A NOVEL INDEX TO ANALYZE POWER QUALITY PHENOMENA USING DISCRETE WAVELET PACKET TRANSFORM

By

AJAY KARTHIK HARI

A THESIS PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE

UNIVERSITY OF FLORIDA

2003

To AMMA, AJAPPA and SANDEEP.

ACKNOWLEDGMENTS

I would like express my sincere thanks to Dr. Alexander Domijan for giving me an opportunity to work on this project. I am indebted to him for offering me a research position in his group and for his gentle and friendly attitude. I would also like to thank Dr. Khai D.T. Ngo and Dr. A. Antonio Arroyo for serving on my thesis committee.

I express my sincere gratitude to Dr. Tao Lin for introducing me to the wavelets and for his constant support during the entire thesis work. I would also like to thank my colleague and friend Alejandro Montenegro for helping me in understanding power quality and EMTP.

I thank my fellow colleague and friend Roop Kishore for patiently reading my thesis and critiquing its grammar. I also extend my thanks to Hemanth for patiently listening to my endless lectures on my thesis. I also thank all my wonderful friends and lab mates.

Last but not least, I would like to thank my parents for their constant support and encouragement.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Abstract of Thesis Presented to the Graduate School
of the University of Florida in Partial Fulfillment of the
Requirements for the Degree of Master of Science

A NOVEL INDEX TO ANALYZE POWER QUALITY PHENOMENA USING DISCRETE WAVELET PACKET TRANSFORM

By

Ajay Karthik, Hari

December 2003

Chair: Dr. Alexander Domijan, Jr.
Major Department: Electrical and Computer Engineering

A novel index to analyze harmonics is proposed in this thesis. Also, a new method to identify and classify harmonics present in a power system is presented. The main goal of the thesis is to identify pitfalls in current power quality indices and to present a new index based on Discrete Wavelet Packet Transform. Wavelets with its unique ability to give good time and frequency localizations simultaneously are best suited for power quality applications. Wavelets can be used to identify, classify and quantify power quality disturbances. This approach is extremely useful for power quality instrumentation purposes as it proposes a very fast and robust algorithm to detect and quantify harmonics. Furthermore, the algorithm developed also has the unique ability to identify additional power quality events occurring along with harmonics. The ability of this algorithm to identify and measure harmonic disturbances in both time and frequency domains will aid in exact disturbance localization and detection. Thereby, it assists in designing of proper mitigation techniques to eliminate power quality disturbances. The primary idea of this

thesis is to develop a power quality index based on energy content of the signal which is suitable to analyze amplitude, frequency varying harmonics and aperiodic signals.

CHAPTER 1
PROLOGUE

Power quality (PQ) is cynosure of all eyes not only in the electric power industry but also in the eyes of various sensitive power customers, like semiconductor industry, where poor power quality combined with down time can cause huge monetary losses. The attention it has captured is also because of an integrated approach used by researchers and engineers throughout the world to solve the problem instead of tackling them individually. It is a multi-disciplinary field encompassing power electronics, signal processing, and hardware design among a host of other fields.

1.1 Definition of Power Quality

Power quality definition is often twisted by different agencies to suit their needs. Utilities often equate it to reliability because doing so will give them better statistics. An equipment manufacturer may define PQ as characteristics of power supply that enables the equipment to work properly. These characteristics may vary from one manufacturer to another. Ultimately, it is a customer driven issue and customer's satisfaction and point of reference occupies the front seat. The following is the widely accepted definition of power quality.

"Power quality can be defined as being any problem manifested in voltage, current, or frequency deviations that result in disoperation or failure of customer equipment." [1]

Thus, it is very important to supply a 60HZ clean sinusoidal waveform without any deviations to the customers. PQ is difficult to quantify. The ultimate measure of PQ is measured by the performance and productivity of the customer's equipment.

1.2 Importance of Power Quality

The proliferation of nonlinear loads in the modern power systems has triggered a growing concern for PQ related issues. The proliferation of power semiconductor devices in power systems along with electronic loads, including personal computers and information technology devices have resulted in waveform distortion in the power systems. The nonlinear elements present in these electronic devices such as diodes, transistors, thyristors etc contribute harmonics to the power system resulting in poor PQ and at the same time they are the most sensitive ones to perilous effects of the poor PQ.

The importance of PQ is augmented by the fact that many things are now interconnected in a network/grid. Failure of any electrical equipment has much more serious consequences in the present day power systems than in the past. The recent New York blackout, though not exactly because of power quality, underscores how interconnected the network is and the impact of the failure of a network can have on our day to day lives. Safe and reliable operation of electric equipment can be ensured with good power quality Also, as the sophistication of electronic equipment increases, there is a need for good power quality and the utilities will leave a bad impression on customers, otherwise. The importance of PQ is more thoroughly understood when its economic value is emphasized. It has a direct impact on all most all the types of customers. The following figure shows the direct economic impact of a particular PQ event on various industries.

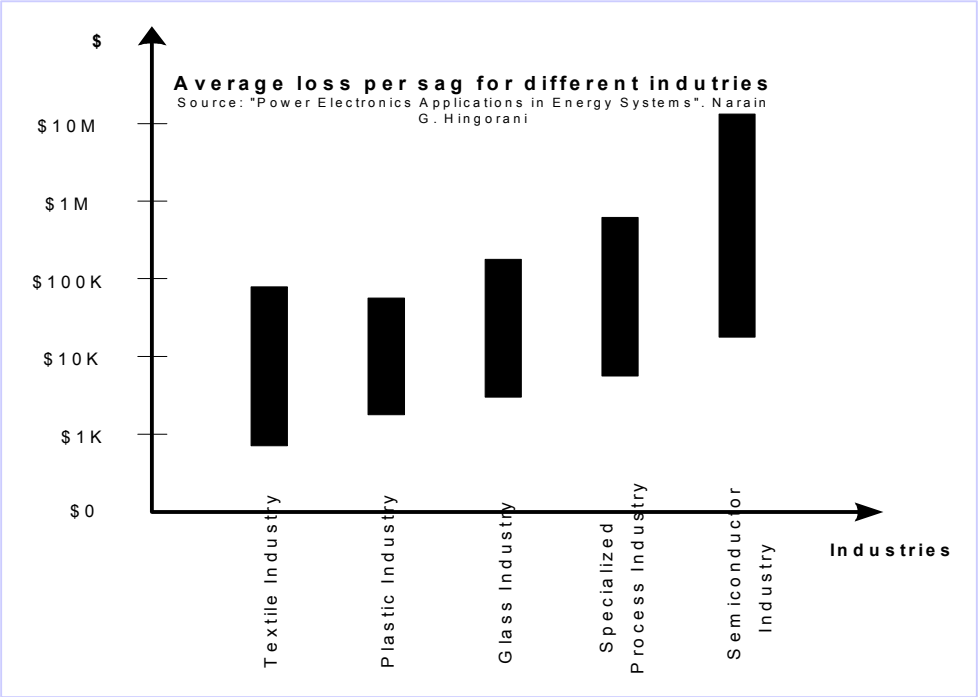


Figure 1-1: Average loss per industry due to particular PQ event.

Apart from obvious financial reasons, there are numerous indirect and intangible costs which are associated with PQ problems. Customer satisfaction is a key factor. Even though, small residential customers do not suffer direct financial loss due to PQ problems but their dissatisfaction can work as propaganda against utilities. Especially when utilities are facing tough competition among each other

1.3 Review of Various PQ Problems

The PQ problems can be categorized briefly as follows:

- Transients
  Impulsive transient and Oscillatory transient.
- Short duration voltage variations
  Voltage Sag and Voltage Swell
- Long duration voltage variations
  Under Voltage and Over Voltage
- Interruptions
  Momentary, Temporary and Long term Interruptions.
- Waveform distortions
  Harmonics, Notching and Noise.

- Voltage fluctuation
- Frequency variation
- Other Miscellaneous problems

  Voltage unbalance, DC offsets Reactive power consumption.

1.4 Scope of the Thesis

A. Domijan, G.T. Heydt et al. in the paper titled "Directions of Research on Electric Power Quality" [(2)] showed various fields of research in the electric power quality area. Which include: Modeling and Analysis, Instrumentation, Sources, Solutions, Fundamental concepts and effects. The present thesis encompasses parts of Time domain, Transfer domain and waveform analysis part of research in the electric power quality area. It is more clearly depicted in Figure 1.2. The present thesis presents new techniques that can be used to analyze PQ waveforms in both time and frequency domain simultaneously. It also proposes a new criterion that can be used to select a Wavelet (defined in the Chapter 2) appropriate for PQ monitoring. It also critically evaluates various PQ Indices widely used and proposes a novel PQ Index. The proposed Index is based on energy content present in a signal. This thesis also forms as a basis for further research for a proposed PQ monitoring device to be developed in PQ&PE Laboratory at the University of Florida.

