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Analysis of Power Quality Disturbances using Wavelet Transform

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***Abstract*—Power quality is under the influence of the variety of small or large disturbances during operating conditions. Any type of disturbance has almost a specific pattern. Any pattern which can be classified possesses a number of distinguishing features. Thus, the first step in any classification process is to consider the problem of what discriminatory features to select and how to extract these features from the patterns. It is quite clear that the number of features needed for prosperous classification depends on the distinguishing quality of the chosen characteristic. Over the recent decades, several different techniques have been adopted for the choice of features in power quality pattern recognition. The power quality disturbances like voltage sag, swell, notch, spike, transients etc can be analyzed using various transform techniques such as Fourier transform, Chriplet transform, S-transform and Wavelet transform. Wavelet transform has received greater attention in power quality as this is well suited for analyzing certain types of transient waveforms. In this seminar, Energy Difference Multi-Resolution Analysis technique (EDMRA) is used to decompose the power quality disturbances.**

This Paper discusses an appropriate type of features be identified then suitable features be extracted. For this purposes, for extracting of discriminative features of power quality by using MRA, at first an appropriate wavelet must be identified respect to each of the input sampled window. To improve the time resolution of faulty waveforms, the waveform must be broken into a set of sub-waveforms by using of MRA. Then classification of PQ disturbances is performed using pattern recognition.

I. INTRODUCTION

The power quality (PQ) problems can originate the consequences of the increasing use of solid state switching devices, nonlinear and power electronically switched loads, unbalanced power systems, lighting controls, computer and data processing equipment as well as industrial plant rectifiers and inverters. On the other hand, a number of causes of transients such as lightning strokes planned switching actions in the distribution or transmission system, self-clearing faults or faults cleared by current-limiting fuses can reveal the PQ problems on the power system. A PQ problem usually involves a disturbance in the voltage or current, such as voltage dips and fluctuations, momentary interruptions, harmonics and oscillatory transients causing failure or mal-operation of the electrical equipments. These failures might trip any protection device initiating a short interruption to the supplied power. Excess current produced by transients may lead to complete damage to system equipment during the transient period. Moreover, if such disturbances are not mitigated, they can lead to failures or malfunctions of various sensitive loads in power systems and may be

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very costly. After detecting the disturbance, it is required to identify the source of disturbance. Power quality problems involve voltage sag, voltage swells, notch, spike, switching transient, impulses, flicker and harmonics etc. In order to improve power quality the detection and classification of power quality disturbances must be fulfilled The classification of a PQ problem is an important issue for operating and protection of the power system because a large class of events is due to the normal operation of power systems, and these events should not cause nuisance tripping of protection equipment in the network. Therefore, there is a growing need to develop PQ monitoring techniques that can classify the potential sources of disturbances. The literature is rich in terms of proposals for the classification of PQ problems.

A. Survey

In this paper, the feature extraction methods of power quality disturbance can be roughly divided into two parts as detection and classification. The detection methods of power quality disturbances such as Fourier transforms, wavelet transforms, S-transforms etc. are given in [1][2][3][4][5][6]. Various literatures concluded that the wavelet transform is suitable for detection of power quality disturbances as it keeps the advantages of both time and frequency domain. In second part, the detected disturbances are classified in a number of typical classes such as voltage sags, voltage swells, and interruptions, etc. which called event classification with causes of disturbances such as faults, capacitor switching, and transformer energizing are classified. The classical major steps for classification of both PQ events and PQ disturbances are feature extraction and classification that constitute a pattern recognition process using multi resolution analysis (MRA) as given in [7][8][9][10][11][12][13][14]. Feature extraction is generally called upon when there is a need to extract specific information from the raw data, which typically in power systems are the voltage and current waveforms. In the classification step, feature vectors that are obtained from the transformation process is applied the classifier algorithm. The classifier algorithm based on artificial neural network and fuzzy logic is discussed in [15][16][17][18][19][20]. Support vector machines based classification of PQ disturbances is given in [21][22][23]. Expert system using Clark approach is advised in [24]. In [25][26] suggested the genetic algorithm approach. All these classifiers uses the basic of MRA and Energy difference MRA (EDMRA) as given in [27][15].

II. Power Quality Disturbances

A. Introduction

Power Quality studies have become an important subject due to wide spread use of sensitive electronic equipments. Moreover the deregulated power sector has enhanced the competition amongst various power producers leading to a need to improve the quality of electric supply. The increased use of nonlinear loads such as power electronics based devices, adjustable speed drives (ASD), personal computers (PCs), un-interruptible power supplies (UPS) and electric arc furnaces (EAFs) in the electric power system over the last decades; create distorted (non-sinusoidal) currents even when supplied with purely sinusoidal voltage. These distorted currents cause voltage and current distortion throughout the system which deteriorates the quality of the electric power that is supplied to consumers owing sensitive devices to voltage and/or current variations. The cause of degradation of power quality must be investigated to improve the quality. The wide uses of accurate electronics devices require extremely high quality supply. Even developed economics of the world are losing billions of dollars to power quality problem. Hence the research of power quality issues is increasing exponentially in the power engineering community in the past decade. In this section, definitions of power quality as per IEEE standard and IEC standard is given in first section. Next section discusses classification of PQ disturbances followed by different approaches to detect it.

