequency of the ST is identically equal to zero for this definition of $\sigma(f)$. This adds no information. Therefore, $S(\tau, f)$ is defined as independent of time and is equal to the average of the function h(t). For the discrete ST, *h(t)* can be written in discrete form as *h[kt]*, where k varies from 0 to N-1 and is known as discrete time series of the signal *h(t)*. Discrete Fourier transform of the time series *h[kt]* can be expressed as:

$$H\left[\frac{n}{NT}\right] = \frac{1}{N} \sum_{k=0}^{N-1} h[kT] e^{\frac{i2\pi nk}{N}} \quad (5)$$

Where $n=0,1,2,3,\ldots, N-1$ and the inverse discrete fourier transform is:

$$h[KT] = \frac{1}{N} \sum_{n=0}^{N-1} \{\sum_{j=0}^{N-1} S\left[\frac{n}{NT}, jT\right]\} e^{\frac{i2\pi nk}{N}} \quad (6)$$

The ST in discrete case is the projection of the vector defined by the time series *h[kt]* onto a spanning set of vectors. Since spanning vectors are not orthogonal and the elements of S matrix are not dependent, each basis vector is divided into N localized vectors by an element by element product with shifted Gaussians, such that sum of these N localized vectors is the original basis vector. The ST of the discrete time series *h[kt]* is given by:

$$S\left[\frac{n}{NT}, jT\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{\frac{-2\pi^2 m^2}{n^2}} e^{\frac{i2\pi mj}{N}} \quad (7)$$

The computation of the ST is efficiently implemented using the convolution theorem and FFT. The following steps are used for the computation of ST.

i) Denote *n/NT*, *m/NT*, *KT* and *jT* as *n*, *m*, *k* and *j* respectively, for the evaluation of ST.
ii) Compute the DFT of the signal *h(t)* using FFT software routine and shift spectrum *H[m]* to *H[m+n]*.
iii) Compute the Gaussian window function for the required frequency n.
iv) Compute the inverse Fourier transform of the product of DFT and Gaussian window function to give the ST matrix.

The output of the ST is an n×m matrix whose rows pertain to frequency and columns indicate time. Each column thus represents the local spectrum for that point in time. From the ST matrix, we obtain the frequency-time contours having the same amplitude spectrum and these contours can be used to visually classify the nature of the disturbance event. A three-dimensional (3-D) mesh of the S-transform output yields frequency-time, amplitude-time, and frequency-amplitude plots. The original software code developed in Matlab for power quality waveform studies.

The nature of this disturbance can be classified by obtaining a few simple features such as standard deviation and amplitude factors. After that, an automated disturbance recognition system based on neural networks classifier has been used. In this stage, eleven back-propagation neural network based pattern recognition system is used to classify the various disturbance waveforms. Fig. 1 shows flowchart of complete process of detection and classification of power quality events.

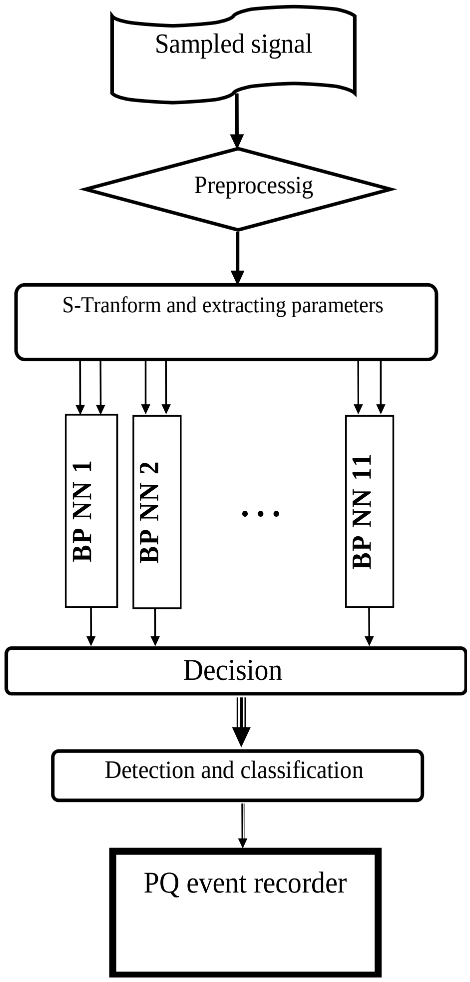


Fig. 1 Flowchart of PQ event monitoring

3 S-Transform of Power Quality Events

In order to test the proposed PQ monitoring system, different types of PQ events has been produced by EMTP simulation in IEEE 34 bus standard system which is shown in Fig. 2. These events are based on IEEE1159 standard definitions and listed as follow:

