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# Power Quality Disturbance Detection and Source Prediction Using Advanced Signal Processing Techniques

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## 1. Introduction

Signal processing techniques have been widely used for analyzing power signals for the purpose of automatic power quality (PQ) disturbance recognition. Among the different signal processing techniques used in extracting features of disturbances from a large number of power signals, the most widely used techniques are the fast Fourier transform (FFT) and the windowed Fourier transform which comprises of the short time Fourier transform (STFT) and the wavelet transform (Moussa et al., 2004). The FFT is ideal for calculating magnitudes of the steady-state sinusoidal signals but it does not have the capability of coping with sharp changes and discontinuities in the signals. Thus, it cannot accurately detect the end of sustained events such as voltage sag, swell, transient and interruption. Although the modified version of the Fourier transform referred to as the STFT can resolve some of the drawbacks of the FFT, it still has some technical problems. In the STFT technique, its resolution is greatly dependent on the width of the window function in which if the window is of finite length, the technique covers only a portion of the signal, thus causing poor frequency resolution. On the other hand, if the length of the window in the STFT is infinite so as to obtain a perfect frequency resolution, then all the time information will be lost. Due to this reason, researchers have switched to wavelet transform from the STFT (Karami et al., 2000).

Some of the well-known wavelet transforms are the continuous wavelet mechanism transform (CWT) and a modification of the CWT which is known as the S-transform. Although CWT based multiresolution analysis monitors the regions of interest closely which is short windows at high frequencies and longer windows at low frequencies, its accuracy is susceptible to noise and if a particular frequency of interest has not been extracted due to octave filter bands, there is a chance of misclassification. To overcome this problem, the S-transform based multiresolution analysis using a variable window (Stockwell, 1996) offers significant advantage with a superior time-frequency localization property and yields amplitude and phase spectrum of the PQ event signals in the presence of noise.

The S-transform is based on a moving and scalable localizing Gaussian window and has characteristics superior to the CWT. It is fully convertible from the time domain to the two-dimensional frequency translation domain and to the familiar Fourier frequency domain.

The amplitude-frequency-time spectrum and the phase-frequency-time spectrum are both useful in defining local spectral characteristics. The superior properties of the S-transform are due to the fact that the modulating sinusoids are fixed with respect to the time axis while the localizing scalable Gaussian window dilates and translates. As a result, the phase spectrum is absolute in the sense that it is always referred to as the origin of the time axis or the fixed reference point (Stockwell et al., 1996). A significant improvement in the detection and localization of PQ disturbances can be obtained from the S-transform (Chilukuri & Dash, 2004).

In this chapter, the background theories of the FFT, CWT and S-transform are first presented. The application of CWT and S-transform for detection of single and multiple PQ disturbances, prediction of incipient faults and prediction of voltage sag sources which may be due to utility or non-utility faults are also described in this chapter.

## 2. Fourier Transform Theory

### 2.1 Fourier Series

Most of the signals in practice are time domain signals in their raw format. That is whatever that signal is measuring, it is a function of time. However, the distinguished information is hidden in the frequency content of the signal. The frequency spectrum of a signal is basically the frequency components or spectral components of that signal. The frequency spectrum of a signal indicates what frequencies exist in the signal. By analyzing a signal in time domain using the Fourier transform, the frequency-amplitude of that signal can be obtained (Langton, 2002).

Distorted waveforms can be decomposed into a fundamental component and a set of harmonics using Fourier analysis which is based on the Fourier series principle. A continuous periodic function,  $x(t)$  has three parts, namely, a dc component, a fundamental sinusoidal and a series of higher order sinusoidal components and can be expressed as,

$$x(t) = a_0 + \sum_{n=1}^{\infty} a_n \cos(w_n t) + \sum_{n=1}^{\infty} b_n \sin(w_n t) \quad (1)$$

where,

$$a_n = \frac{1}{T} \int_{-T/2}^{T/2} x(t) dt \quad (2)$$

$$b_n = \frac{2}{T} \int_{-T/2}^{T/2} x(t) \cos(nwt) dt \quad (3)$$

$w_n$  : frequency component which is given by  $w_n = 2\pi n f$

$n$  : harmonic component

Fourier functions are symmetrical which are odd, even or half way symmetric. When the functions are odd, which means,  $x(t) = -x(-t)$ , then  $a_n$  and  $b_n$  become,

$$a_n = 0 \quad \text{and} \quad b_n = \frac{4}{T} \int_0^{T/2} x(t) \sin(n\omega t) dt \quad (4)$$

In the case of even functions, that is  $x(t) = x(-t)$ ,  $a_n$  and  $b_n$  become,

$$b_n = 0 \quad \text{and} \quad a_n = \frac{4}{T} \int_0^{T/2} x(t) \cos(n\omega t) dt \quad (5)$$

In half wave symmetric function case, in which  $x(t) = -x(t+T/2)$ , then,

$$a_n = 0 \quad \text{and} \quad b_n = \frac{8}{T} \int_0^{T/4} x(t) \sin(n\omega t) dt \quad (6)$$

## 2.2 Fourier Transform

The Fourier transform of a continuous-time signal,  $x(t)$  is given by,

$$F(X) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt \quad (7)$$

and the inverse of the transform is given by,

$$x(t) = \int_{-\infty}^{\infty} F(X) e^{j2\pi ft} dX \quad (8)$$

The Fourier transform consists of two parts, namely the real and imaginary parts, given as,

$$F(X) = \text{re}F(X) + \text{im}F(X) \quad (9)$$

where,

$$\text{re}F(X) = \int_{-\infty}^{\infty} x(t) \cos(2\pi ft) dt \quad (10)$$

$$\text{im}F(X) = - \int_{-\infty}^{\infty} x(t) \sin(2\pi ft) dt \quad (11)$$

The magnitude and phase of the Fourier transform can be expressed as,

$$|F(X)| = \left[ (\text{re}F(X))^2 + (\text{im}F(X))^2 \right]^{\frac{1}{2}} \quad (12)$$

$$\phi(X) = \tan^{-1} \left[ \frac{\text{im}F(X)}{\text{re}F(X)} \right] \quad (13)$$

### 2.3 Sampling

The sampling theory states that under a certain condition it is possible to recover with full accuracy the values intervening between regularly spaced samples. The condition is that the function should be band limited and have a Fourier transform that is nonzero over a finite range of the transform variable and zero elsewhere (Bracewell, 2000). The Fourier transform  $F(X)$  is a summation of discrete signals,  $x(nt)$  and it is given by,

$$F(X) = \sum_{n=-\infty}^{\infty} x(nt)e^{-j2\pi fnt} \quad (14)$$

The frequency domain function becomes,

$$x(t) = \frac{1}{f_s} \int_{-f_s/2}^{f_s/2} F(X)e^{j2\pi fnt} dX \quad (15)$$

where,

$f_s$  : sampling frequency used to obtain the samples of a signal.