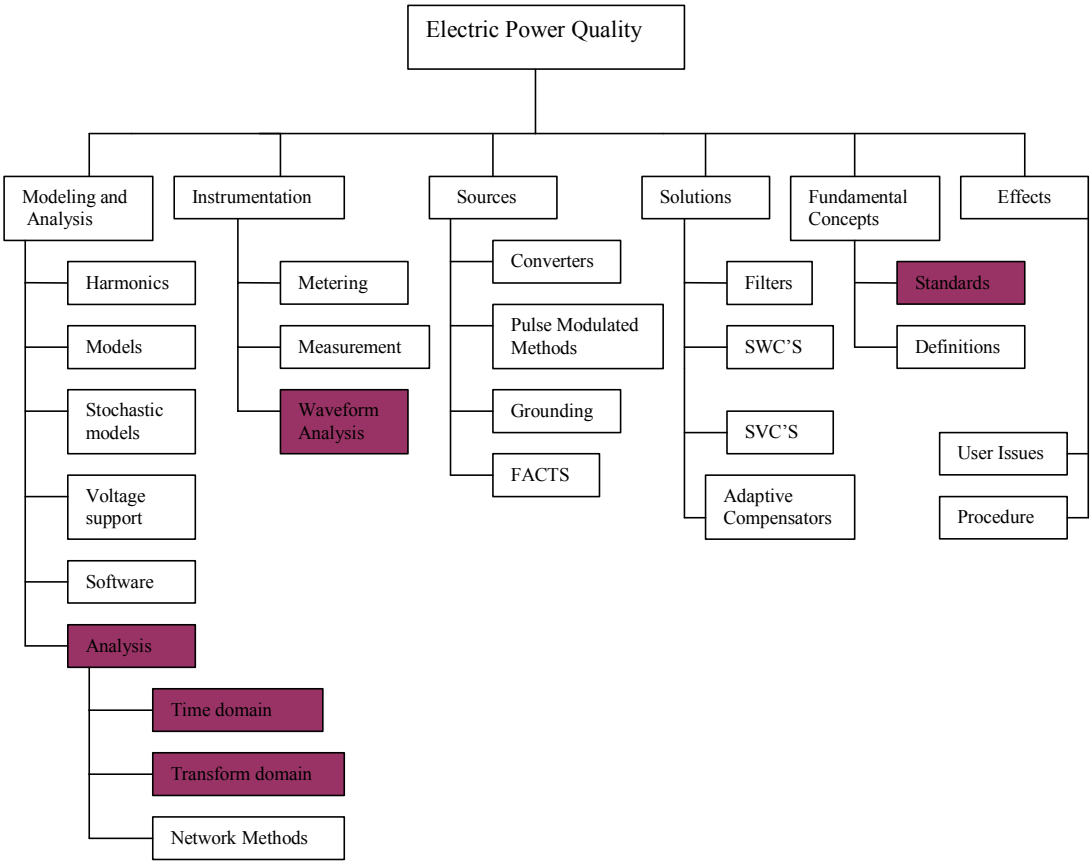


Figure 1-2 Main aspects of electric power quality. Shaded boxes show the areas addressed in this thesis

In other words, the goal of the present thesis is to use wavelet transform (WT), an advanced signal processing tool, to analyze the time-frequency-energy properties of PQ signals and use it as a basis to classify the PQ events and to develop a PQ Index exploiting the unique time-frequency properties of the Wavelet transform.

1.5 Organization of Thesis

The present thesis is divided into five chapters. It can be further split into two parts: the first part deals with introduction to wavelet transform theory (chapter 2) and selection of appropriate wavelet (chapter 3); while, the second part deals with introduction to PQ

indices and proposal of a new index(chapter 4) ,Furthermore, a discussion on results (chapter 5) obtained is presented . More detail explanation of the organization follows:

Chapter 2: This chapter starts out with historical background of wavelet transform theory and explains basic theory of wavelet transforms. It also justifies the selection of WT for PQ applications. Furthermore, it compares and contrasts various other signal processing techniques with respect to WT.

Chapter 3: This chapter deals with selection of appropriate wavelet filter bank for PQ applications. It starts out with a brief description of various wavelet families present in literature and explains the criterion behind the selection of a particular wavelet family for PQ application. The chapter ends by justifying the selection by using various signal processing techniques.

Chapter 4: In this chapter, a close look is taken at various PQ indices present in the literature. The problems with existing Indices are explained. Then a novel index is proposed.

Chapter 5: Results obtained are presented in this chapter, followed by a discussion on the results obtained. The Index proposed is critically evaluated.

Chapter 6: Conclusions from the results and scope for further work is presented in this chapter.

CHAPTER 2
INTRODUCTION TO WAVELET TRANSFORMS

Wavelet transforms have been in existence for a long time. It was first mentioned by Alfred Haar in his doctoral dissertation in 1909 and it was mentioned in its present theoretical form by Jean Morlet in 1975 while working for Elf Aquitaine under Alex Grossmann. Other important contributors include Dr. Ingrid Daubechies, Stephane Mallat and Yves Meyer. The wavelet transform has been found to be particularly useful for analyzing noisy, aperiodic, transient and intermittent signals. It has a very different ability to examine the signal simultaneously in both time and frequency.

2.1 Definition of Wavelet Transform

Wavelets, little wave like functions, are used to transform the signal under investigation into another representation which presents the signal information in a more useful form. This transformation of the signal is known as the wavelet transform (WT). Mathematically, WT [3] is defined as the inner product of wavelet function $\psi(a,b)$ and real signal s (t):

$$T(a, b) = \int_{-\infty}^{+\infty} S(t), \psi^*_{(a,b)}(t)$$

where

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$$

The parameters a and b are called dilation and translation parameters respectively.

2.2 Why Wavelets for Power Quality

The occurrence of power quality events should be detected and located in time, the content of these events should also be monitored accurately so as to classify the events and carry out appropriate mitigations techniques to alleviate PQ problems. There is a need for a powerful tool that can be used to classify the PQ events both in time and frequency domain. Wavelets satisfy this need and scores over other Time-Frequency methods such as Short Time Fourier Transform (STFT). These advantages are explained in more detail in the following sections of this chapter.

Also, Wavelet basis functions have compact support, which means that basis functions are non-zero over a finite interval, unlike sinusoidal Fourier basis functions which extend infinitely. This property along with unique property of wavelet basis to be squeezed (dilation) and movement along axis (translation) gives greater flexibility in analyzing localized features of analyzing signal.

Furthermore, recent advances in PQ mitigation techniques are based on extraction of harmonic components instead of traditional fundamental component. Thus, time-frequency domain based techniques come into picture as they give a distinct advantage of eliminating selected harmonics, subject to availability of accurate information on individual harmonic components.

2.3 Disadvantages of Traditional Signal Processing Tools

2.3.1 Fourier Transforms

The Fourier transform (FT) of a finite energy function $f(t) \in L^2(R)$ of a real variable t is given by

$$f(\omega) = \int_{-\infty}^{\infty} f(t)\exp(-j\omega t)dt.$$

It is evident from the above definition that FT cannot be carried out until the entire waveform in the whole axis $(-\infty,\infty)$ is known. The above equation can be evaluated at only one frequency at a particular time. [4] This causes great difficulties while processing non stationary signals. Even though, faster algorithms exist to carry out this computation they cannot be implemented for real time signals. This is undesirable from PQ monitoring point of view.

As explained before FT fails to give time domain information of the signal and is thus a serious handicap for PQ analysis and Instrumentation techniques based on it.

Fast Fourier transform (FFT) and its variants are generally used in spectral analyzers and also other PQ monitoring instruments. It suffers from all the disadvantages mentioned above and also due to its spectral leakage component; it does not accurately show the spectrum. This will in turn lead to imprecisely calculated signal parameters such as magnitude, phase and frequency. Furthermore, it is very difficult to distinguish between the harmonics and transients in an FFT spectrum.

2.3.2 Short-time Fourier transforms

Short-time Fourier transforms [4] are very intuitive. In order to achieve time-frequency localization, it obtains the frequency content of a signal at any instant ‘t’ by windowing the signal using an appropriate window function and then FT the remaining portion of it. More crudely, it is removing the desired part of the signal and then performs FT on it. Thus, it is some times referred as windowed Fourier transform or running window Fourier transforms.

Mathematically, if f (t) is the signal under consideration and $\phi(t)$ is the window function used to obtain a windowed function, say, $f'(t) = f(t) * \phi(t - t')$, then STFT evaluated at location (t', ω) in the time-frequency plane is given by

$$G_{\phi}f(t', \omega) := \int_R f(t)\phi(t - t')e^{(j\omega t)}dt$$

STFT needs to know the signal information only in the interval of the window function used. This is a major improvement from FT, where it needs to know the signal information over the entire time axis. The major disadvantage of STFT comes from uncertainty principle. Low frequencies can hardly be depicted using short windows and short pulses are poorly located in time with long windows. From the above two sections, it can be safely concluded that traditional FT poses a serious handicap for PQ monitoring. Also, other variants of FT such as STFT also have serious drawbacks.

2.4 Advantages of Wavelet Transforms

As presented in the previous section, traditional signal processing tools have some serious drawbacks for PQ applications. A more viable alternative is the use of wavelet transform. The wavelet transform has good localization in both frequency and time domain. This makes it an attractive option for PQ applications. WT is apt for studying non-stationary power waveforms. Unlike, the sinusoidal function used in FT, wavelets are oscillating waveforms of short duration with amplitude decaying quickly zero at both ends and thus are more suitable for short duration disturbances. The wavelet's dilation and translation property gives time and frequency information accurately. Apart from it this process of shifting enables the analysis of waveforms containing nonstationary disturbance events. To enhance the electric power quality, sources of disturbances must be detected and then appropriate mitigation techniques have to be applied. In order to

achieve this, a real-time PQ analyzer with an ability to do time-frequency analysis is required. Hence wavelets transforms with its ability to give good Time-Frequency resolution is suitable for PQ applications.

Another important application in PQ is data compression. [5] A single captured event recorded for several seconds using monitoring instruments can produce megabytes of data. This increases the cost of storing and transmitting data. Again, WT comes into picture. Its ability to concentrate a large percentage of total signal energy in a few coefficients helps in data compression. Thus, it reduces the need to store huge voluminous of data and reduces costs associated with it.

In this research project, discrete wavelet packet transform, popularly called DWPT, an enhancement of multi resolution algorithm (MRA) using discrete wavelet transform (DWT) has been used as a tool for PQ analysis. DWPT has many inherent advantages over DWT [3], which are explained in more detail after a formal introduction to discrete wavelets in the following sections.

2.5 Discrete Wavelet Transform

In the previous section, wavelet transform was defined as the inner product of wavelet function $\psi(a,b)$ and real signal s (t):

$$T(a, b) = \int_{-\infty}^{+\infty} S(t), \psi^{*}{}_{(a,b)}(t)$$

where

$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})$ and the parameters a and b are called dilation and translation parameters respectively. This is called continuous wavelet transform (CWT).

Discrete wavelet transform [3] is defined for a continuous time signal, s(t) where discrete values of a and b are used. The DWT is thus the discretized counter part of CWT, which is defined as

$$T(a, b) = \frac{1}{\sqrt{am}} \sum_{n} S(t)\Psi[\frac{k - nb_o a_o^{m}}{a_o^{m}}]$$

where

The integer's m and n control the wavelet dilation and translation respectively;

a_o is a specified fixed dilation step parameter set at a value greater than 1;

And, b_o is the location parameter which must be greater than zero.

But, common choices for discrete wavelet parameters a o and b o are 2 and 1 respectively. This type of scaling is popularly called 'dyadic grid' arrangement.