B. Power Quality: Definitions

IEEE Standard 519-1992[28] defines power quality as “the concept of powering and grounding sensitive equipment in a manner that is suitable for the operation of that equipment.” Power quality is defined in the IEEE-100 Authoritative Dictionary of IEEE Standard [29] Terms as: “The concept of powering and grounding electronic equipment in a manner that is suitable to the operation of that equipment and compatible with the premise wiring system and other connected equipment.” The IEC-61000 International Electro technical Commission defines Electromagnetic Compatibility [30] as “the ability of an equipment or system to function satisfactorily in its electromagnetic environment without introducing intolerable electromagnetic disturbances to anything in that environment” The term power quality (PQ) is a combination of voltage quality and current quality used to quantify the voltage and/or current deviations from the ideal waveforms. Ideal waveforms are characterized by sinusoidal wave shape with fixed frequency and fixed amplitude that equal the rated or nominal values. Power quality, loosely defined, is the study of powering and grounding electronic systems so as to maintain the integrity of the power supplied to the system. As per **customer** power quality problem is any power problem manifested in voltage, current or frequency deviations those results in failure or mis-operation of customer equipment [**?**]. A **utility** may define power quality as reliability and show statistics demonstrating that its system is 99.98 percent reliable [**?**]. A **manufacturer** of load equipment may define power quality as those characteristics of the power supply that enable the equipment to work properly.

C. Classification of Power Quality Issues

There are different classifications for power quality issues, each using a specific property to categorize the problem. Some of them classify the events as"steady-state" and "non-steady-state" phenomena. In some regulations (e.g., ANSI C84.1) the most important factor is the duration of the event. Other guidelines (e.g., IEEE-519)
use the wave shape (duration and magnitude) of each event to classify power quality problems. Other standards (e.g., IEC) use the frequency range of the event for the classification. For example, IEC 61000-2-5 uses the frequency range and divides the problems into three main categories: low frequency (<9 kHz), high frequency (>9
kHz), and electrostatic discharge phenomena. In addition, each frequency range is divided into "radiated" and" conducted" disturbances. The magnitude and duration of events can be used to classify power quality events. In the magnitude-duration plot, there are nine different parts. Various standards give different names to events in these parts. The voltage magnitude is split into three regions:

- Interruption: voltage magnitude is zero
- Undervoltage: voltage magnitude is below its nominal value
- Overvoltage: voltage magnitude is above its nominal value

The duration of these events is split into four regions: very short, short, long, and very long. The borders in this plot are somewhat arbitrary and the user can set them according to the standard that is used. IEEE standards use several additional terms (as compared with IEC terminology) to classify power quality events. The classification of power quality disturbances according to IEEE is given in Table 2.1[31].
The ideal voltage curve in a three-phase electrical power network can be defined as follows: sinusoidal waveform, constant frequency according to the grid frequency, equal amplitudes in each phase according to the voltage level, defined phase-sequence with an angle of 1200 between them. Every phenomenon, affecting those parameters, will be seen as decrease in voltage quality.

D. Approaches for Detection of Different Power Quality Disturbances

Waveform evaluation consists of both spectrum and transient analysis. There are a few algorithms of voltage and current waveform analysis. The evaluation of the algorithm efficiency involves the estimation of its accuracy combined with the required computational power. Unfortunately, the latter has an important meaning in case of real-time metering. However, implementing new algorithms is not always necessary. Sometimes it is enough to apply broadly known tools in a new way to achieve better results. In order to find out the sources and causes of harmonic distortion, one can detect and localize those disturbances for further classification. To analyze these electric power system disturbances, data is often available as a form of a sampled time function that is represented by a time series of amplitudes. Fourier analysis is a family of mathematical techniques, all based on decomposing signals into sinusoids. Fourier transform can be applied to both continuous signal and discrete signal. It can be either periodic or aperiodic. The combination of these two features generates the four categories [2].
Aperiodic-Continuous: This includes, for example, decaying exponentials and the Gaussian curve. These signals extend to both positive and negative infinity without repeating in a periodic pattern. The Fourier Transform for this type of signal is simply called the Fourier Transform.
Periodic-Continuous Here examples include: sine waves, square waves, and any waveform that repeats itself in a regular pattern from negative to positive infinity. This version of the Fourier transform is called the Fourier series.
Aperiodic-Discrete These signals are only defined at discrete points between positive and negative infinity, and do not repeat themselves in a periodic fashion. This type of Fourier transform is called the Discrete Time Fourier Transform.