According to the Nyquist-Shannon sampling theorem, the sampling rate is twice the highest frequency in a signal. This theorem states that perfect reconstruction of a signal is possible when the sampling frequency is greater than twice the maximum frequency of a signal being sampled or equivalently, that the Nyquist frequency exceeds the highest frequency of a signal being sampled. If lower sampling rates are used, the original signal information may not be completely recoverable from the sampled signal (Shannon, 1998).

### 2.4 Discrete Fourier Transform

Discrete Fourier Transform (DFT) is a special case of the Fourier transform which converts time-domain sequence into an equivalent frequency domain sequence. The inverse DFT performs the reverse operation and converts frequency domain sequence into an equivalent time domain sequence. To find the Fourier transform of sampled and finite length signals, the DFT is used and it is given by,

$$X(f) = \frac{1}{N} \sum_{n=0}^{N-1} x[n]e^{-j2\pi nf/N} \quad (16)$$

where,

$x[n]$  : a sequence obtained by sampling the continuous signal  $x(n)$

The frequency function,  $x[n]$  is then given by,

$$x[n] = \sum_{n=0}^{N-1} X(f) e^{j2\pi f / N} \quad (17)$$

### 2.5 Fast Fourier Transform

The Fast Fourier Transform (FFT) is a mathematical algorithm used to reduce the calculation time as compared to using the DFT. It is a powerful algorithm used in signal processing analysis made in the twentieth century (Walker, 1996). It is an efficient algorithm that is used for converting a time-domain signal into an equivalent frequency-domain signal, based on the DFT with fewer computations required. The FFT reduces the computational complexity from  $N^2$  in DFT to  $N \log N$  multiplications. In other words, the results of FFT are the same as DFT, but the only difference is that the FFT algorithm is optimized to remove the redundant calculations. This means that for a 1024-point, the FFT needs just 10,240 operations as compared to 1,048,576 operations for the DFT. FFT is still one of the most commonly used operations in digital signal processor and all modern signal processing to provide a frequency spectrum analysis (Chassaing, 2005).

The FFT can be obtained from the DFT as follows,

$$X(f) = \frac{1}{N} \sum_{n=0}^{N-1} x[n] e^{-j2\pi n f / N} \quad (18)$$

Cooley and Tukey (1948) came up with a computational breakthrough of FFT which allows the computation of  $N$  point DFT as a function of only  $2N$  instead of  $N^2$ . The FFT can then be written as,

$$FFT(x, f) = \frac{1}{2N} \sum_{n=0}^{2N-1} x[n] e^{-j2\pi n f / 2N} \quad (19)$$

By separating  $x[n]$  into its odd and even parts, the FFT is expressed as,

$$FFT(x, f) = \frac{1}{2N} \sum_{n=0}^{N-1} x[2n] e^{-j2\pi(2n)f / 2N} + \frac{1}{2N} \sum_{n=0}^{N-1} x[2n+1] e^{-j2\pi(2n+1)f / 2N} \quad (20)$$

### 3. Continuous Wavelet Transform

Wavelets are mathematical functions that divide data into different frequency components, and then study each component with a resolution matched to its scale. The fundamental idea behind wavelets is to analyze signal according to scale rather than frequency. The scale is defined as a frequency inverse. Wavelets have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelet techniques can divide a complicated function into several simpler ones and study them separately. This property, along with fast wavelet algorithms which are comparable in efficiency to the FFT algorithms, makes the wavelet techniques very

attractive in analysis and synthesis problems. Different types of wavelets have been used as tools to solve problems in signal analysis, image analysis, medical diagnostics, geophysical signal processing, statistical analysis, pattern recognition, and many others. By using wavelet multiresolution analysis, a signal can be represented by a finite sum of components at different resolutions so that each component can be adaptively processed based on the objectives of the application. This capability of representing signals compactly and in several levels of resolutions is the major strength of the wavelet analysis.

There are essentially two types of wavelet transforms, continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The CWT type is usually preferred for signal analysis, feature extraction and detection tasks whereas the DWT type is more appropriate for performing some kind of data reduction. CWT uses a time-window function that changes with frequency. This adaptive time window function is derived from a prototype function known as the mother wavelet which is scaled and translated to provide information in the frequency and time domains, respectively (Poularikas, 2000). Thus, a transformed signal is a function of two variables, the translation and scale parameters, respectively. The term wavelet means a small wave in which the smallness refers to the condition that this window or function is of finite length. The term mother implies a function with different region of support that is used in the transformation process. In other words, the mother wavelet is a model for generating the window functions.

The CWT of a continuous signal, is expressed in terms of wavelet coefficients, for different values of scaling factor,  $s$  and translation factor,  $d$ , as:

$$CWT_x(s, d) = \int_{-\infty}^{\infty} x(t) \psi_{s,d}^*(t) dt \quad (21)$$

where,

$x(t)$  : signal as a function of time

$\psi_{s,d}(t)$  : mother wavelet which is given as,

$$\psi_{s,d}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-d}{s}\right) \quad (22)$$

Substituting (22) into (21), the CWT can be written as,

$$CWT_x(s, d) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t) \psi^*\left(\frac{t-d}{s}\right) dt \quad (23)$$

As for the scaling factor, large values of this factor provide a broad time-width windowing function located in the low frequency domain. On the other hand, small values of this factor provide a narrow time-width windowing function in the high frequency domain.

The CWT has a filter-bank interpretation in which each wavelet basis function can be thought of as a filter through which the original signal is passed. Each filter, however, has a fixed relative bandwidth as opposed to the fixed absolute bandwidth in the STFT (Poularikas, 2000).