1. *Flicker* which has been simulated by connecting an arc furnace.
2. *Harmonics* has been simulated by connecting an adjustable speed drive
3. *Interrupt* has been simulated by a solid three phase short circuit close to the measuring point
4. *Voltage sags* has been simulated by connecting a large load
5. *Voltage swell* has been simulated by disconnecting a large load from system
6. *Impulse* has been simulated by using Hydler model which based on voltages are defined as:

$$V = \frac{Amp(t/T_f)^n}{(1+(t/T_f)^n}e^{(t/\tau)} \quad (8)$$

7. *Surge* has been simulated by switching a large capacitor in the system
8. *Notch* has been simulated by connecting a three phase rectifier with a highly inductive load

In this paper three different combinations of PQ events has been considered. These events are:

9. *Flicker and harmonic*
10. *Harmonic and Sags*
11. *Flicker and sags*

To illustrate the use of S-transform for detecting power quality events, the simulated signals are sampled with 2 KHz sampling rates. Fig. 3 shows a voltage waveform with harmonic and flicker which has been generated with EMTP.

The 3-D meshes for the signal shown in Fig. 3 are shown in Fig. 4. From the 3-D plot, the magnitude, frequency, and time information of the event can be detected. Three contours of frequency-time and magnitude-frequency and magnitude-time are shown in Fig. 5. In all of the plots, the frequency magnitude