TABLE I: CLASSIFICATION OF POWER QUALITY DISTURBANCES ACCORDING TO IEEE

Categories	Typical Spectral Content	Typical Duration Voltage	Typical Voltage Magnitude
1. Transient			
1.1 Impulsive	5 *ns* rise	50 *ns*	
Nanoseecond	1 *µs* rise	50 *ns* - 1 *ms*	
Microsecond	0.1 ms rise	< 1 *ms*	
Millisecond			
1.2 Oscillatory			
Low Frequency	< 5 kHz	0.3 - 50 *ms*	0 - 4 Pu
Medium Frequency	5-500 kHz	20 *µs*	0 - 8 Pu
High Frequency	< 5 kHz	5 *µs*	0 - 4 Pu
2. Short Duration Transient			
2.1 Instataneous			
Interruption		0.5-30 cycle	< 0.1 Pu
Sag		0.5-30 cycle	0.1 - 0.9 Pu
Swell		0.5-30 cycle	1.1 - 1.8Pu
2.2 Momentory			
Interruption		0.5 cycles-3 s	< 0.1 Pu
Sag		30 cycles-3 s	0.1 - 0.9 Pu
Swell		30 cycles-3 s	1.1 - 1.4Pu
2.3 Temporary			
Interruption		3 sec-1 min	< 0.1 Pu
Sag		3 sec-1 min	0.1 - 0.9 Pu
Swell		3 sec-1 min	1.1 - 1.2 Pu
3. Long Duration Transient			
3.1 Sustained Interup.		> 1 min	0.0 Pu
3.2 Undervoltage		> 1 min	0.4 - 0.9 Pu
3.3 Overvoltage		> 1 min	1.1 - 1.2 Pu
4. Voltage Imbalance		Steady state	0.5-2%
5. Waveform Distribution			
5.1 DC Offset		Steady state	0 - 0.1%
5.2 Harmonics	0-1000	Steady state	0 - 20%
5.3 Interharmonics	0-6 kHz	Steady state	0 - 2%
5.4 Notching		Steady state	
5.5 Noise	Broadband	Steady state	0 - 1%
6. Voltage Fluctuation	< 25 Hz	Intermidient	1 - 2%
7. Power Frequency Osci.	< 10 sec		

Periodic-Discrete These are discrete signals that repeat themselves in a periodic fashion from negative to positive infinity. This class of Fourier Transform is sometimes called the Discrete Fourier Series, but is most often called the Discrete Fourier Transform. Mostly frequency related transform are fashion while analyzing signals. Several software procedures have been developed for this purpose as listed below:

Discrete Fourier Transform (Dft)

The Discrete Fourier Transform is the widely used DSP algorithm. The N-point DFT of $x(k)$ of a sequence $x(n)$ of length N is given by

$$X(k) = \sum_{n=0}^{n=N-1} x(n)e^{\frac{j2\Pi kn}{N}} \quad (2.1)$$

where k=0,1,2,....N-1

An approach to compute the DFT is to use a recursive computation scheme. The most popular approach is the Goertzels Algorithm. Goertzel algorithm is used to implement the Non-Uniform Discrete Fourier Transform. Particularly for evaluating filter response like IIR, FIR filters. The spectrum at the exact frequencies of interested can be estimated. This is because the Goertzel algorithm is suitable for the implementation of a non-uniform discrete Fourier transform (NDFT)[2][1].

Fast Fourier Transform (FFT)

In view of the importance of the DFT in various digital signal processing applications, such as linear filtering, correlation analysis, and spectrum analysis, its efficient computation is a topic that has received considerable attention by many mathematicians, engineers, and applied scientists. An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the only difference is that an FFT is much faster. The radix is the size of an FFT decomposition.Radix-2, radix-4, radix-8, spilt radix are the types of radix. The FFT algorithms are found to be more accurate than evaluating the DFT definition direct computation when round-off error is present. Decimation in frequency (DIF) or decimation in time (DIT) algorithms can be used to analyze signal [2][1].

In most cases the power quality disturbances are non stationary and non periodic. For power quality analysis is useful to achieve time localization of the disturbances (determining the start and end times of the event) which can not be done by Fourier transform. The limitation is obvious especially for transient phenomena's (quick variations), difficult to observe visually. The frequency spectrum provides informations about frequency spectral components but no information about time localization [2][1].

Short Time Fourier Transform (Stft)

The short-time Fourier transform (STFT), is a Fourier-related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. STFT extracts several frames of the signal to be analyzed with a window that moves with time. If the time window is sufficiently narrow, each frame extracted can be viewed as stationary so that Fourier transform can be used. With the window moving along the time axis, the relation between the variance of frequency and time can be identified. This STFT can be classified into continuous-time STFT, discrete-time STFT [2][1].