### 3.1 Understanding the Mother Wavelet

All the wavelets are generated from a single basic wavelet  $\psi(t)$ , the so-called mother wavelet, by scaling and translation:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right) \quad (24)$$

where,

$s$  : scale factor

$\tau$ :translation factor

The factor  $s^{-1/2}$  is for energy normalization across the different scales. The term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. In other words, the mother wavelet is a prototype for generating the other window functions.

Each mother wavelet has its own characteristics and will project different types of resolutions. The mother wavelets selected will serve as prototypes for all windows in the process. All the windows that are used are dilated and shifted versions of the mother wavelet functions. The common question commonly asked on WT is, which mother wavelet function generates the best resolution for detection of disturbances. There are different types of mother wavelet, namely, the Morlet, Meyer, Gaussian, Mexican hat, Haar and Daubechies wavelets. The Morlet wavelet is commonly used for signal analysis and therefore it is used for analysis of power disturbances.

### 4. S-transform Theory

The S-transform produces a time-frequency representation of a time series. It uniquely combines a frequency-dependent resolution that simultaneously localizes the real and imaginary spectra. The basis functions for the S-transform are Gaussian modulated cosinusoids, so that it is possible to use intuitive notions of cosinusoidal frequencies in interpreting and exploiting the resulting time-frequency spectrum. With the advantage of fast lossless invariability from time domain to time-frequency domain, and back to the time domain, the usage of the S-transform is very analogous to the Fourier transform. In the case of non-stationary disturbances with noisy data, the S-transform provides patterns that closely resemble the disturbance type and, thus, requires a simple classification procedure. Furthermore, the S-transform can be derived from the CWT by choosing a specific mother wavelet and multiplying a phase correction factor. Thus, the S-transform can be interpreted as phase-corrected CWT (Lee & Dash, 2003). The S-transform generates contours, which are suitable for classification by simple visual inspection unlike wavelet transform that requires specific methods like Standard-Multi resolution analysis (Jaya et al, 2004).

By using a simple rule base or a neural network along with the features extracted from the S-transform contours, one can easily dispense with the visual inspection procedure of the S-transform. The derivation of S-transform from CWT is described as follows:

The CWT of a function is defined as,



$$W(\tau, d) = \int_{-\infty}^{\infty} h(t)w(t-\tau, d) dt \quad (25)$$

where,

$w(t, d)$  : mother wavelet

The S-transform is obtained by multiplying the CWT with a phase factor as expressed below,

$$S(\tau, f) = W(\tau, d) e^{i2\pi f \tau} \quad (26)$$

Substituting (25) into (26), the S-transform can be written as,

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t)w(t-\tau, d) e^{i2\pi f \tau} dt \quad (27)$$

where,

$d$  : scale which can defined as inverse of  $f$ .

The mother wavelet for this particular case is defined as,

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{-i2\pi f t} \quad (28)$$

and can also be written as,

$$w(t, f) = G(\tau, f) e^{-i2\pi f t} \quad (29)$$

where,

$G(\tau, f)$  : modulation function

Considering the mother wavelet in (29), the S-transform written in terms of  $h(t)$  is defined as:

$$S(\tau, f) = \int_{-\infty}^{\infty} h(t)G(\tau-t, f) e^{-i2\pi f t} dt \quad (30)$$

The modulation function  $G(\tau, f)$  is given by,

$$G(\tau, f) = \frac{|f|}{\sqrt{2\pi}} e^{-(t^2 / 2\sigma^2)} \quad (31)$$

where  $\sigma$  is a Gaussian window width which is given by,

$$\sigma(f) = T = \frac{1}{|f|} \quad (32)$$

Substituting (31) and (32) into (30), the final S-transform equation becomes,

$$S(\tau, f) = \frac{|f|}{\sqrt{2\pi}} \int_{-\infty}^{\infty} h(t) e^{-(t-\tau)^2 f^2 / 2} e^{-i2\pi ft} dt \quad (33)$$

where,  
*f*: frequency  
*t* and  $\tau$  : time

The S-transform distinguishes itself from the many time-frequency representations available by uniquely combining progressive resolution with absolutely referenced phase information. It is known that progressive resolution gives a fundamentally sounder time-frequency representation (Daubechies, 1990). Referenced phase means that the phase information given by the S-transform is always referenced to time  $t = 0$ , which is also true for the phase given by the Fourier transform. This is true for each S-transform sample of the time-frequency space. This is in contrast to the CWT approach, where the phase of the wavelet transform is relative to the center in time of the analyzing wavelet. Thus, as the wavelet translates, the reference point of the phase translates. This is called “locally referenced phase” to distinguish it from the phase properties of the S-transform. From one point of view, local spectral analysis is a generalization of the global Fourier spectrum. However, the fundamental principle of S-transform analysis is that the time average of the local spectral representation should result identically in the complex-valued global Fourier spectrum (Stockwell, 2006). This leads to phase values of the local spectrum that are obvious and significant.

The S-transform has unique properties in which it uniquely combines frequency dependent resolution with absolutely reference phase, so that the time average of the S-transform equals the Fourier spectrum. It simultaneously estimates the local amplitude spectrum and the local phase spectrum, whereas the CWT approach is only capable of probing the local amplitude and power spectrum. It independently probes the positive frequency spectrum and the negative frequency spectrum, whereas many wavelet approaches are incapable of being applied to a complex time series. It is sampled at the discrete Fourier transform frequencies unlike the CWT where sampling is done randomly (Stockwell, 2006).

## 5. Application of Continuous Wavelet Transform for Power Quality Disturbance Detection

The CWT program was written using the four mother wavelet functions as shown in Figures 1 to 4. Voltage sag signals were obtained from the utility PQ monitoring for the purpose of analysing the signals using the CWT with the four mother wavelets (Faisal, 2009).