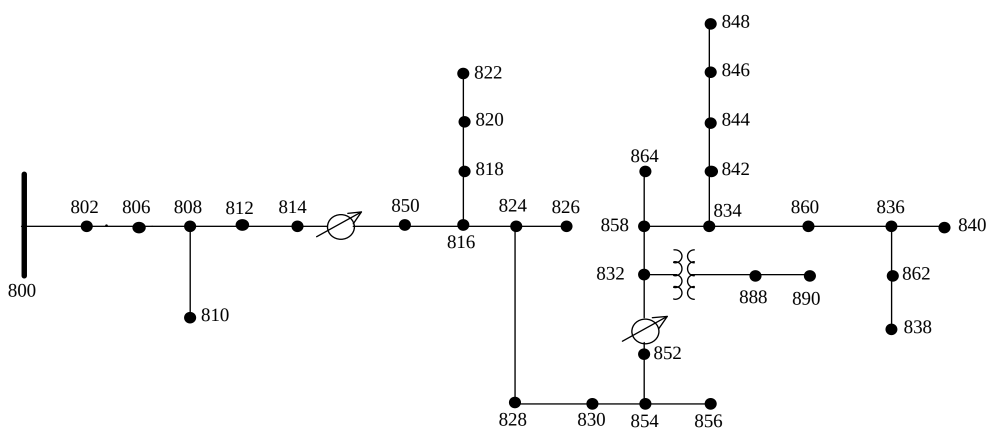


Fig. 2: IEEE 34 bus standard network

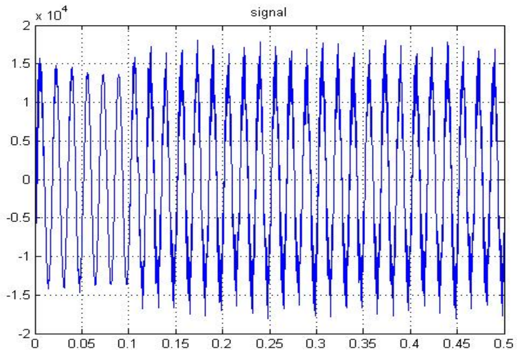


Fig. 3: Voltage waveform with harmonics and flicker

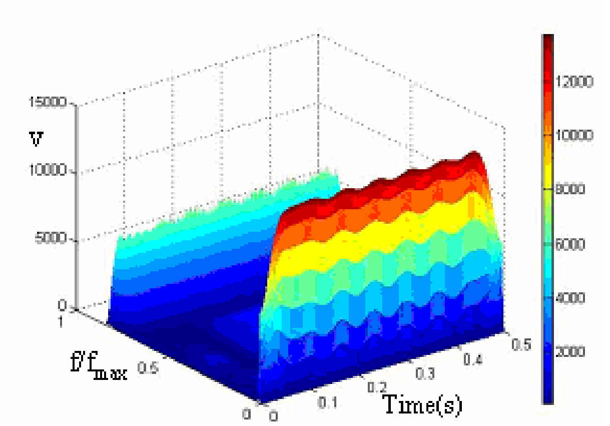
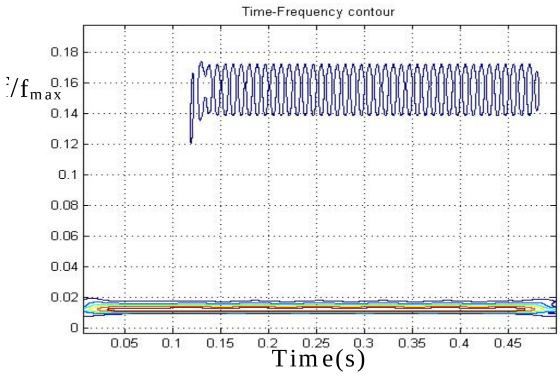
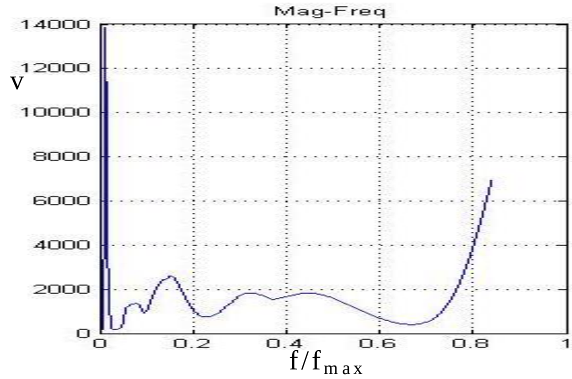


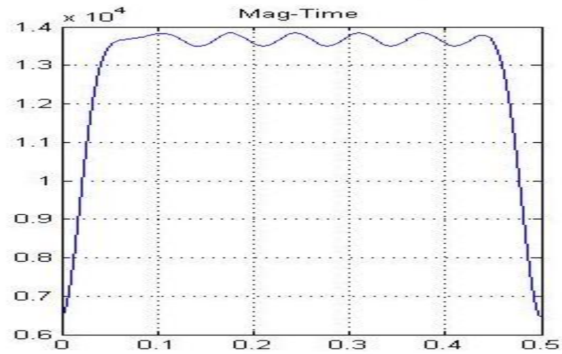
Fig. 4: The 3-D presentation of voltage-time-frequency of the waveform in Fig. 3



(a)



(b)



(c)

Fig. 5: Contours of the 3-D mesh shown in Fig. 4 (a) frequency-time contour (b) magnitude-frequency contour (c) magnitude-time contour

is normalized with respect to the sampling frequency and is given by f/f_{max}. The frequency-time contour of the PQ disturbances clearly reveals the nature of the disturbances. For example, Fig. 5(a) presents the actual signal showing harmonics contents of the signal. In Fig. 5(b), the normalized time-frequency contour obtained from S-transform is shown. This contour gives the maximum output of the normalized frequency-time graph. Fig. 5(c) gives the magnitude-time spectrum obtained by searching rows of S-transform matrix. This figure clearly shows the voltage amplitude changes which is due to flicker and the time of its occurrence.

From these results, it is quite obvious that in case of S-transform output, one can detect, localize, and quantify the disturbance completely. However, the wavelet transform alone cannot give all of the information which is extracted from the S-transform and requires the use of Fourier transform for quantifications of the signal magnitude, total harmonic distortions, etc [3]. The frequency-time contours of the S-transform output shows a decrease or increase in magnitude for voltage which provides a better visual classification strategy in comparison to the wavelet transform (similar to time versus rms or peak value of voltage). The magnitude versus time graph quantifies the voltage.