Continuous-time STFT: The continuous-time case, the function to be transformed is multiplied by a window function which is nonzero for only a shorter period of time. The Fourier transform (a one-dimensional function) of the resulting signal is taken as the window to slide along the time axis, resulting in a two-dimensional representation of the signal. Short time Fourier transforms can be mathematically, represented as,

$$X(\tau,\omega)=\int_{-\infty}^{\infty}x(t)\omega(t-\tau)e^{-j\omega t}dt \qquad (2.2)$$

Where $\omega(t)$ is the window function, commonly a Hann window or Gaussian "hill" centered around zero, and $x(t)$ is the signal to be transformed. $X(\tau, \omega)$ is essentially the Fourier Transform of $x(t)w(t - \tau)$, a complex function representing the phase and magnitude of the signal over time and frequency.

Discrete-time STFT: In the discrete time case, the data to be transformed could be broken into chunks or frames (which usually overlap each other, to reduce artifacts at the boundary). Each chunk is Fourier transformed, and the complex result is added to a matrix, which records magnitude and phase for each point in time and frequency. This can be expressed as:

$$X(m,\omega)=\sum_{n-\infty}^{\infty}x(n)\omega(n-m)e^{-j\omega n} \qquad (2.3)$$

In this case, m is discrete and ω is continuous, but in most typical applications the STFT is performed on a computer using the Fast Fourier Transform, so both variables are discrete and quantized. Again, the discrete-time index m is normally considered to be"slow" time and usually not expressed in as high resolution as time n. Power quality disturbances cover a broad frequency spectrum, starting from a few Hz (flicker) to a few MHz (transient phenomenon). The frequency spectrum of a signal affected by a transient voltage contains high frequency components and also low frequency components. It is difficult to analyze such a signal using the STFT because the window size and implicit time-frequency resolution are fixed.

Wavelet Transform (Wt)

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a"brief oscillation" like one might see recorded by a seismograph or heart monitor. Wavelets can be combined, using a"shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal [2][1][7]. A wavelet transform is the representation of a function by wavelets. The wavelets are scaled and translated copies (known as"daughter wavelets") of a finite-length or fast-decaying oscillating waveform (known as the"mother wavelet"). Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals. Wavelet transform is a transform which is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. Wavelet transforms are classified into discrete wavelet transforms (DWTs) and continuous wavelet transforms (CWTs). Both DWT and CWT are continuous-time (analog) transforms. They can be used to represent continuous-time (analog) signals. CWTs operate over every possible scale and translation whereas DWTs use a specific subset of scale and translation values or representation grid.

Continuous Wavelet Transform: Where $x(t)$ is the signal to be analyzed, $\psi(t)$ is the mother wavelet or the basis function. All the wavelet functions used in the transformation are derived from the mother wavelet through translation (shifting) and scaling (dilation or compression).

$$XWT(\tau, s) = \frac{1}{\sqrt{|s|}} - \infty \int^{\infty} x(t)\psi\left(\frac{t-\tau}{s}\right)dt \qquad (2.4)$$

The mother wavelet used to generate all the basis functions is designed based on some desired characteristics associated with that function. The translation parameter τ relates to the location of the wavelet function as it is shifted through the signal. Thus, it corresponds to the time information in the Wavelet Transform. The scale parameter s is defined as 1/*frequency* and corresponds to frequency information. Scaling either dilates (expands) or compresses a signal. Large scales (low frequencies) dilate the signal and provide detailed information hidden in the signal, while small scales (high frequencies) compress the signal and provide global information about the signal. Notice that the Wavelet Transform merely performs the convolution operation of the signal and the basis function. The above analysis becomes very useful as in most practical applications, high frequencies (low scales) do not last for a long duration, but instead, appear as short bursts, while low frequencies (high scales) usually last for entire duration of the signal.

Discrete Wavelet Transform: The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT). The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonalto its discrete translations implies some mathematical conditions on them which are mentioned everywhere e. g. the dilation equation

$$XWT(m,n) = \frac{1}{\sqrt{{a_0}^m}} \sum x(k)\psi^*\left(\frac{k - nb_0{a_0}^m}{{a_0}^m}\right) \qquad (2.5)$$

Both the scaling factor ${a_0}^m$ and the shifting factor $n\,b_0{a_0}^m$ are functions of the integer parameter m, where m and n are scaling and sampling numbers respectively and m = 0,1, 2, By selecting a_0 = 2 and b_0=1, a representation of any signal *xk* at various resolution levels can be developed by using the MRA.

III. Multi Resolution Analysis (MRA)

A. Introduction

Due to its ability to extract time and frequency information of signal simultaneously, the WT is an attractive technique for analyzing PQ waveform. It is particularly attractive for studying disturbance or transient waveform, where it is necessary to examine different frequency components separately. WT can be continuous or discrete. Discrete WT (DWT) can be viewed as a subset of Continuous WT (CWT). This includes multi resolution analysis (MRA), energy calculation and energy difference multi resolution analysis (EDMRA) for disturbance signal. It also includes the application of EDMRA for different power quality disturbance.