When certain criteria are met it is possible to completely reconstruct the original signal using infinite summations of discrete wavelet coefficients rather than continuous integrals. This leads to a fast wavelet transform for the rapid computation of the discrete wavelet transform and its inverse. DWPT, which is used in this research project is based upon discrete wavelet transform. It allows for adaptive partitioning of the time-frequency plane. It is a generalization of multi resolution algorithm explained in the following section.

2.6 Wavelet Packets and Multi Resolution Algorithm

MRA was initially developed to decompose the signal into various resolution levels to facilitate a very fast time-frequency analysis. A multi-stage filter bank is used to decompose the signal into various levels using a Low Pass(LP) filter and a High Pass(HP) filter as shown in the figure 2.1. [6] The LP filter will result in approximate coefficients of the original signal and the HP filter in detailed coefficients of the signal.

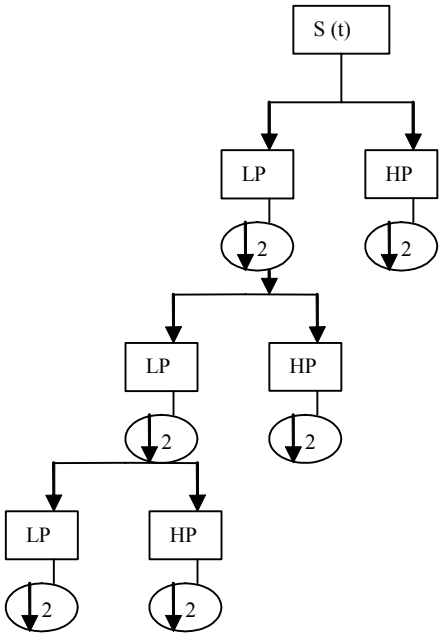


Figure 2-1: MRA using LP and HP

DWPT, as stated earlier, is a generalization of the DWT. The difference is that in the WP signal decomposition, both the approximation and detailed coefficients are further decomposed at each level. This leads to a decomposition tree which is shown in Figure 2.2. This will lead to an array of wavelet packet coefficients with M levels and each containing N coefficients. A total of N coefficients from this M*N array can be selected to represent the signal.

The main advantage of DWPT is better signal representation than decomposition using MRA. The DWT technique is not suitable for harmonic analysis because the resulting frequency bands are not uniform. In DWPT, with clever manipulation of sampling frequency, the important harmonics such as odd harmonics can be made center frequency of the resulting frequency bands. Furthermore, DWPT gives uniform bands is

important for harmonic identification purposes. A level 2 decomposition using DWPT filter bank can be depicted as follows

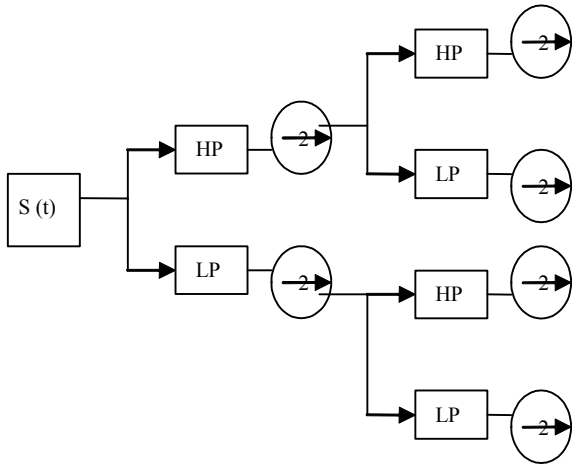


Figure 2-2: Depicting DWPT filter bank implementation of a signal

Similar to DWT, LP filter gives approximation coefficients and HP filter gives detailed coefficients. The coefficients are given by the following equations:

Let $\Phi(t)$ be the scaling equation (or dilation equation) associated with the mother wavelet. Then, the scaling function can be convolved with the signal to produce approximation coefficients given by

$$A_{m,n} = \int_{-\infty}^{\infty} s(t)\phi_{m,n}(t)dt$$

The function of mother wavelet can be convolved with the signal to produce detail coefficients given by

$$D_{m,n} = \int_{-\infty}^{\infty} s(t)\psi_{m,n}(t)dt$$

The following explanation forms the basis of the next chapter and much of the research done for this thesis. As explained earlier DWPT can be used to separate

harmonics. It can be best illustrated as follows. Let us assume a signal with fundamental frequency 60HZ and 3rd, 5th, 7th and 9th Harmonics. Let the sampling frequency be 1920 Hz. Then the maximum measurable frequency is 960Hz (Sampling theorem). The figure depicted in the next page shows the decomposition and how the harmonics are separated using DWPT.

Frequency ordering after DWPT is very important and it has to be understood. [(7)] The decomposition resulting from a high pass filter is always a mirror image. Thus, before doing any further analysis, it is of great importance to sort out the frequency in desired order. The example illustrated in the following page [(8)] shows level three DWPT decomposition and the first frequency band is 0-120Hz thus, its center frequency is 60Hz. Hence selection of sampling frequency is very important and it should be done in an intelligent manner such that the important frequencies one is dealing with are usually the center frequency of the band. The maximum level of decomposition one has to go for decomposition varies from application to application. Usually, for power system applications it is 60Hz/50 Hz. But, due to the presence of sub-harmonics present in the power systems it is advisable to go further down.

At the same time, as the number of nodes increase with increase in decomposition levels, it makes analysis more complicated or in other words, it reduces the readability.

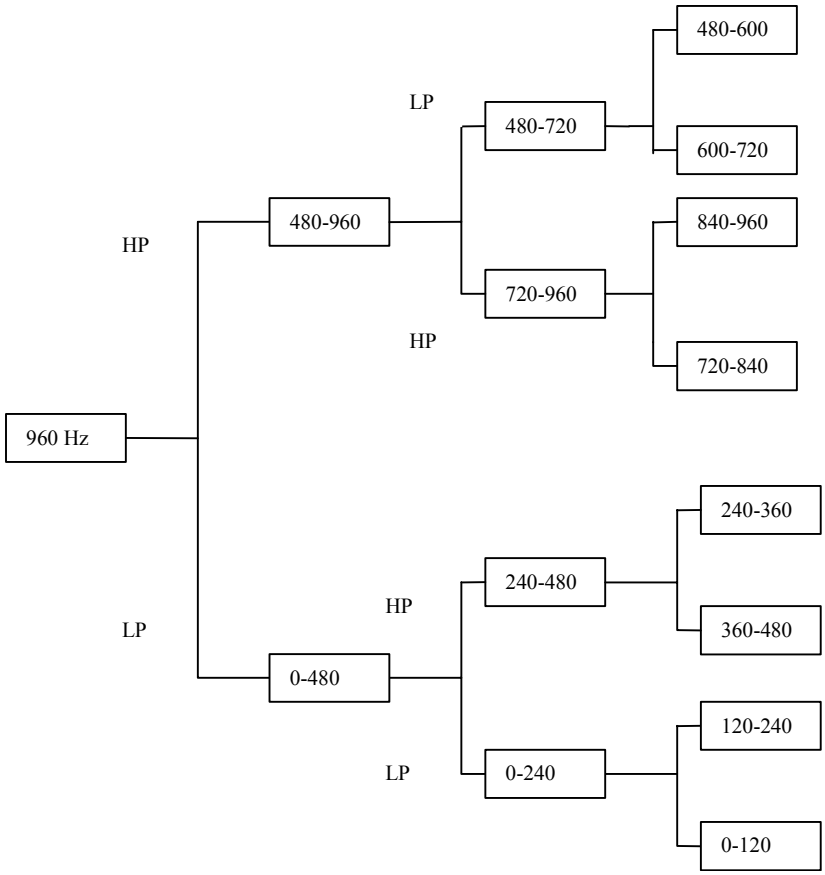


Figure 2-3 Frequency band's in Hz of a level 3 DWPT decomposition with a sampling frequency 1920Hz

Note that the center frequency in each of the nodes is exactly odd harmonics of 60 Hz.

CHAPTER 3
SELECTION OF APPROPRIATE WAVELET

3.1 Introduction

More often than not power researchers tend to neglect the choice of appropriate wavelet filter for their application. The selection of wavelet assumes more importance if one wants to implement their algorithm in DSP and develop an instrument out of it. It is a general trend among researchers to take db10 (more appropriately higher order db coefficients) to study harmonics and db4 or db3 to study transient related phenomena. In this paper, we have made an effort to study various wavelet families, which exist in the literature, suitable to study PQ problems and to suggest a suitable wavelet filter that can be used to study harmonics in particular.

3.2 Introduction to Wavelet Families

Today, there are a number of wavelet families which exist. Each one of them has a particular application. In fact, one can develop a wavelet family to suit ones particular needs. But to study PQ phenomena there are some wavelet families like Daubechies etc which already exist in the literature. Some of the widely used wavelet families that can be used to study the PQ phenomena are

1. Daubechies
2. Symlets
3. Coiflets
4. Biorthogonal Wavelets.

3.3 Analysis of Harmonics in Time-Frequency Plane

In the analysis of harmonics in time-frequency plane, it is very important to exactly localize the harmonics in the frequency plane. The DWPT algorithm (as explained in the previous chapter) partitions the time-frequency plane, one partition for every decomposition. It allocates the lower interval to low pass filtered part and higher frequency interval to the high pass filtered part. Thus, it is very important to select an appropriate wavelet filter appropriate whose frequency is close to an ideal filter.