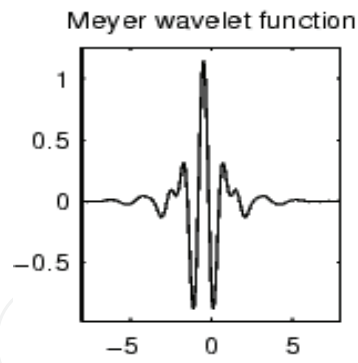


Fig. 1. Meyer Wavelet Function

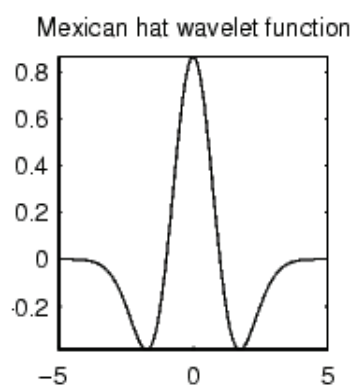


Fig. 2. Mexican Hat Wavelet Function

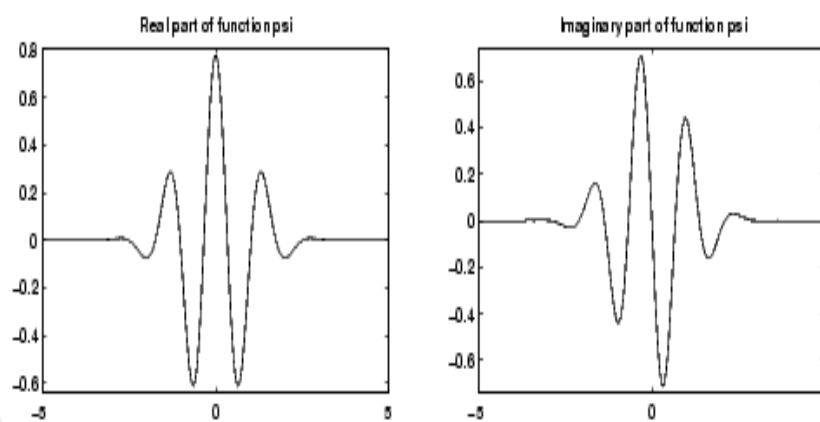


Fig. 3. Gauss Wavelet Function

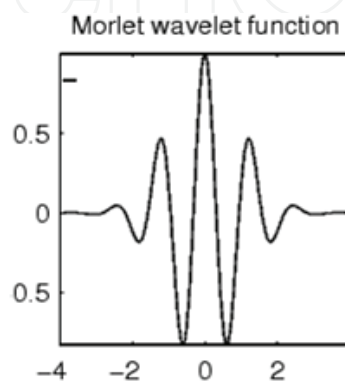


Fig. 4. Morlet Wavelet Function

### 5.1 CWT Analysis with the Meyer Wavelet Function

Visually, using the Meyer wavelet function (Figure 1) in the CWT analysis, voltage sags can be easily detected as shown in Figure 5. The Meyer wavelet gives high values of CWT coefficients, around 4 to 5. These high value coefficients will enable a clear distinction to be observed in the detection of voltage sags. It can also be used in the extraction of the CWT features for the classification of disturbances. In the feature extraction process, the standard deviation and the mean of the amplitude would be calculated and later used in the classification of the power quality disturbances. The scale axis which is actually the frequency inverse correctly identifies the existence of the system frequency of 50 Hz which is located at a high scale of 20.

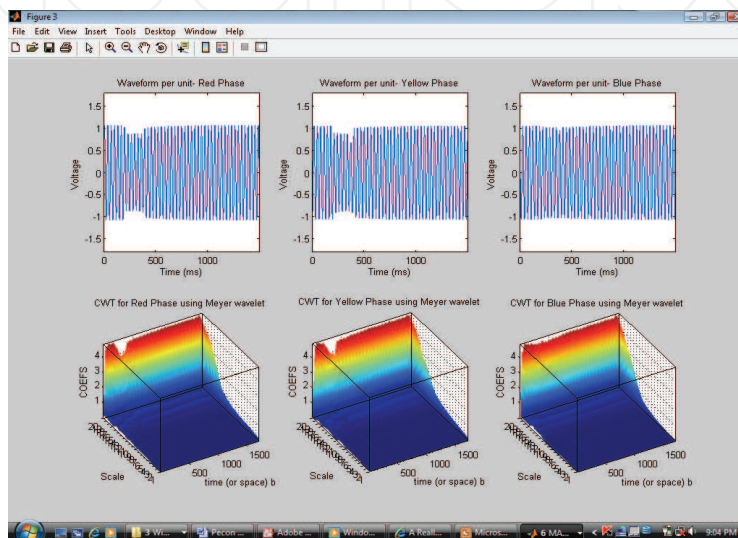


Fig. 5. Analysis of voltage sag using the Meyer wavelet

### 5.2 CWT Analysis with the Mexican Hat Wavelet Function

The results of CWT analyses using the Mexican Hat wavelet show that the CWT coefficients are with values around 4 as shown in Figure 6. From visual inspection, the signature that depicts a voltage sag event are not obvious by using the Mexican hat wavelet function as compared to using the Meyer wavelet.

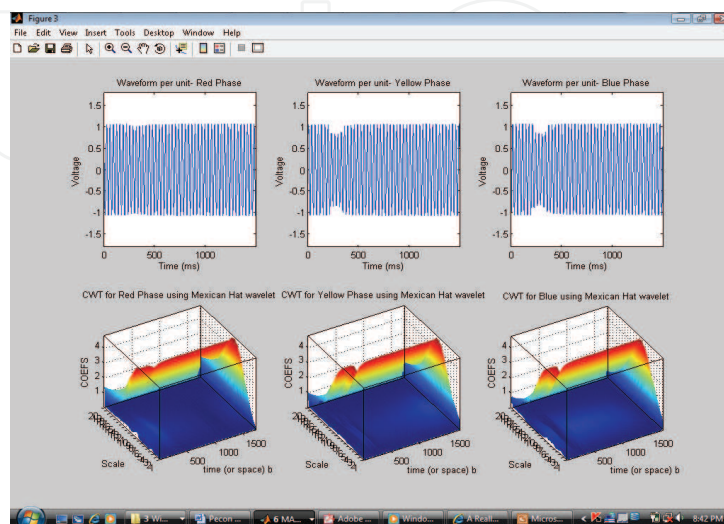


Fig. 6. Analysis of voltage sag using the Mexican Hat Wavelet

### 5.3 CWT Analysis with Gauss Wavelet Function

The results of CWT analyses using the Gauss wavelet function are as shown in Figure 7. Similar to the Meyer wavelet function, the Gauss wavelet enables one to detect the signature of voltage sag easily. The Gauss wavelet gives the highest values of CWT coefficients, that is, around 6. These high value coefficients will enable a very clear distinction to be observed in the detection of voltage sags.