B. Multi Resolution Analysis

The discrete wavelet transform resolves sampled signal into its approximation and details by using the scaling function and wavelet function respectively. The MRA technique of the wavelet transform decomposes the original signal into several other details and approximation with different levels of resolution. From these decomposed signals, the original signal in time domain can be recovered without losing any information by applying inverse wavelet transform. MRA allows the decomposition of signal into various resolution levels. The level with course resolution contains approximate information about low

frequency components and retains the main features of the original signal. The level with finer resolution retains detailed information about the high frequency components. This is an elegant technique in which a signal is decomposed into scales with different time and frequency resolutions, and can be efficiently implemented by using only two filters: one HPF and one LPF. The results are then down sampled by a factor of two and thus same two filters are applied to the output of LPF from the previous stage. The HPF is derived from the wavelet function (mother wavelet) and measures
the details in a certain input. The LPF, on other hand, delivers a smooth version of input signal and this filter is derived from a scaling function, associated to the mother wavelet[27][15].For a recorded digitized time signal $a0(n)$ which is a sampled copy of $x(t)$ as shown in Fig., the smoothed version (called the Approximation) .. .. $a1(n)$ and the
detailed version $d1(n)$ after a first-scale decomposition are given by

$$a_1(n) = \sum_k h(k-2n)a_0(k) \qquad (3.1)$$

$$d_1(n) = \sum_k g(k-2n)a_0(k) \qquad (3.2)$$

where, $h(n)$ has a low-pass filter response and $g(n)$ has a high-pass filter response. The coefficients of the filters $h(n)$ and $g(n)$ are associated with the selected mother wavelet and a unique filter is defined for each. The next higher scale decomposition is based on $a(n)$ instead of $c_0(n)$ as shown in Fig. 3.1. At each scale, the number of the DWT coefficients of the resulting signals.

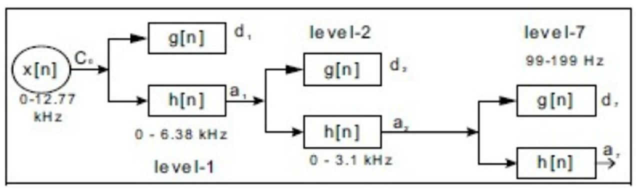


Figure 3.1: wavelet decomposition using MRA

Nevertheless, the level where the peak appears for the signal is relied on the sampling rate. In MRA, since both the high pass filter and the low pass filter
are half band, the decomposition in frequency domain for a signal sampled with a sampling frequency of fs can be demonstrated as in Fig 3.2.

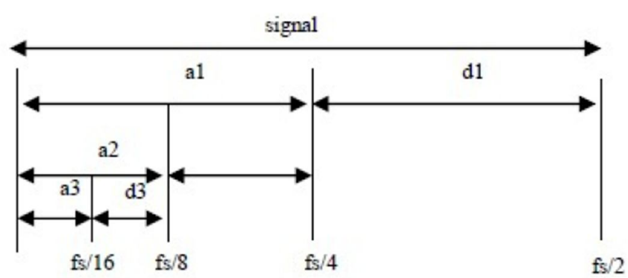


Figure 3.2: The wavelet decomposition in frequency domain

This filtering operation continues in this way. A given signal $f(k)$ is expanded in terms of its orthogonal basis of scaling and wavelet functions. In essence, it is represented by one set of scaling coefficients, and one or several sets of wavelet coefficients [27][15].

$$f(k) = \sum_n a_1(n)\phi(k-n) + \sum_n \sum_{j=1} d_j(n) 2^{\frac{-j}{2}} \psi(2^j k - n) \qquad (3.3)$$

The sampled waveform was decomposed into different resolution levels according to MRA. Then the energy of the detail information at each decomposition level i is calculated according to the following equation:

$$Ei = \sum_{j=1}^{N} D_{ij}^2 \qquad (3.4)$$

where Dij ; i = 1; ...; l is the wavelet (detail) coefficients in wavelet decomposition from level 1 to level l. N is the total number of the coefficients at each decomposition level and Ei is the energy of the detail at decomposition level i. In order to identify different kinds of PQ disturbances, the energy difference (ED) at each decomposition level is calculated, which is the difference of the energy Ei with the corresponding energy of the reference (normal) waveform at this level $Eref$

$$EDi = Ei \_ Eref \tag{3.5}$$

By observing this EDi feature vector at different resolution levels and following the criterion proposed later in this section, one can effectively detect, localize and classify different kinds of PQ disturbances. This method is named as Energy Difference of MRA (EDMRA) method [15]. The major advantages of this method include two aspects. The first one is that by using this method, one can significantly reduce the dimensionality of the analyzed data. For a l levels multi resolution decomposition, only a l-dimensional feature vector need to be observed. This is a significant reduction compared to the original sampled waveform. The second advantage is that this method keeps all the necessary characteristics of the original waveform for analysis. Different PQ characteristics are represented by the energy difference at different resolution scale, which provides an effective way for different types of PQ detection.