3.3.1 Frequency Characteristics of Daubechies Wavelets:

Ingrid Daubechies has proposed 10 wavelets often represented as db1, db2…db10 or some times db2, db4…..db20. Where, db stands for Daubechies and the numbers 1, 2…10 stand for number of zero moments in the former representation and numbers 2, 4,..20 stand for number of non-zero scaling coefficients in the latter representation. In this thesis the former approach is being used as it is used by the MATLAB wavelet tool box and makes programming and interpretation easier. To facilitate this, Daubechies wavelets were decomposed into low pass and high pass filters. The frequency characteristics of both the low pass and high pass filters have to decrease faster near the filter band edges. This will give good frequency separation and there by localization in the time-frequency plane will be lot easier. Another advantage is that it will reduce frequency leakage into neighboring bands. For example decomposition of Daubechies wavelet db5 is shown in fig 3.1

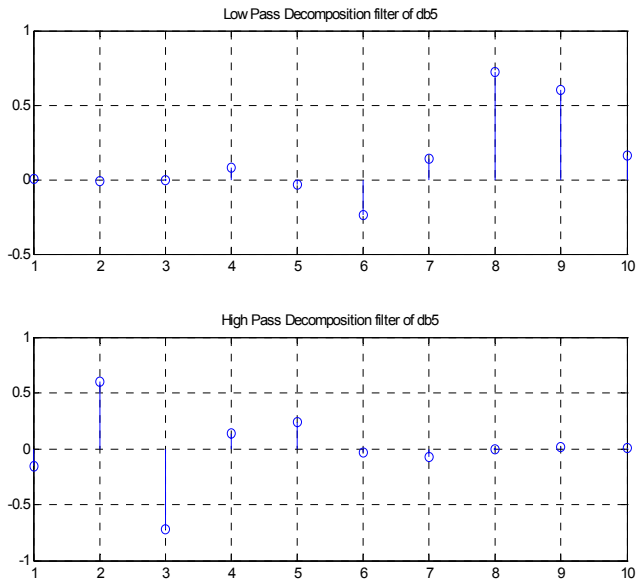


Figure 3-1: Low pass and high pass decomposition filters of ‘db5’

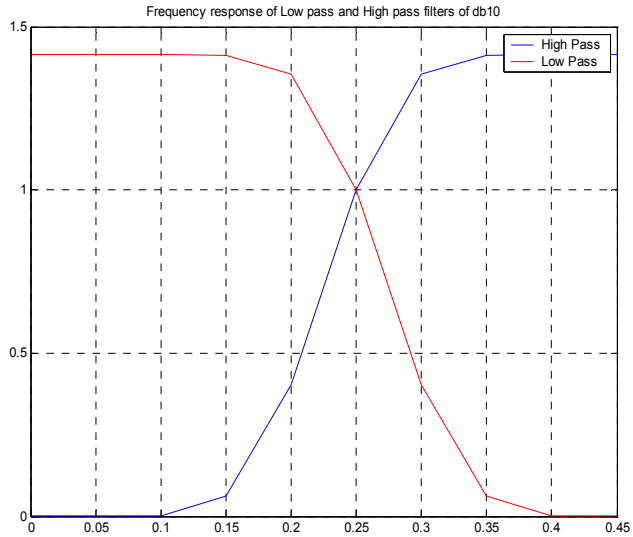
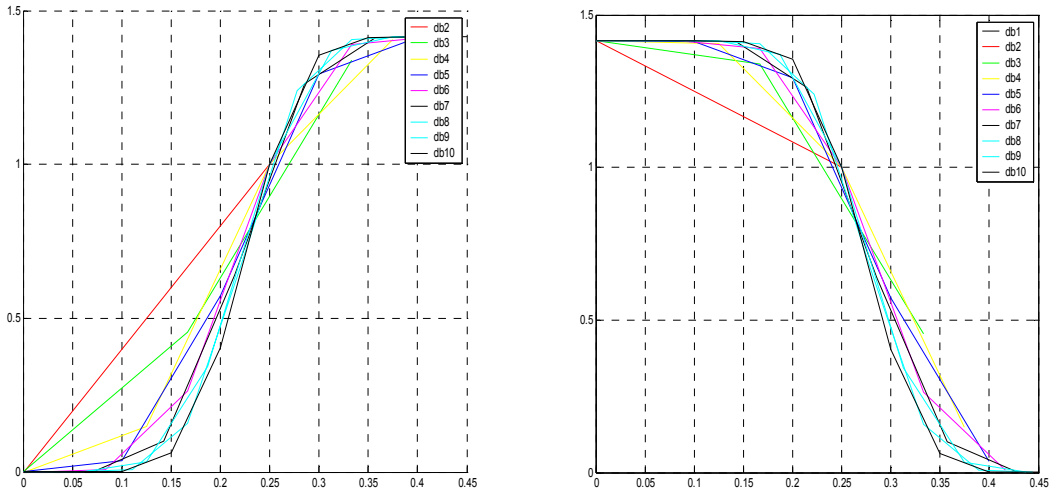


Figure 3-2: Frequency response of low pass (red) and high pass (blue) decomposition filters of ‘db10’

To make this study more effective frequency response’s of all the families were individually and taking the best out of each one of it, a comparison was made. The following figures will make this explanation more clear.



3-3 (a) 3-3(b)

Figure 3-3: Frequency responses of all the wavelets in Daubechies families. (a) High pass decomposition filter. (b) Low pass decomposition filter

In a similar fashion, the frequency response's of all the wavelets in Symlets, Coiflets and biorthogonal families were calculated and plotted. All the relevant graphs are attached in the appendix. From fig 3.3, it is clear that db10 has the best frequency response suited to our application i.e. the frequency characteristics decrease faster near the filter band edges.

Following the same rule of thumb we can say that coif5 and sym8 have good frequency characteristics. Frequency response of biorthogonal wavelets are not in the same league of the other 3 families.

3.3.2 Comparison of Best Frequency Responses from the Wavelet Families

As explained in the previous paragraph, the best frequency responses from the 3 families under investigation are Daubechies 10 (db10), Symlets 8(sym8), Coiflets 5(coif5). To find out the better among them for our application, all the 3 were plotted out in a same graph as shown below

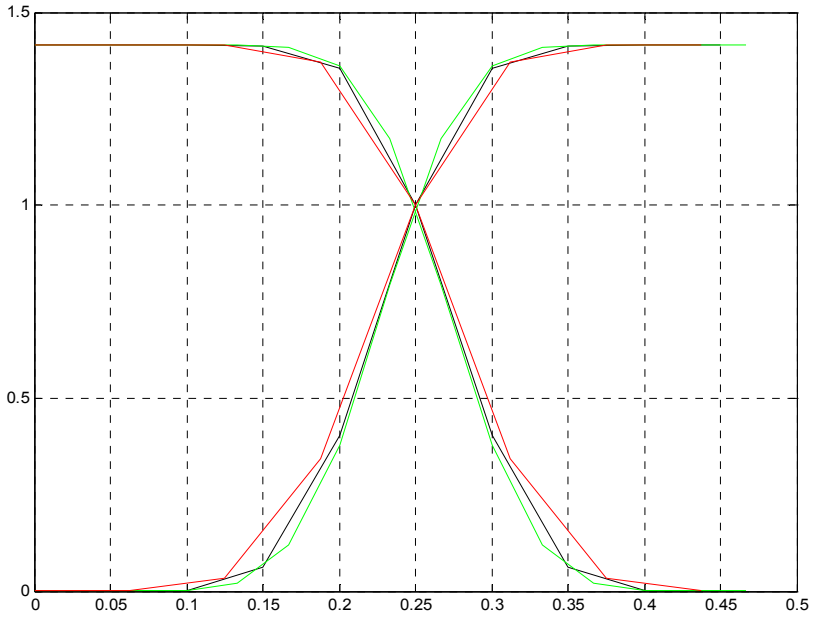


Figure 3-4: Low pass and high Pass frequency characteristics of db10 (black), Coif5 (green) and Sym8 (red)

It can be seen from the graph that all the three have similar frequency responses and coif 5 has the best response among them. The selection now depends upon the accuracy range required for the application. For PQ applications more the accuracy, the better it is. Since, all the 3 have almost similar Frequency Responses it would be a good idea to see the complexity of computation of them.

3.4 Complexity of Computation

Complexity of computation using the above filters becomes a very cardinal issue while implementing them on a DSP board. The low pass and high pass wavelet filters are discrete in nature. For an N point filter to process it requires N^2 multiplications and N^2 -1 addition's.

Table 3-1: Shows the complexities of various wavelets under investigation

S. No	Name of the Wavelets	Complexity
1	db10	160399
2	Sym8	65791
3	Coif5	810899

From the above table, it is clear that coif5 has the highest complexity but again it has the best frequency and phase response. When sampling frequency is around 1930Hz (Typical value for PQ applications), it is more sensible to opt for a wavelet with better frequency response. Furthermore, the benchmarks of the latest DSP processors released by companies like TI and Analog Devices for Data Acquisition, Test and Measurement applications can do complex multiplications in 19ns. Thus, it is better and more realistic to choose coif5 because its complexity is not too high, when compared to db10, and will not burden the DSP.

3.5 Quantification of the Selected Wavelet

A scientific approach was adopted to select the wavelet for this particular application. To ascertain this selection the selected wavelet i.e. coif 5 was tested for various characteristics that are suited for this application, especially, the behavior of wavelet, when it is used in the DSP board for real time monitoring.

3.5.1 Spectrum Leakage

As explained in the previous section the frequency response of coif5 is sharper at the edge of the band. Hence, it should show less frequency leakage when compared to

other wavelets. To quantify this theory, a sine wave was decomposed using coif1 and coif5 wavelet filters and by applying DWPT. The equation of the sine wave tested is:

X=0.1*sin(2*pi*60*t)+0.1*sin(2*pi*180*t)+2*sin(2*pi*300*t)+0.1*sin(2*pi*420*t)

With t=0:5.2083e-004:1 (a sampling period of 1920Hz.).The graph depicted in the next page has Nodes of level 3 decomposition on x-axis and magnitude (Peak voltage) on the Y-axis. As explained in the previous chapter. Each node corresponds to a frequency band. The number of nodes is given 2 power(level). The frequency band for a level three decomposition with sampling frequency 1920Hz is given as follows:

Table 3.2 Depicts frequency ranges of various nodes in Level 3 DWPT decomposition with sampling frequency of 1920 Hz

Nodes	1	2	3	4	5	6	7	8
Frequency Range (Hertz)	0-120	120-240	240-360	360-480	480-600	600-720	720-840	840-960

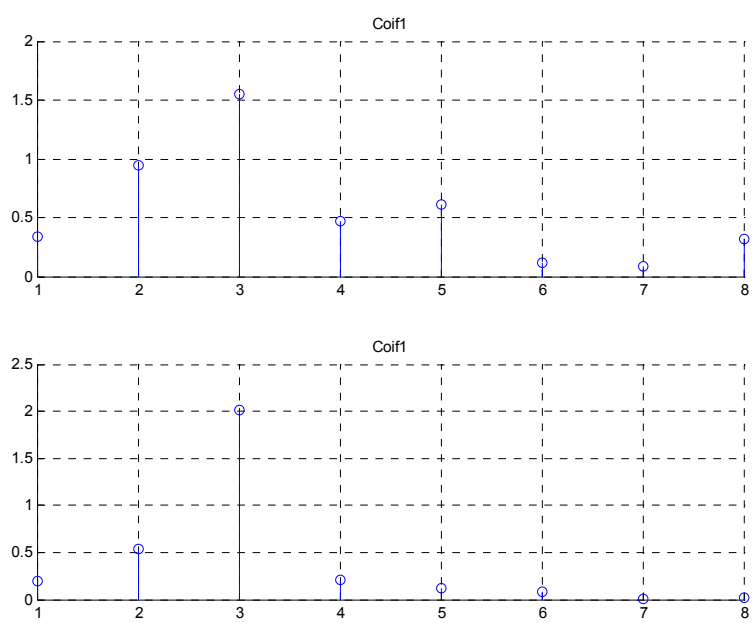


Figure 3-5: spectrum leakage of Daubechies filters. X-axis denotes nodes in Level 3 decomposition of DWPT.