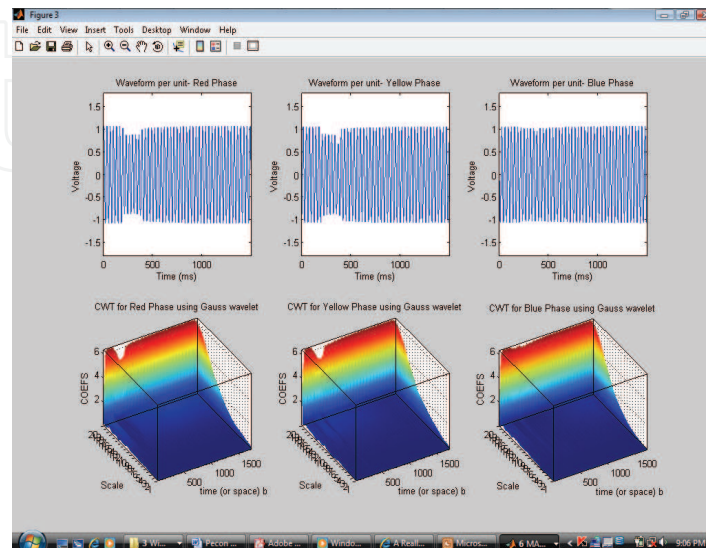


Fig. 7. Analysis of voltage sag using the Gauss Wavelet

### 5.4 CWT Analysis with Morlet Wavelet Function

Similar to the Meyer and Gauss wavelet functions, the Morlet wavelet enables one to visualize the signature of voltage sag easily. The Morlet wavelet gives lowest values of the CWT coefficients, that is, around 3. However, the low coefficient values will not give a very clear distinction in the extraction of the features for the purpose of disturbance classification. The contours of the CWT are also not very smooth and therefore such information may be misleading because the signature of rugged surface highlights the existence of harmonics. In this study, no harmonics exist in the signal.

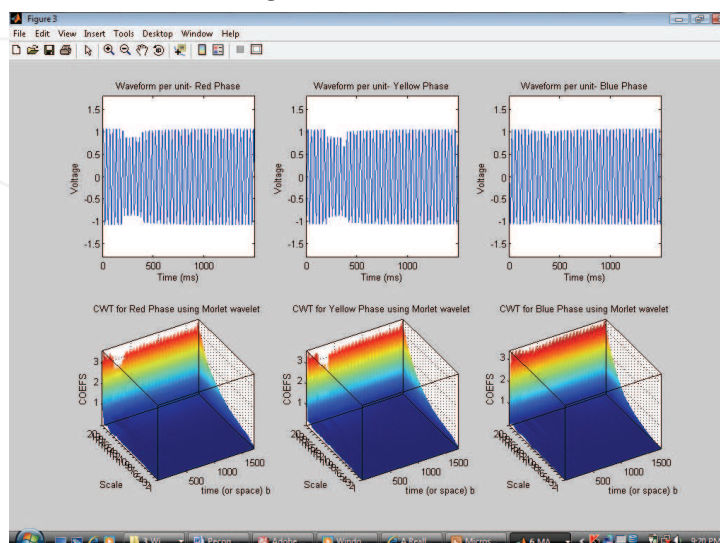


Fig. 8. Analysis of voltage sag using the Morlet Wavelet

From the analyses done on the twenty voltage sag data, it is confirmed that the best result in the detection of voltage sag will depend on the selection of the mother wavelet. The selection of a wavelet that closely matches the signal is important in the detection of the waveform. From the findings, it is noted the Gauss wavelet function gives the most accurate detection of voltage sag. The resolution of the contour is very clear and the high coefficient amplitudes are useful for the extraction of voltage sag features to be used in the power quality disturbance classification.

## 6. Using the S-transform for Detection of Voltage Disturbances and Incipient Faults in Power Distribution Networks

To illustrate the use of the S-transform for voltage disturbance and incipient fault detection, a case study at an industrial plant in Malaysia is presented (Faisal et al, 2009). The plant had complained of frequent occurrences of nuisance tripping and damages to its production equipment for the last one year and put the blame on the power utility. To understand the problem, the power utility installed a power quality recorder in the plant for three months and the recorded data were then analyzed by this new technique. From the analysis of results, 3 voltage sags (Figure 9), 3 notches (Figure 10) and 12 unknown events (Figure 11) were detected. In Figure 9, the S-transform contour shows the existence of voltage sags in three phases while in Figure 10, minor notches in the S-transform contour are detected. The causes of the voltage sags were due to lightning strokes on the utility power lines. The cause of the notches (Figure 10) was found out after implementing a thermal scan at the main switch board conductors in which the cause was due to lose connection at the blue phase conductor. The results in Figure 11, showed frequent occurrences of incipient faults at the red phase of a factory power supply. Overall, 12 events were recorded at the red phase. Locating faults based solely on substation measurements has always been time consuming and difficult, and locating subtle incipient faults is even more challenging because of the low magnitude signals often involved. The signature of the change in the feeder current due to incipient fault is very delicate and difficult to detect. However, based on analysis performed in this study, the S-transform is able to perform efficient detection and isolation for both incipient and abrupt faults in power supply systems. Thus, the existence of the incipient fault is only detectable by using the S-transform.