IV. SIMULATION AND RESULTS

A. Introduction

Power quality analysis comprises of various kinds of electrical disturbances such as voltage sags, voltage swells, harmonic distortions, flickers, imbalances, oscillatory transients and momentary interruptions. In this work, voltage sag, swell and harmonics etc are analyzed using wavelet transforms. In this section, different test signal are generated using MATLAB programming. Then wavelet transform is applied to it and results are plotted.

B. Generation of Test Signal

The simulation data is generated in MATLAB based on the model given in [**?**]. One pure sine-wave signal (frequency = 50 Hz, amplitude 1p.u) and seven PQ disturbance signals are generated. The disturbance signal includes voltage sag, voltage swell, harmonics, low frequency transient, high frequency transient, impulse, voltage fluctuation, notching and flicker. Table 1 gives the signal generation models and their controlled parameters [8]. A pure sine wave at 50 Hz frequency and magnitude of 1.0 p.u. as well as other PQ disturbances such as high frequency, low frequency transients, harmonics, voltage sag, swells and flicker in pure sine wave without spectrum noise are generated using model equations with the help of MATLAB. All the input signals are generated with total 1280 samples for five cycles (256 samples per cycles). Its recording time and sampling frequency of the signal was 0.1 seconds and 6.6 KHz respectively (i.e.1280/0.1 = 12.8 *kHz*). A ten level distorted signal MSD has been carried out using Daub-4 mother wavelet for detection purpose. For more critical analysis, ten

TABLE II. SIGNAL MODELS AND THEIR PARAMETERS

PQ Dist.	Model	Parameter
Sine-wave	$x(t) = A\sin(\omega t)$	A=1.0
Sag	$x(t) = A\sin(\omega t)\,[1 - \alpha(u(t - t_1) - u(t - t_2))]$	$0.1 < \alpha < 0.9$
Swell	$x(t) = A\sin(\omega t)\,[1 + \alpha(u(t - t1) - u(t - t2))]$	$0.1 < \alpha < 0.8$
Harmonics	$x(t) = A[\sin(\omega t) + \alpha_3 \sin(3\omega t) + \alpha_5 \sin(5\omega t)]$	$0.1 < \alpha 3 < 0.2$ $0.05 < \alpha 5 < 0.1$
Flicker	$x(t) = A\sin(\omega t)\,[1 + \beta \sin(\omega t)]$	$0.1 \le \beta \le 0.2$ $0.1 \le \gamma \le 0{:}2$
High Freq. transient	$x(t) = A\sin(\omega t) + \alpha e^{-t/\lambda} \sin(\beta\omega t)$	$20 \le b \le 80$ $0.1 \le \lambda \le 0.2$ $0.1 \le \alpha \le 0.9$
Low Freq. transient	$x(t) = A\sin(\omega t) + \alpha e^{-t/\lambda} \sin(\beta\omega t)$	$5 \le b \le 20$ $0.1 \le \lambda \le 0.2$ $0.1 \le \alpha \le 0.9$

level EDMRA has been carried out for obtaining detailed energy distribution to classify different PQ disturbances as shown in Fig.4.1.

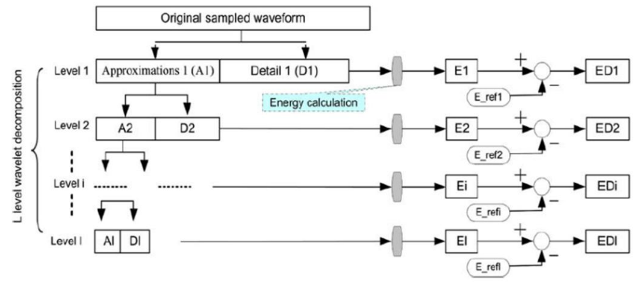


Figure 4.1: EDMRA system

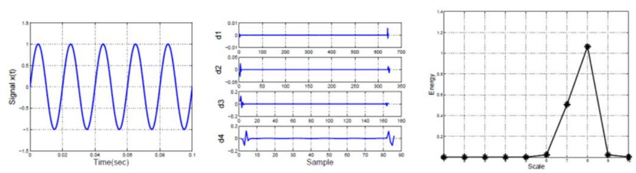
C. Results

Here the power quality disturbance signals are given to Daubechies db4 wavelet family. The observed detailed signals up to 4*th* level and energy content in detailed signals at each level is determined at plotted for power quality disturbance signals.