It is clear from figure 3.5 that coif1 has more leakage than coif5.

3.5.2 Scaling Property

It is very important to check this property for any digital filter. It basically checks if the output is 'proportional' to the input. This property ensures that the filter does not have any inconsistencies and with the including of appropriate scaling/correction factor, it can be used for real time measurements.

To check the scaling property of coif5, two signals; one with double the amplitude of other was processed using coif5 wavelet filter and its scalability was tested. It was found that the ratio between the resultant coefficients of the two filters is exactly two. This makes the selected filter more suitable for data acquisition. The following table depicts the scaling property more clearly.

Table 3.3: Peak voltages at 8 nodes of DWPT decomposition using coif5

X=1*sin(2*pi*60*t)	X=2*sin(2*pi*60*t)
V1peak = 1.0444	V1peak =2.0888
V2peak =0.0684	V2peak =0.1369
V3peak =0.0155	V3peak =0.0310
V4peak =0.0053	V4peak =0.0107
V5peak =0.0037	V5peak =0.0073
V6peak =0.0022	V6peak =0.0045
V7peak =9.2321e-004	V7peak =0.0018
V8peak =3.7354e-004	V8peak =7.4708e-004

The above steps ensure that when implemented in a DSP, the selected wavelet 'coif5' is suitable for data acquisition and measurement purpose.

CHAPTER 4
PROPOSAL OF A NOVEL POWER QUALITY INDEX

4.1 Introduction

The system operators have the responsibility to deliver electric power in accordance with the standards set by their clients. With ever increasing number of sensitive power customers, reporting about quality of power back and forth between customers and system operators has increased. In order to characterize quality of power being supplied and received by customers, there is a need to develop standards, preferably common one which is accepted world wide. The development of such an index will remove any differences that may arise between the supplier and customer.

An ideal power quality index should be able to summarize the degree of distortion present in a system Also, to avoid ambiguity the number of indices should be kept at minimum. [9] It should

- be as simple as possible and easily interpretable by layman.
- Representative of the actual distortion and its impact
- Readily implementable in practical equipment.
- Valid for all topologies and conditions.
- Allow comparisons of performance in time-domain.

4.2 Power Quality Indices

Most of the PQ indices are proposed long back and some of them have been developed for other applications. With increasing importance given to PQ and huge distortions found in present day power systems some of them do not exactly characterize the distortion. Furthermore, they are not applicable to many cases and violate electric

engineering principles in some of the cases. A list of power quality indices is provided in the following table [10]

Table 4-1: Summary of power quality indices

Index	Definition/Formula	Application
Total Harmonic Distortion	$\sqrt{\sum_{i=2}^{\infty} I_i} / I_i$	General purpose
Power Factor	$P_{tot}/(\lvert V_{rms}\rvert * \lvert I_{rms}\rvert)$	General purpose; Revenue metering
Telephone Influence Factor	$W_i \sqrt{\sum_{i=2}^{\infty} I_i} / I_{rms}$	Audio circuit interference
C message Index	$C_i \sqrt{\sum_{i=2}^{\infty} I_i} / I_{rms}$	Communications interference
IT product	$\sqrt{\sum_{i=1}^{\infty} (I_i W_i)^2}$	Audio circuit interference; Shunt capacitor stress
VT product	$\sqrt{\sum_{i=1}^{\infty} (V_i W_i)^2}$	Voltage distortion index
K factor	$\sum_{h=1}^{\infty} h^2 I_h^2 / \sum_{h=1}^{\infty} I_h^2$	Transformer derating
Crest factor	V_{peak}/V_{rms}	Dielectric stress

Many of the indices presented in the table 4.1 have evolved over a period of time and have been proposed after many years of practical observations. It is not easy to discard them from usage. Some of them are applicable to some specific purposes, while others are for general purposes. But, they fail to characterize PQ phenomena and thus

there is a need for new indices to suit the present day needs. The present thesis is a step in that direction.

4.3 Drawbacks Associated with Harmonics

4.3.1 Total Harmonic Distortion

The most popular PQ index used is total harmonic distortion (THD). [11] It is probably the most popular way of characterizing distortion due to harmonics. It is widely used not only in the field of power systems but also in the field of Electronic circuits to characterize non linearity present in a circuit/system. Unfortunately, it has some serious drawbacks.

Basically, THD is the ratio of energy content in harmonics to that of fundamental component. The term harmonics and the index associated with it i.e. THD is often used to describe perturbations present in the waveform. But, this has some serious problems if one closely examines the definition of harmonics. The term harmonics means multiples and is originated from the musical tones whose frequency is integral multiples i.e. harmonics of a fundamental tone. Similarly, in power systems, harmonics refer to frequencies that are integral multiples of fundamental frequency (60Hz/50Hz). Thus, THD becomes problematic when non-integer harmonics are present and also if the signal is aperiodic.

The other significant pitfall of THD is that all frequencies are weighed equally. The value of THD obtained is same for a signal with 5th harmonic which has the same value of a signal with 3rd harmonic. But, it is a known fact that they have different effect on power systems. THD fails to capture this information. It also fails to convey any information about phase angles of the harmonics. [12] The index is not affected by the presence of phase angles.

The other significant drawbacks include the fact that THD is not applicable when the fundamental frequency is absent. If a 60 Hz voltage is switched as in a PWM drive for an I.M. the resulting induction motor stator voltage is around 60+/-0.2 Hz. Furthermore, another serious pitfall is that it is possible to have THD excess of 100% i.e. it is theoretically possible to have THD of 140% [13]. This is not a good figure of merit because it does not make sense to say 140% THD distortion and the amount of distortion at 140% is not twice as that of 70%.

Another pitfall of THD which has some important consequences is that it does not give time domain information. For example, if a power system has time varying harmonics, THD or as a matter any other PQ index fails to capture this information. Also, it can not distinguish between harmonics with sag or swells.

4.3.2 Power Factor

The traditional definition is suitable only for fundamental component i.e. 60 Hz. Although there are some modifications of PF which exist in literature such as

$$PF= \cos(\theta)/ (\sqrt{(1+THD^2)})$$

This modification is extremely handy but when the application of THD in the field of power quality is questioned, there is a need to suggest a new change for PF definition. Also, PF fails to address the time-varying loads. In some extreme cases, PF changes from 0.5 to 0.85 lagging in 3-4 seconds. Any improvement in the definition of power factor or development of any index in this area would definitely benefit power electronic engineers who design the Power Factor Correction (PFC) devices. The importance of PFC in power quality need not be further underscored. Apart from this, it can also help to improve the revenue metering.

The following table shows some of the drawbacks of THD in terms of numbers and makes the above claims more clear.

Table 4-2: Drawbacks of THD in terms of numbers

Waveform under consideration	THD	Reason
110sin(60)+10sin(180)	9.0909%	Equal weightage to higher frequency components
110sin(60)+10sin(660)	9.0909%	
110sin(60)+10sin(660+80°)	9.0909%	Can not characterize phase angles
110sin(60)+10sin(180)+2sin(220)	9.0909% (actually Not Applicable)	Can not quantify Inter harmonics
For t=0 to 0.6 seconds 110sin(60) For t=0.6 to 0.8 seconds 110sin(60)+10sin(180) for t=0.8 to 10 seconds 110sin(60)+10sin(300)	12.86% (Not Applicable)	The answer shown is not correct as THD is not applicable to this frequency varying harmonics case. Also, the signal is aperiodic

4.3.3 Other Indices

Other factors such as VT product can also be improved. They also suffer from the same defects mentioned above. Also, K-factor summarizes the harmonic distortion into one number. The stray losses which occur due to harmonics are a small portion of the total losses for the low-order harmonics. The stray losses are so small that the increase in net loss due to it can be negligible. It means that effect of heating for a distorted current is nearly the same as the heating for a sinusoidal current with same value. There is a need for an index that can measure the heating effect of various loads.

4.4 Criterion for New Index

The above sections make it clear that there is a need for a new index for PQ applications. In order to propose a new index suitable for PQ applications we need an index which can address in both time and frequency domain. All the indices present in the literature are suitable for periodic case which possesses Fourier components. In this proposal, Wavelet Transforms are utilized to propose a novel index.

In signal processing the energy content of a particular signal is given by

$$E=\int f^2(t)\,dt$$

It is nothing but the area under the squared signal. Parseval's theorem states that energy content of a signal in time domain is equal to energy of the signal in frequency domain. It is given by

$$E=\int f^2(t)\,dt = 1/(2\prod) * \int f^2(f)\,dt.$$

where f(t) is the equation in frequency domain. This property is very handy and can be used to develop an index which gives both time domain and frequency domain information.