In analyzing oscillatory transients, voltage impulses, etc., it will be useful to get S-transform output for another window width. The S-transform output at different frequency yields some more parameters for discriminating various types of transient disturbances. For instant Fig. 6 shows oscillatory transient waveform and it lasts for short time duration. These transients can be categorized into several groups like impulsive, notched, or oscillatory. Figs. 7 show 3-D presentation of voltage-time-frequency created by S–transform. These

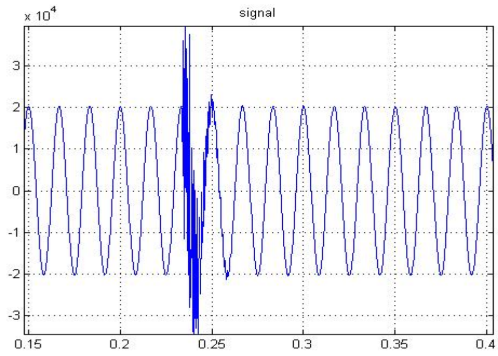


Fig. 6: High frequency oscillatory voltage

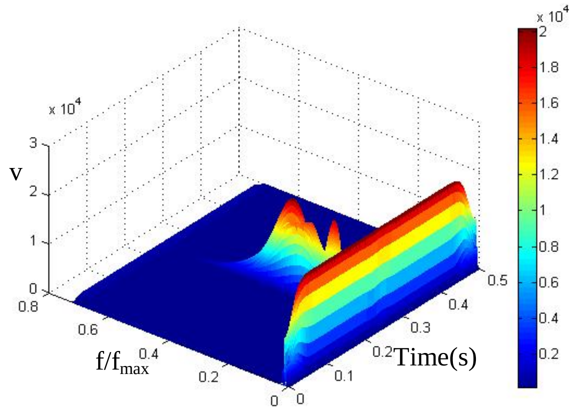
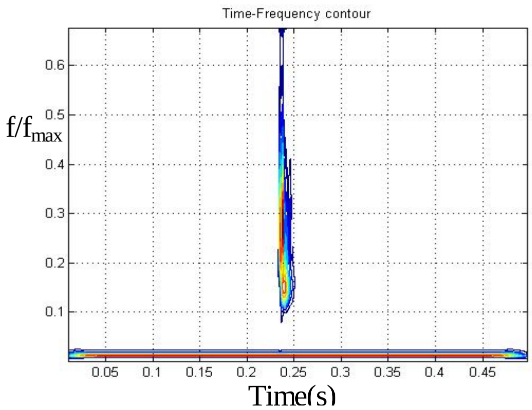


Fig. 7: The 3-D presentation of magnitude-time-frequency of the waveform in Fig. 6

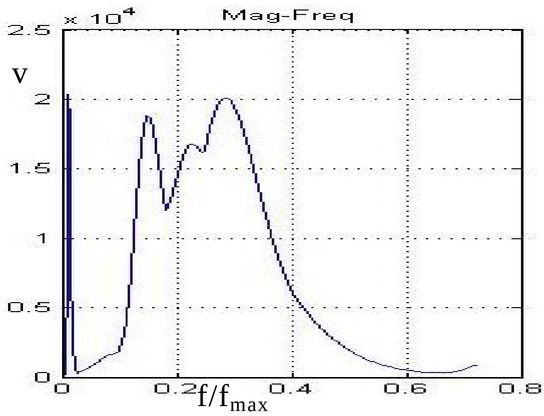
contours clearly show power quality transients patterns suitable for classifying these events.

4 PQ DISTURBANCE RECOGNITION SYSTEM

Power quality disturbance recognition involves a broad range of disturbance categories and varying degree of irregularities. Description of PQ events considered for recognition is outlined in the previous section. The generalized S-transform generates the time frequency contours, which clearly display the disturbance pattern for visual inspection. As the S–transform provides us a time-frequency representation (TFR) of the signal with frequency dependent resolution, the standard deviation of the TFR curve is taken as a measure to classify these signals. It is observed that for a pure sinusoid, the standard deviation curve is linear over the entire range (this value is taken as a reference), where for the sags, the standard deviation falls below this reference value and rises above the reference for the swells. We have set this reference, as a boundary. The standard deviation above this represent voltage swell and the standard deviation below it represent voltage sag. It is observed that during the test for



(a)