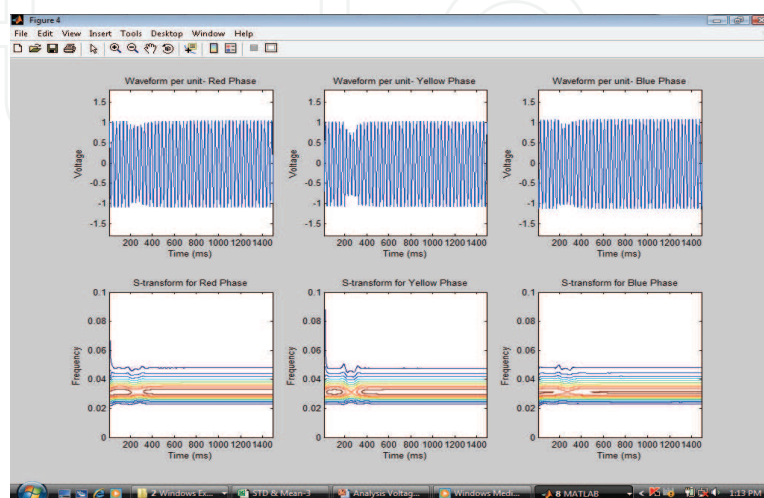


Fig. 9. Detection of multiple voltage sags using S-transform

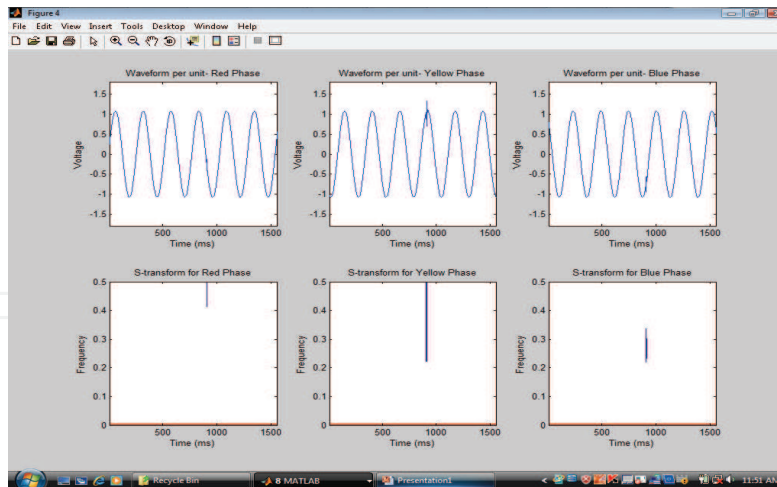


Fig. 10. Detection of notches using S-transform

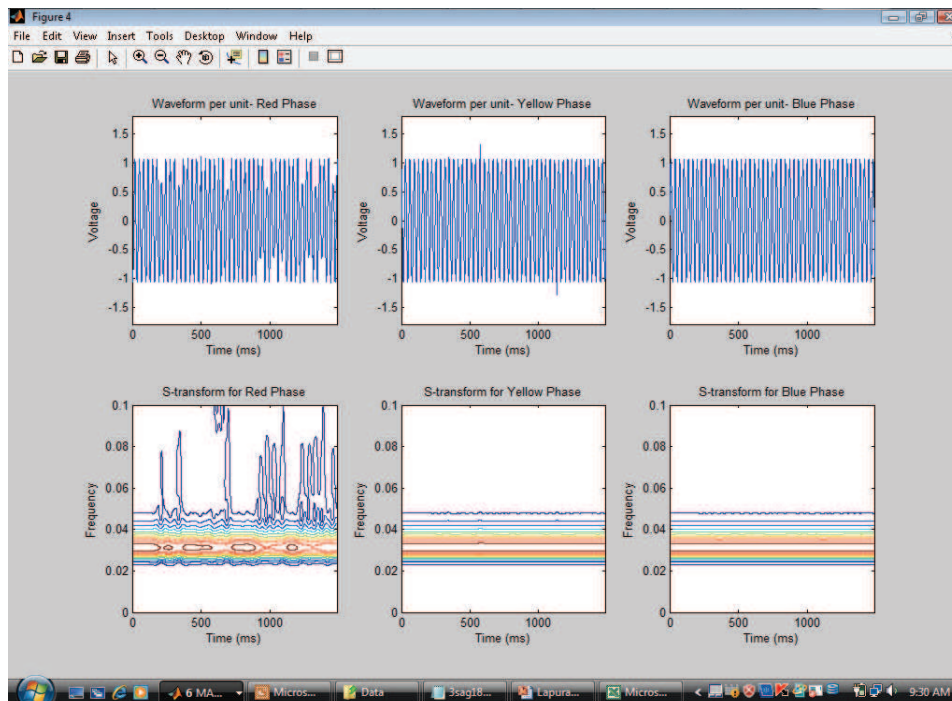


Fig. 11. Detection of incipient fault at the red phase using S-transform

## 7. Using the S-transform for Voltage Sag Source Prediction

The identification of sources of disturbances is very critical in power quality diagnosis so as to provide the necessary information to customers for resuming back their operations. A disturbance source can originate from either inside a facility or outside in a distribution network. One method of predicting the source of voltage sag at a monitoring point is by determining whether the source is from either upstream or downstream. The concept of automatic sag source prediction is shown in Figure 12. A power quality recorder (PQR) is installed at point M in a power supply network. If voltage sag occurs in the network, the PQR will detect and record the disturbance depending upon its voltage threshold setting which is based on the definition of voltage sags. The source of sag can appear either

upstream or downstream with respect to point M. Upstream side can be defined as the side that supplies the fundamental power into the monitoring point at steady state conditions whereas the downstream side is defined as the side that leaves the fundamental power from the monitoring point.

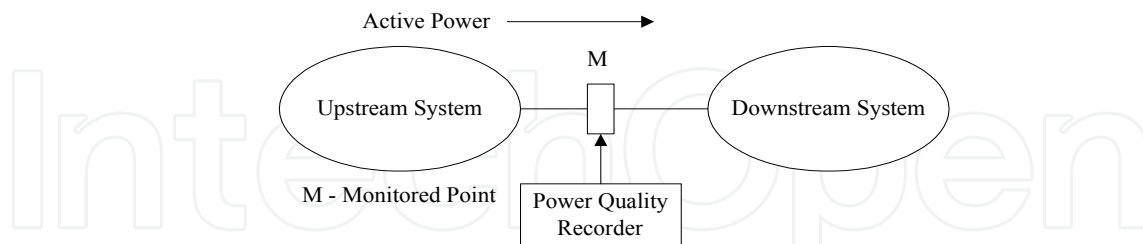


Fig. 12. Concept of upstream and downstream voltage sags

Several methods have been developed for performing sag source prediction (Polajžer, 2007). The obtained results showed that all the existing methods do not work well, particularly in cases of asymmetrical voltage sags due to upstream events and therefore further development is still needed to increase the degree of sensitivity and confidence in the existing techniques for performing automatic sag source prediction. Here, a novel method based on the S-transform is proposed for improving the sensitivity of the sag source prediction (Faisal & Mohamed, 2009). The S-transform is used for producing the time-frequency representation for the voltage and current waveforms. The time-averaged amplitudes and spectral contents for all these signals are extracted from the time-frequency values which are then used to determine the origin of voltage sags.