The energy content of a signal is chosen because it is very handy when we are dealing with aperiodic waveforms and very useful as it can characterize subharmonics, inter-harmonics, etc. present in the system. This idea of using energy content for PQ applications was proposed by A. Domijan et al. This formed a basis for research on PQ indices. Many other variants of THD were proposed based on this idea but they all suffer from THD mindset and other inherent problems associated with THD. In the present thesis, the energy of the signal is found out using wavelet transforms. Wavelets as mentioned before give both time and frequency domain information and thus can be used

to find out an index which can be analyzed in both the domains. The following section explains in detail the approach used to find out the energy of the signal

4.5 Wavelet Energy

In this thesis, the signal under investigation is decomposed using DWPT (explained in Chapter 2). The coefficients of the signal are then used to find out the energy. This process is more clearly explained with the following figure

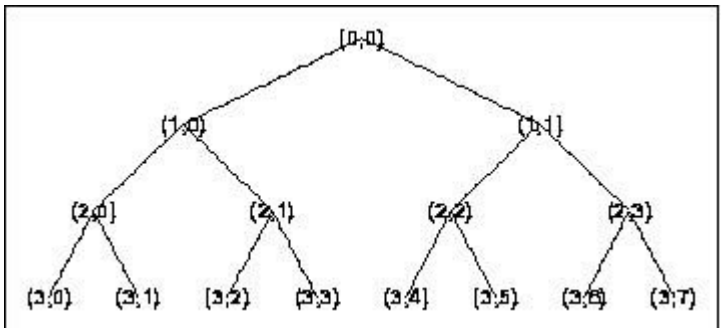


Figure 4-1 Level 3 decomposition of a signal using DWPT

The decomposition is done using the DWT. The coefficients are given by

$$C_j = \langle S, \psi_{j,k} \rangle$$

where

S (t) is the signal under consideration.

$\psi_{j,k}$ is the wavelet filter used for analysis; j denotes the level of decomposition and j gives the node in the decomposition level k.

4.5.1 Wavelet Energy in Frequency Domain

The energy of the signal [14] in each band is given by

$$E_j = \sum_k |C_j(K)|^2.$$

The total energy of the signal is thus given by

$$E_{tot} = \sum_j \sum_k |C_j(k)|^2 = \sum_j E_j \ .$$

It is always better to represent any index in normalized values, in other words, it is desirable to remove any units associated when developing any index. In this case, the present PQ index under development needs to quantify the deviation of a signal under consideration with a perfect 60Hz sinusoidal wave. Thus, normalizing the energy in each band with total energy makes sense.

The normalized energy or 'relative wavelet energy' (RWE) in each band is given by

$$P_j = \frac{E(j)}{Etot}$$

If the analyzed signal is a pure sine wave with 60 Hz then the relative wavelet energy in the band containing 60 Hz should be exactly equal to one. In other words, there should be no leakage of energy in other bands and it should be exactly concentrated in the 60Hz band.

An intuitive theory based on the above discussion can be proposed. It can be stated that if the 'relative energy' in a frequency band containing fundamental frequency component is equal to one, then harmonics are absent in the system. This statement assumes that the frequency band is as narrow as possible.

As explained, the wavelet filter selected for our application coif5 is close to ideal filter but not exactly ideal. Infact, realization of a causal ideal digital filter is not possible. The RWE for a pure 60 Hz sine wave is found out to be 0.9957 i.e. an error of 0.0043 is present. This error can be either removed by a scaling factor or it can be cleverly used in the index such that its effect is negated. The latter approach has been used here.

The following example shows the RWE for an ‘impure’ sine wave i.e. sine wave with harmonics. The sine wave under consideration is

$$100*\sin 60+10*\sin 180+10*\sin 300+5*\sin 420$$

This waveform is decomposed using DWPT up to level 3. The sampling frequency is 1920 Hz. The decomposition exactly follows the Table 3.1 and Fig 3.5.

Table 4-3 RWE in each various frequency bands

Frequency band Hz	Relative Wavelet Energy
0-120	0.9745
120-240	0.0157
240-360	0.0070
360-480	0.0022
480-600	0.0006
600-720	0.0001
720-840	0.0000
840-960	0.0000

4.5.2 Wavelet Energy in Time Domain

In order to define useful quantifiers it is very important to study the temporal evolution of the signal. The analyzed signal is divided into non overlapping windows of length L. Thus, the number of time windows for the signal is give by [14]

Number of time windows, N_t= (Total length of the analyzed signal)/ L.

The mean wavelet energy at resolution level j for time window i is given by:

$$E_j^{(i)} = \frac{1}{N_j} \sum_{k=(i-1)L+1}^{i.L} |C_j(k)|^2$$

Where N_j represents the number of wavelet coefficients at the resolution j in the time interval i. Then the total mean energy at this time window is given by

$$E_{tot} = \sum_j E_j^{(i)}$$

The relative energy in time domain is given by

$$P_j^{(i)} = \frac{E(j)^i}{Etot^i}$$

The following table shows the RWE in time domain for a pure 60 Hz sine wave which is analyzed from 0 to 1 second. The sine wave is decomposed to level 3 using DWPT with coif 5 filter bank. The total number of coefficients after decomposition at level 3 is 265, which in fact gives us the length of the signal under consideration. The window length, L is taken to be 33 and thus N t= 8 (rounded off to nearest integer). The energy for a pure sine wave is evenly distributed throughout in its time domain. But, this will definitely change when there is a sine wave with harmonics and swell or time varying harmonics. The energy will be concentrated at the time instant where swell/sag occurs and thus it can be easily distinguished.

Table 4-4 RWE in various time divisions

Time Interval (sec)	Relative Wavelet Energy
0-0.1245	0.1129
0.1245- 0.2490	0.1288
0.2490- 0.3735	0.1233
0.3735-0.4980	0.1288
0.4980-0.6225	0.1233
0.6225-0.7470	0.1288
0.7470-0.8715	0.1233
0.8715-0.99610	0.1308

4.6 Wavelet Energy Based Harmonic Detection and Classification

The following section proposes a new methodology to detect and classify the presence of harmonics in a power system. Various types of harmonics are usually found in power systems. They could be broadly classified as

1. Regular harmonics: periodic-odd, even, inter-harmonics.
2. Amplitude varying harmonics with respect to time
3. Frequency varying harmonics with respect to time.
4. Sub-harmonics
5. Harmonics with sags and swells.

There is a need to detect harmonics which occur with additional PQ events. This can help engineers in designing appropriate mitigation techniques for PQ. This can be achieved using scalograms.

Scalogram is a plot of time-frequency-energy. It is analogous to spectrogram, which is a plot of energy density surface of the short time Fourier transforms. To put, in simpler terms, scalogram is a plot of squared magnitude of the wavelet transform values. The scalogram surface highlights the location and scale of dominant energetic features within the signal.

Using DWPT, the signal under consideration is decomposed into coefficients at various bands. The energy of the signal at each band can be found out by squaring and summing all the coefficients as explained in section 4.5. The following is the procedure to be followed when plotting scalograms.

1) Using DWPT, decompose the signal under consideration into different resolutions (levels). The energy in each node can be calculated using the procedure described in section 4.4. The maximum level a signal can be decomposed is given by 2 log (M). Where, M is the discretized length of the signal under consideration. Let the Energy in each band is given by E (i)

2) Using DWPT, decompose an ideal 60Hz pure sine wave into the same number of levels as for the above mentioned signal. Let the Energy in each band is given by E1 (i)

3) The deviation of the signal from ideal behavior is found out by taking the squared difference of the energies of the above two signals as shown below:Deviation in Energy = $(E(i)-E1(i))^2$

4) A plot between nodes in a particular decomposition level with the 'Deviation in Energy' is a scalogram in frequency domain.

The plot obtained from the above procedure exactly identifies the additional frequencies present in the system. Consider a sine wave with the following equation. For

t=0 to 1 seconds with sampling frequency 1920Hz. Each band has a width of 120 Hz Therefore; the maximum frequency in the 8th band is 860.

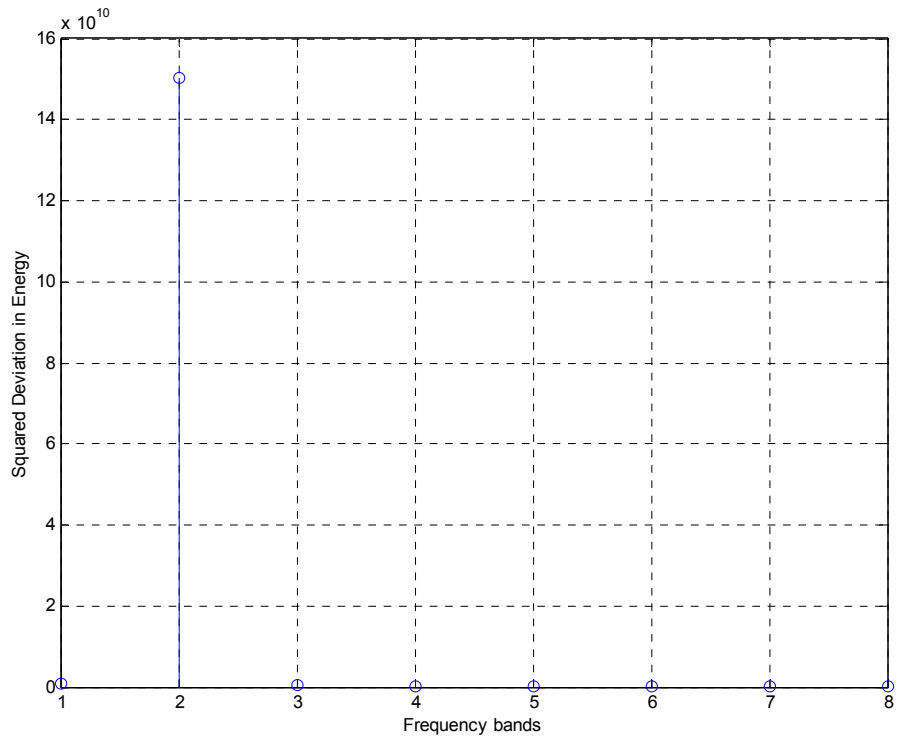


Figure 4-2: Identification of 3rd harmonic and its deviation from ideal behavior using frequency scalogram.

To detect and classify the presence of additional PQ events along with harmonics there is a need to draw a scalogram in time domain. This will aid in detecting any other PQ events occurring with harmonics or even if the harmonics are amplitude changing or frequency changing with time. This is extremely useful in detecting harmonics with sags/swells, amplitude varying harmonics and frequency varying harmonics.

Advantages:

1) This is very handy in PQ instrumentation as it has the capabilities of classifying the PQ events.

2) The squared deviation of energy gives how much the wave is distorted and the deviation from ideal behavior.

3) While implementing in a Digital Signal Processor (DSP), automatic detection can be done using simple pattern recognition algorithm [15].