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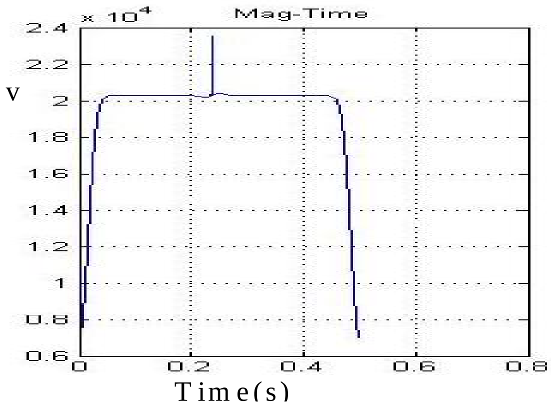

(c)

Fig. 8: Contours of the 3-D meshes shown in Fig. 7
(a) frequency-time contour (b) magnitude-frequency contour (c) magnitude-time contour

different percentages of sag or swell, there is a proportionate decrease or increase in the standard deviation above the reference. Further, it is to be noted that the FFT used in the S–transform calculation provides both the amplitude and frequency components of the signal.

For classifying both steady-state and transient disturbances, standard deviations at two different Gaussian window widths (k=1, and k=5) are taken and an amplitude factor is determined from the S–transform matrix. These features have been used in a

Table 1: Accuracy of detection and classification of PQ events

PQ Events	Accuracy with 1000 epochs	Accuracy with 2000 epochs
Flicker	99%	99.5%
Harmonics	97%	98%
Interrupt	97%	99%
Voltage sags	97.5%	98.5%
Voltage swell	98.5%	99.5%
Impulse	98%	99%
Surge	98%	99.5%
Notch	97%	99%
Flicker and harmonic	96%	97%
Harmonic and Sags	97%	98.5%
Flicker and sags	95%	97%
TOTAL	97.20%	98.5%

back-propagation multilayered neural network to provide classification of the power quality events.

A general form of the proposed method includes a unit, as shown in Fig. 1, to identify the presence of a disturbance as well as to detect any signal interruption. This part is also used to detect the presence of harmonics in low-frequency disturbances. The recognition system has 11 units and each unit is a four-layer back-propagation neural network to learn the feature vectors. By try and error the number of neurons in the hidden layer has been found in such a way to give the best results. For a particular class of signal, the unit corresponding to that class should ideally exhibit an output of one while the other neurons exhibit an output of zero. The log-sigmoid transfer function was chosen because of its output range (0–1) is perfect for learning to output Boolean values. A processing unit is added to select the unit(s) with the highest excitation as the class of the signal.

Table 1 shows the accuracy of detection and classification of power quality events when network is trained for 1000 and 2000 epochs. These results show that the proposed method is doing very well in detecting and classifying these types of disturbances.

4 Conclusion

In this paper, the S-transform and neural network has been used to monitor power quality disturbances in a power system. The S-transform is used to generate contours and feature vectors for pattern classifications. It is shown that the proposed system provides a complete characterization of both steady state and transient PQ signals by using neural network based decision system. The method is applied on 11 sets of power quality events, which obtained from EMTP computer simulations, and accurate results are obtained.

References:

[1] S.Santoso, W.M.Grady, E.J.Powers, and A.C.Parsons, "Power Quality Disturbance Waveform Recognition Using Wavelet- Based neural Classifier part .I. Theoretical Foundation," IEEE Trans. on Power Delivery, Vol. 15,pp. 222-228, Jan. 2000.

[2] Surya Santoso, Edward J. Powers, W. Mack Grady, Antony C. Parsons, "Power Quality Disturbance Waveform Recognition Using Wavelet-Based Neural Classifier- part2: Application", IEEE Trans. on Power Delivery, Vol. 15, No. 1,pp. 229- 235, January 2000.

[3] Francisco Jurado, Jose R. Saenz, "Comparison between STFT and wavelets for the Analysis of Power Quality Event" Elsevier Science, Electric Power System Research 62, pp. 183-190, 2002.

[4] P.K.Dash, B.K.Panigrahi and G.Panda," Power Quality Analysis Using S-Trans" IEEE Trans. on Power Delivery, vol. 18, no. 2, pp 406-409, April 2003.

[5] I.W.C.Lee, P.K.Dash, "S-Transform-Based Intelligent System for Classification of Power Quality Disturbance" IEEE Transaction on Industrial Electronics, Vol. 50, No. 4, 2003.