Pure Sine Wave

Test signal is

$$x(t) = \sin(2\pi f t)\ ) \qquad (4.1)$$



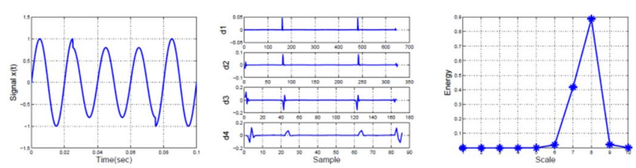
(a) Original Signal (b) Detailed Signal (c) Energy plot

Figure 4.2: Wavelet transform of pure sine wave

Sag

In pure sine wave 20% sag is created during 25msec to 75msec

$x(t) = \sin(2\pi f t) - 0.2 \sin(2\pi f t)$ (4.2)



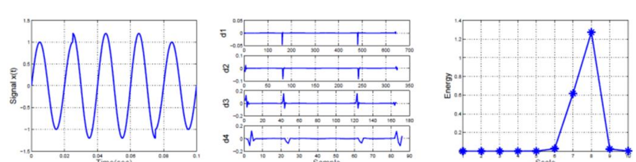
(a) Original Signal (b) Detailed Signal (c) Energy plot

Figure 4.3: Wavelet transform of sag

Swell

In pure sine wave 20% swell is created during 25msec to 75msec

$x(t) = \sin(2\pi f t) + 0.2 \sin(2\pi f t)$ (4.3)



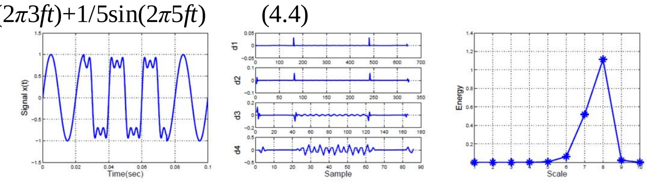
(a) Original Signal (b) Detailed Signal (c) Energy plot

Figure 4.4: Wavelet transform of swell

Harmonics

In pure sine wave third and fifth harmonic is created during 25msec to 75msec

$x(t)=\sin(2\pi ft)+1/3\sin(2\pi 3ft)+1/5\sin(2\pi 5ft)$ (4.4)



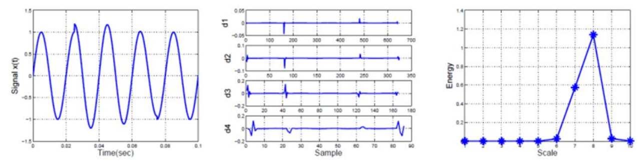
(a) Original Signal (b) Detailed Signal (c) Energy plot

Figure 4.5: Wavelet transform of Harmonics

Flicker

In pure sine wave flicker is created during 25msec to 75msec

$x(t) = \sin(2\pi ft) + 0.2\sin(2\pi 0.15ft)\sin(2\pi ft)$ (4.5)



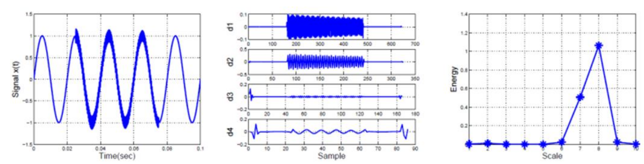
(a) Original Signal (b) Detailed Signal (c) Energy plot

Figure 4.6: Wavelet transform of flicker

High Frequency Transient

In pure sine wave high frequency transient is created during 25msec to 75msec

$x(t) = \sin(2\pi ft) + 0.2e^{\frac{-t}{0.15}}\sin(2\pi 50ft)$ (4.6)



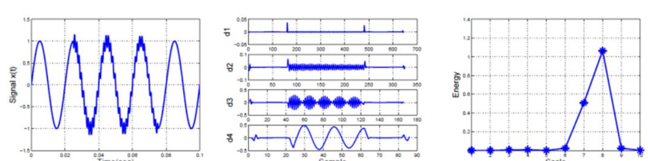
(a) Original Signal (b) Detailed Signal (c) Energy plot

Figure 4.7: Wavelet transform of high frequency transient

Low Frequency Transient

In pure sine wave low frequency transient is created during 25msec to 75msec

$x(t) = \sin(2\pi ft) + 0.2e^{\frac{-t}{0.15}}\sin(2\pi 15ft)$ (4.7)



(a) Original Signal (b) Detailed Signal (c) Energy plot

Figure 4.8: Wavelet transform of low freq. transient

D. EDMRA Calculations

Taking pure sign energy as reference, %change in energy with respect to maximum energy of pure sine wave is calculated e.g. in case of sag at i^{th} level

$$\%EDMRA_i = \frac{E_i^{sag} - E_i^{\sin}}{\max(E_i^{\sin})} x100 \qquad (4.8)$$

This pattern of EDMRA is plotted with respect to level of decomposition with Daubechies wavelets as shown in Table.4.2 Fig.4.9