4) This can be used for both PQ classification and detection.

5) In fact, the above energy deviation can also be called an 'index'. Though an unconventional index that is measured/calculated using graphs.

4.7 Signal Energy Distortion

A more conventional index based on the above principle is presented in this section. This index, which we call, signal energy distortion (SED) tries to condense the information of a signal under analysis into a single number.

The signal energy distortion is given by

$$SED=\sum (P(i)-P1(i))$$

where

i is the number of nodes in decomposition level j.

or, Max number of harmonics present

P=RWE in each node for a signal under consideration.

P1=RWE in each node for a pure 60Hz sinusoidal wave.

The above index gives the deviation in frequency domain of a sine wave from a pure 60Hz sine wave.

To capture time domain information, the following formulae are very helpful:

$DEV_{time}(i) = P(i)-P(i+1)$

If $DEV_{time}(i) = 0$ for all i, then harmonics not varying with time

else,

$SED_{time}(i) = P(i) - P1(i)$, gives the deviation due to additional PQ events occur.

While, SED gives the distortion in the waveform under consideration, SED_{time} gives the time instant or time range where additional PQ events along with harmonics took place.

In other words, SED_{time} is extremely helpful to capture the PQ events which occur along with harmonics. There are instances where it has been observed that 2 or more PQ events take place simultaneously. PQ monitoring for over 6 months of time at the Dairy Research Unit (DRU) for a period of 6 months by the Power Quality Laboratory at the University of Florida reinforces the same fact. It is very common to see:

- Harmonics along with sags and swells.
- Frequency changing harmonics with time
- Time varying harmonics.

Advantages:

1. It is applicable for aperiodic waveforms.

2. It accelerates with frequency i.e. it gives weightage according to effect of a particular frequency component on frequency component.

3. It gives time domain information regarding additional PQ events occurring with Harmonics.

4. Obtaining a value more than 100% distortion is not possible unlike, THD.

5. A fresh look at the problem instead of traditional THD and its variants.

This index is critically evaluated and tested on all permutations of test cases in next section.

CHAPTER 5
CRITICAL EVALUATION OF THE PROPOSED METHOD

A detailed theoretical idea to the methodology proposed to classify and detect harmonics was presented in the last chapter. Furthermore, a novel index based on the same methodology was also proposed. The index proposed in this thesis is critically evaluated in this chapter. It is an undeniable fact that the veracity of any theory proposed in an engineering field has to be proven by extensive testing under various conditions. The methodology proposed in this thesis is tested under simulated conditions. Using MATLAB a variety of cases are generated and tested on the various algorithms developed.

5.1 Test Cases

To evaluate the indices proposed, various test cases were generated using MATLAB. The following are the test cases:

1. Periodic cases
   - Odd and even harmonics, inter-harmonics, sub-harmonics.
2. Aperodic cases
   - Harmonics with additional PQ events such as sags/swells
   - Time varying harmonics (amplitudes of harmonics that change with time)
   - Frequency varying harmonics (harmonics with different frequencies at different instances of time)

All these test cases were generated in MATLAB. The algorithms were developed using 'Wavelet Tool Box' in MATLAB.

5.2 Detection and Classification of Harmonics

Wavelet Energy based detection and classification was introduced formally in section 4.6. Also, a systematic procedure required to draw scalograms was explained.

Furthermore, scalogram based detection and classification was also demonstrated with examples. In the present chapter, this methodology is thoroughly investigated with the following test cases. In all the test cases the following frequency ranges were used:

Table 5-1: Frequency bands corresponding to DWPT nodes at level 3 decomposition

Node	Frequency Range Hz.	Center Frequency Hz.
1	0-120	60
2	120-240	180
3	240-360	300
4	360-480	420
5	480-600	540
6	600-720	660
7	720-840	780
8	840-960	900

In all the test cases the following time windows were used

Table 5-2: Time ranges corresponding to the time windows of each node decomposed

Time Window	Time Range Seconds	Time instant (average) Seconds.
1	0-0.1	0.05
2	0.1-0.2	0.15
3	0.2-0.3	0.25
4	0.3-0.4	0.35
5	0.4-0.5	0.45
6	0.5-0.6	0.55
7	0.6-0.7	0.65
8	0.7-0.8	0.75
9	0.8-0.9	0.85
10	0.9-1.0	0.95

5.2.1. Periodic Test Cases

5.2.1.1 Waveform with regular harmonics i.e. odd and even harmonics

Test conditions:

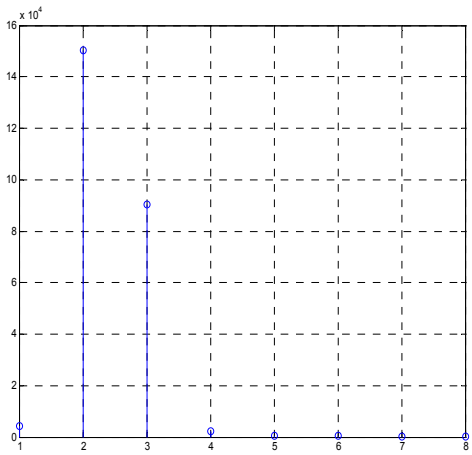
Waveform: 110sin60+11sin180+11sin300

Sampling frequency=1920Hz

Decomposition level=3

Number of nodes =2^3 =8.

Frequency in each band= 0-120 Hz in first band and so on till 860Hz in 8th band.



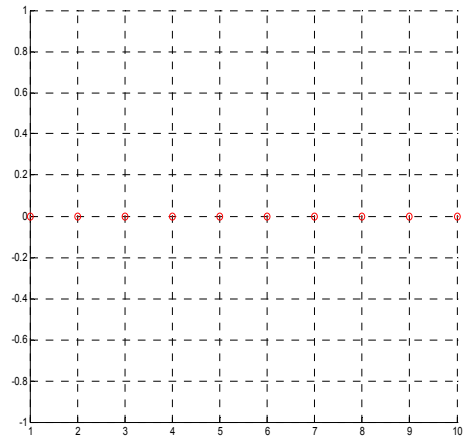


Fig 5.1 (a) **Fig 5.1 (b)**

Figure 5-1 (a) X-axis Frequency bands (1-8) Y-axis Squared Energy Deviation, 5.1 (b) X-axis: Time intervals (1-10) Y-axis Squared Energy deviation

5.2.1.2 Explanation

In the 'frequency-energy deviation' scalogram, the deviation in 2nd and 3rd bands can be clearly seen. The centre frequencies of 2nd and 3rd bands correspond to 180 and 300Hz respectively. Furthermore, there is no deviation in time domain. This indicates that, there are no additional PQ events along with harmonics.

5.2.2. Harmonics with Additional PQ events

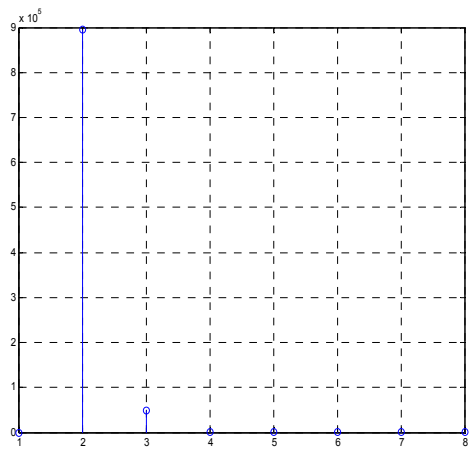
5.2.2.1 Harmonics with sags and swells

Test conditions are the same as above i.e. 5.2.1.a1The following is the equation of the waveform

t=0 to 0.6 seconds; X= 110sin60+10sin180

t=0.6 to 0.8 seconds; X=140sin60+10sin180

t=0.8 to 1 seconds; X=110sin60+10sin180.



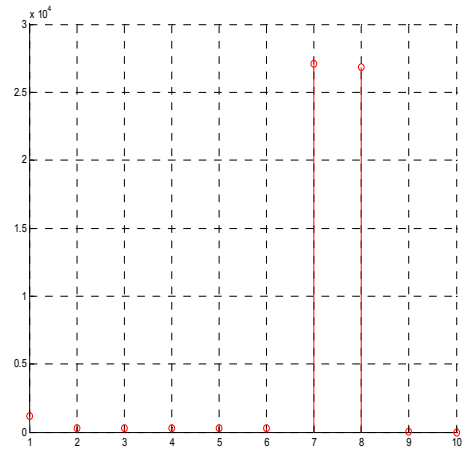


Fig 5.2 (a) **Fig 5.2 (b)**

Figure 5-2 (a) X-axis Frequency bands (1-8) Y-axis Squared Energy Deviation 5.2 (b) X-axis: Time intervals (1-10) Y-axis Squared Energy deviation

5.2.2.2 Explanation

In the 'frequency-energy deviation' scalogram, the deviation in 2nd band can be clearly seen. The central frequency of 2nd band is 180Hz. But this does not show that there is a swell. Time-Energy scalogram is useful here. There is a deviation in time domain at 7th, 8th interval i.e. from 0.6 seconds to 0.8 seconds and the energy is also positive. This indicates that there is a swell from 0.6 to 0.8 seconds. Thus, by using a very simple pattern recognition algorithm one can classify harmonics.

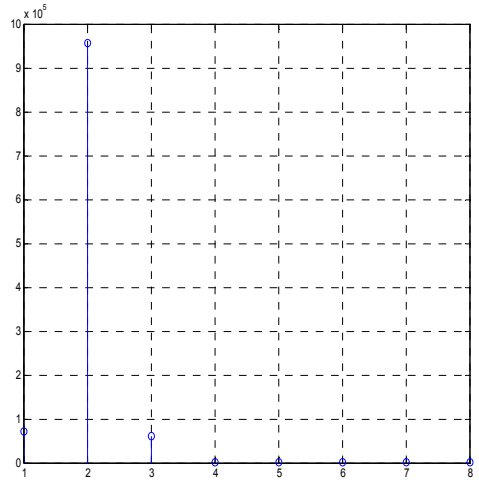
5.2.2.3 Amplitude varying harmonics

Test conditions are the same as above. The waveform under consideration is as follows:

Time, t1=0 to 0.6 seconds; x1=110sin60

t2=0.6 to 0.8 seconds; x2=110sin60+30sin180

t3=0.8 to 1.0 seconds; x3=110sin60+60sin180.