In the proposed voltage sag source prediction method, the features that characterize both the voltage and current waveforms are extracted from the time and frequency resolutions of the S-transform. 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. The S-transform will generate time frequency contours, which clearly display the disturbance patterns for ease of visual inspections. It will also generate the relevant contours for both voltage and current waveforms. From these contours, the values of the disturbance voltages, currents and powers are derived.

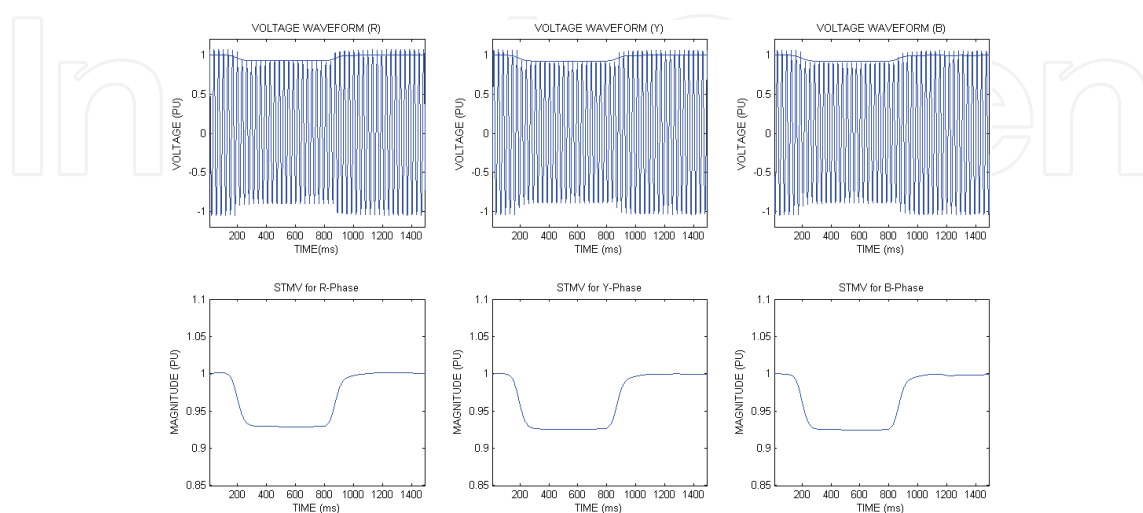


Fig. 13. Plots of the S-matrix locus for voltage values



In this study, the first set of features is based on the maximum values for all the columns in the S-transform contours for voltages. Examples on the graphical representations of the maximum value plots for voltages are shown in Figure 13. The first rows showed the original waveforms for the voltage values. The plots in the second rows are the loci of the maximum values for voltage from the S-transform. Features can be extracted from these maximum value plots to characterize voltage sags and swells.

The second sets of features are selected based on the maximum values for all the columns in the S-transform for currents and disturbance powers. The values are termed as S-transform maximum current (STMI) and S-transform disturbance power (STDP). Examples on the maximum value plots for currents and powers are shown in Figures 14 and 15. In Figure 14, the first rows showed the original waveforms for the current values. The plots in the second rows are the loci of the maximum values for currents from the S-transform. In Figure 15, the plots show the loci of the S-transform disturbance powers for each phase during the voltage disturbances. The disturbance powers are derived from the voltage and current contours of the S-transform. Features can also be extracted from the current and disturbance power plots to identify the origin of the disturbances.

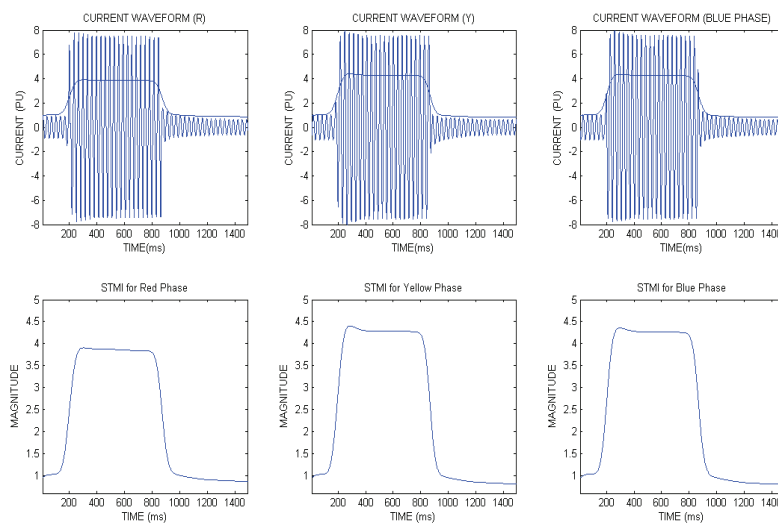


Fig. 14. Plots of the S-matrix locus for current values

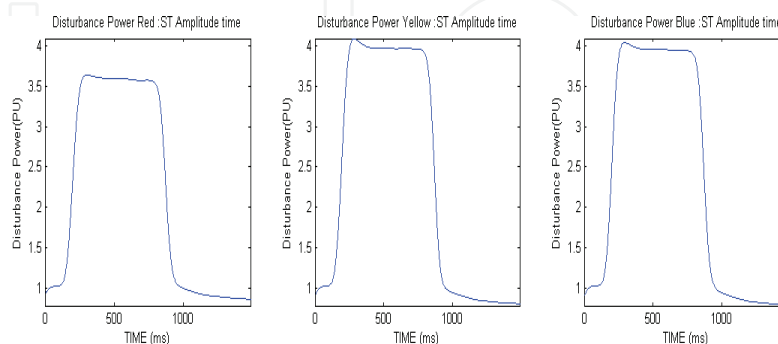


Fig. 15. Plots of the S-matrix locus for disturbance powers (downstream sag source)

When faults occur either at the transmission system or distribution system, they typically draw energy from the power system. Energy is just the value of the power flow multiply with the specified duration. In Figures 14 and 15, the plots of both the current and

disturbance power showed increase of the maximum values for both current and disturbance power during the disturbance. The increase of the maximum value plots for disturbance power during the disturbance will show that the origin of the disturbance is downstream.