TABLE III. ENERGY DIFFERENCE MRA WITH DAUBECHIES WAVELETS

sag	swell	harmonics	Flicker	High Freq Transient	Low Freq Transient
0	0	0	0	0.216125	0
0	0	0	0	1.03364	0.009397
0.018793	0.018793	0.0093967	0.009397	0.009397	0.51682
0.009397	0.009397	0.1221575	0	0.009397	0.742342
0.009397	0.018793	0.5168201	0.009397	0	0
-0.17854	0.347679	3.8056756	0.122157	-0.0094	0
-8.39128	10.43037	1.1745912	6.399173	-0.02819	0.009397
-16.5946	19.63917	4.7077617	7.113325	-0.06578	-0.0094
0.046984	0.037587	0.0093967	0.319489	0.018793	0
0.009397	0	0	0.009397	0	0

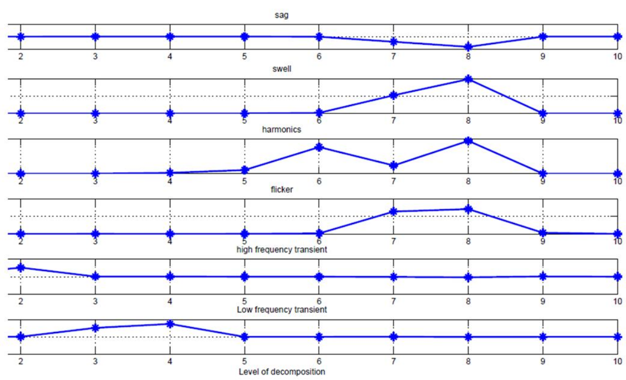


Figure 4.9: EDMRA using Daubechies wavelets

Again the same EDMRA is plotted with respect to level of decomposition with Symlets wavelets as shown in Table.4.3 and Fig.4.10

TABLE IV. ENERGY DIFFERENCE MRA WITH SYMLETS WAVELETS

sag	swell	harmonics	Flicker	High Freq Transient	Low Freq Transient
0	0	0	0	0.240159	0
0	0	0	0	1.159027	0.010442
0.010442	0.010442	0.014417	0	0	0.532526
0.020883	0.020883	0.1461836	0.010442	0	0.856218
0.041767	0.041767	4.5212488	0.020883	0	0
-0.13574	0.459434	7.2987366	0.1253	0.010442	0
-19.1396	23.02391	-2.902788	13.04166	-0.07309	0.010442
-4.80317	5.774251	1.0441683	2.652188	-0.02088	0.010442
0.1253	-0.10442	0.0208834	0.06265	0.010442	-0.01044
-0.05221	0.041767	-0.010442	0	-0.0144	-0.0144

From Fig.4.9, 4.10, and Table 4.2, 4.3 the important features of energy distribution can be categorized as follows:
1. ED7, ED8 show a great variation when sag or swell occurs.
2. ED5, ED6 will show variation when the voltage suffers from harmonic distortion.
3. High frequency transient can be detected from ED1 and ED2
4. ED3 and ED4 shows variation when the voltage low frequency transients.

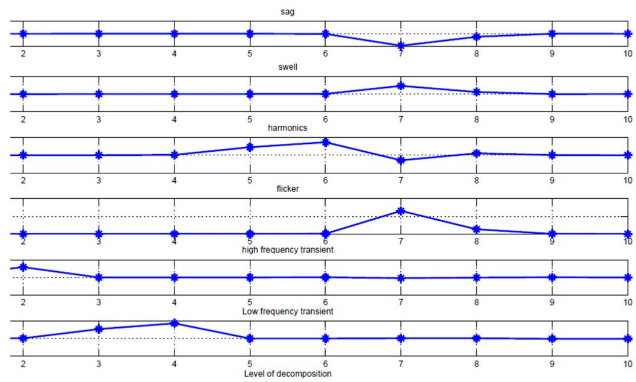


Figure 4.10: EDMRA using Symlets wavelets

Thus, when a distorted signal contains high frequency elements, the low level energy distribution will show variation and when the distorted signal contains low frequency elements the high level energy distribution will show variation.

V. Conclusion and Future Scope

The paper demonstrates the wavelet transform based MRA as an effective tool for the assessment and analysis of PQ events. The advantage of using wavelet and MRA to extract features is to get very precise time information about the event. The starting and duration of sag, swell, transients can be determined using first level detail. The procedure in effect offers a good time resolution at high frequencies, and good frequency resolution at low frequencies. The energy distribution of level 10 using multi-resolution technique has been used to access the performance of the wavelets The approach is very suitable especially when the signal has high frequency component for short duration and low frequency components for long duration. Since most of the signals encountered in PQ assessment are of this type Wavelet transform method to analyze PQ disturbances proves to be much better than the other advanced digital processing techniques. The features extracted using wavelet transform can be applied as an input to a classifier for automatic classification of different PQ events. The effects of noise have to study for the identification and detection capability of wavelet based power quality (PQ) method.

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