If voltage sag originates from upstream, the change in the current and power profile will show either reduction or minor increase. Example on plots for voltages, currents and disturbance powers due to upstream sag sources are shown in Figures 16, 17 and 18.

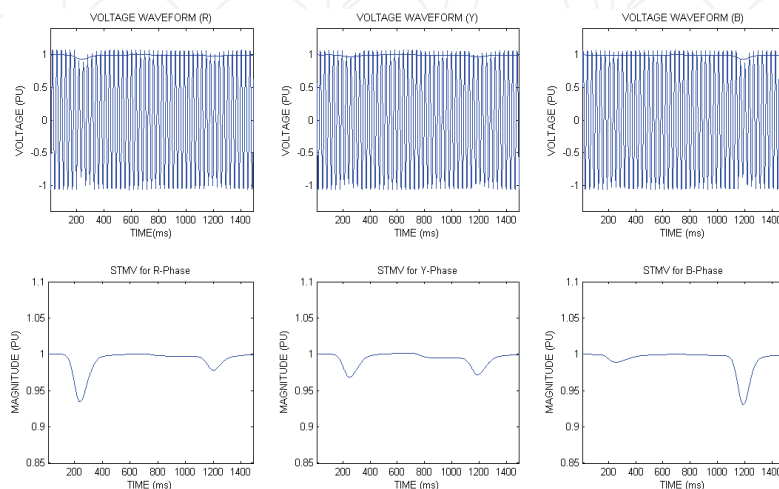


Fig. 16. S-matrix locus for voltages (upstream sag source)

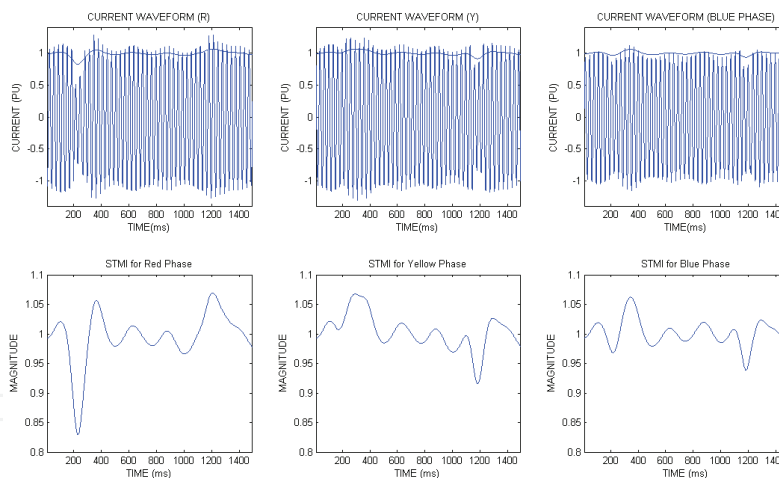


Fig. 17. S-matrix locus for currents (upstream sag source)

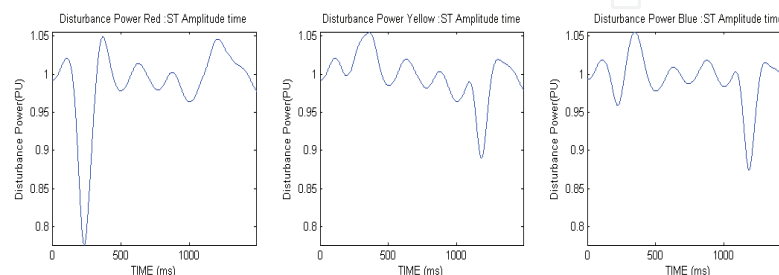


Fig. 18. Plots of the S-matrix locus for disturbance powers (upstream sag source)

The S-transform disturbance power plots are used to indicate the origin of the disturbances from the monitoring point. If during a disturbance, the power flow shows increase in power, then the source of the disturbance is downstream whereas if the power flow indicates decrease in power, then the source of the disturbance is upstream from the monitoring point.

## 8. Conclusion

The application and performance of CWT and S-transform for detection of multiple PQ disturbances and incipient faults and prediction of voltage sag sources which may originate from upstream or downstream have been presented. From the analyses done to evaluate the effectiveness of using CWT with the various mother wavelet functions in the detection of voltage sags, it is confirmed that the Gauss wavelet function gives the most accurate detection of voltage sag. A novel approach for detecting multiple power quality disturbances and incipient faults using the S-transform techniques has also been presented. The S-transform is proven to be very effective in analyzing and detecting multiple voltage disturbances and incipient faults in underground cable system. The S-transform accurately detects minor voltage and current transients generated from defects in underground cables. The usefulness of the S-transform is further illustrated by applying it for predicting the source of voltage sags. The numerical results obtained with actual power quality data recorded in a power distribution system indicated that the S-transform is effective in locating the sources of voltage sags which originate from either upstream or downstream. The results proved that the S-transform technique has the potential for use in the existing Power Quality Monitoring System for performing diagnosis of real-time power quality measurement data.

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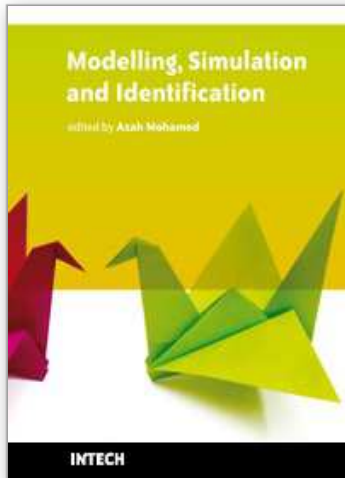
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Modeling, simulation and identification has been actively researched in solving practical engineering problems. This book presents the wide applications of modeling, simulation and identification in the fields of electrical engineering, mechanical engineering, civil engineering, computer science and information technology. The book consists of 17 chapters arranged in an order reflecting multidimensionality of applications related to power system, wireless communication, image and video processing, control systems, robotics, soil mechanics, road engineering, mechanical structures and workforce capacity planning. New techniques in signal processing, adaptive control, non-linear system identification, multi-agent simulation, eigenvalue analysis, risk assessment, modeling of dynamic systems, finite difference time domain modeling and visual feedback are also presented. We hope that readers will find the book useful and inspiring by examining the recent developments in the applications of modeling, simulation and identification.

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