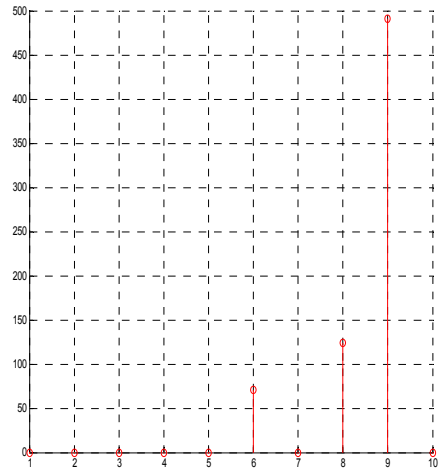


Fig 5.3 (a) **Fig 5.3 (b)**

Figure 5-3 (a) X-axis Frequency bands (1-8) Y-axis Squared Energy Deviation 5.3 (b) X-axis: Time intervals (1-10) Y-axis Squared Energy deviation

5.2.2.4 Explanation

In the 'frequency-energy deviation' scalogram, the deviation in 2nd band can be clearly seen. The central frequency of 2nd band is 180Hz. Furthermore, there is a deviation in time domain at 6th, 7th, 8th, 9th interval i.e. from 0.6 seconds to 0.8 seconds and the energy is also increases with increasing harmonic amplitude. This indicates that amplitude varying harmonics are present.

5.2.2.5 Frequency Harmonics with respect to time.

Test conditions are the same as above i.e. 5.2.1.a1

The following is the equation of the waveform

t=0 to 0.5 seconds; X= 110sin60+30sin420

t=0.5 to 0.8 seconds; X=110sin60+30sin300

t=0.8 to 1 seconds; X=110sin60+30sin300.

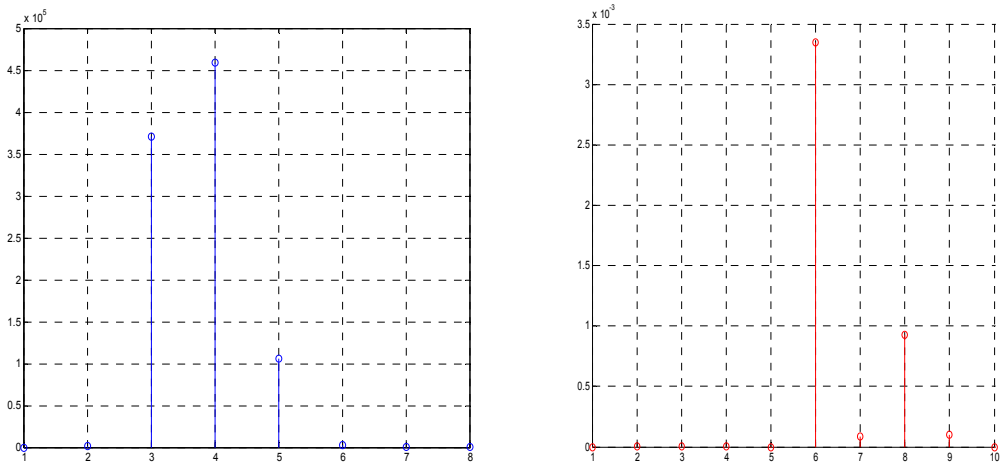


Figure 5-4 (a) X-axis frequency bands (1-8) Y-axis squared energy deviation 5.4 (b) X-axis: time intervals (1-10) Y-axis squared energy deviation

5.2.2.6 Explanation

In the 'frequency-energy deviation' scalogram, the deviation in 3rd and 4th bands can be clearly seen. The central frequencies of 3rd and 4th band are 300Hz and 420 Hz. respectively. Furthermore, there is a deviation in time domain at 6thand 9th interval i.e. at 0.6 seconds and 0.8 seconds. This indicates that frequency varying harmonics are present and the time instant at which it takes place can also be captured.

5.3 Signal Energy Distortion

Signal energy distortion (SED) condenses the information of a waveform under analysis into one number. This idea behind the index and its advantages were mentioned in the previous chapter. In the current chapter it is tested under various test conditions mentioned in section 4.1.

5.3.1. Periodic Test Cases

5.3.1.1 Waveform with regular harmonics i.e. odd and even harmonics

Test conditions:

Sampling Frequency=1920Hz

Decomposition Level=3

Number of nodes $=2^3=8$.

Frequency in each band= 0-120 Hz in first band and so on till 860Hz in 8th band.

Table 5-3: Comparison between THD and SED for various waveforms

Waveform	THD %	SED %	DEV_{time}	$SED_{(time)}$ %	Comments
t=0 to 1 seconds 110sin60+11sin740+11sin420	14.14	1.91	-	Not Required	No Additional PQ events
t=0 to 1 seconds 110sin60+11sin300+11sin420	14.14	1.87	-	-do-	No change in THD
t=0 to 1 seconds 110sin60+11sin433+11sin515	N.A	1.90	-	-do-	THD not applicable for interhamronics

5.3.2. Harmonics with additional PQ events

Test conditions:

Sampling Frequency=1920Hz

Decomposition Level=3

Number of nodes $=2^3=8$.

Frequency in each band= 0-120 Hz in first band and so on till 860Hz in 8th band.

Table 5-4: Performance of SED for harmonics with additional PQ events

Waveform	SED %	DEV $_{time}$	$SED_{(time)}$ %	Comments
t=0 to 0.6 seconds X= 110sin60+10sin180 t=0.6 to 0.8 seconds X=140sin60+10sin180 t=0.8 to 1 seconds X=110sin60+10sin180.	6.22	7th and 8th time window	SED_7=4.11 SED_8=4.08	Additional PQ events found in 6th and 7th time window The deviation of signal from ideal behavior is given by $SED_{(time)}$
t=0 to 0.6 seconds X= 110sin60 t=0.6 to 0.8 seconds X=110sin60+30sin180 t=0.8 to 1 seconds X=110sin60+60sin180.	7.32	7th and 9th time window i.e. it tracks time instant where the change energy takes place	SED_7=1.36 SED_9=3.12	Additional PQ events found in 7th and 9th time window Amplitude varying harmonics is found
t=0 to 0.6 seconds X= 110sin60+30sin420 t=0.6 to 0.8 seconds; X=110sin60+30sin300 t=0.8 to 1 seconds X=110sin60+30sin300.	6.83	6th and 7th time window.	SED_6=0.22 SED_7=0.33	Frequency varying harmonics were found. Their deviation in time domain is found to be less. As harmonics change form 420 to 300.

CHAPTER 6
EPILOGUE

6.1 Conclusions

The energy deviation based index and harmonic classification methodology proposed is extremely handy for PQ instrumentation. The proposed index has been shown in chapter 5 to be far better than THD. It overcomes the limitations posed by THD and it is more apt for PQ than THD.

Furthermore, the unique ability of SED to give time domain information and knowledge about additional PQ disturbances, present along with harmonics, is extremely helpful for developing appropriate PQ mitigation techniques. Also, the algorithm proposed for this approach is extremely robust and fast. This algorithm can be programmed on a Digital Signal Processor (DSP) and can be used for real time monitoring of PQ.

The proposed index has many advantages over traditional variations of THD suggested by various researchers. One achievement of the proposed index is that it does not suffer from THD mindset. The index proposed satisfies all the basic electrical engineering principles and quantifies the harmonic distortion using the energy content of the signal.

In summary, the advantages of the new index and classification methodology proposed are as follows:

- It gives deviation in both frequency and time domain.

- A single algorithm detects, classifies and quantifies harmonics present in a power system.
- The proposed algorithm is fast, robust and easy to implement in a DSP.
- It is suitable for real-time monitoring.
- It is suitable for aperiodic signals and gives weightage to higher frequency components depending upon the signal deviation it causes.

6.2 Further Work

Signal Energy Distortion (SED) as a measure of harmonics present in a system has been proposed and supported in this thesis through simulations. This idea (methodology) can to be implemented in a DSP. It requires any where between 3-4 months to implement this idea in a DSP board.

The suggested pattern recognition algorithm has to be developed. This has to be developed prior to implementation of the proposed methodology in a DSP.

Furthermore, empirical testing should be done for a long period of time so as to find out what value of SED is bad for the distribution system or transmission system.

THD is used as a linearity indicator in microelectronic circuits, it posses several problems in electronic circuits as well. A study about its drawbacks and the possible application of SED to it should be studied in detail.

Shannon's Entropy gives a measure of order/disorder of the signal [(14)]. This can give us the deviation of an analyzed signal from a pure 60Hz sine wave. This has to be further investigated and studied in detail as it gives a number for distortion. This is used as a distortion indicator in the field of communications and signal processing. Its application for power quality has to be exploited in detail.

6.3 Afterpiece

This thesis is an attempt towards achieving better PQ indices or possibly one index which can sum up all the information in a single number. There is a tradeoff here: More the preciseness of information we are looking for, lesser the clarity. In other words, the ambiguity of the index increases with increasing information one is seeking to get.

There is an urgent need among the researchers and engineers throughout the world to debate the pros and cons of the existing indices. Although, a need for new PQ indices has been identified by A. Domijan, G.T. Heydt and others back in 1993. There has been little work in this direction and even the debate started by them is abating slowly. Joseph Joubert said

> *"It is better to debate a question without settling it than to settle a question without debating it."*

I am in full agreement with him. It is better to have a debate on PQ indices even without settling to one. It is often difficult to come up with an index in a short period of time yet, a debate in this direction would make engineers more aware of the pitfalls of the indices while applying them.

LIST OF REFERENCES

1. Dugan R.C., McGranaghan M.F., Beaty H.W., Electric Power Quality, McGraw-Hill, New York, 1996.

2. Domijan A., Heydt G.T., Meliopoulos A.P.S., Venkata S.S., West S., Directions of research on power quality, IEEE Transactions on Power Delivery 8(1), 1993, 429-436.

3. Addison P.S., The Illustrated Wavelet Transform Handbook: Introductory Theory and Applications in Science, Engineering, Medicine and Finance, IOP Publishing, Ltd, Bristol, 2002.

4. Goswami J.C., Chan A.K., Fundamentals of Wavelets: Theory, Algorithms and Applications, John Wiley & Sons & Inc, New York, 1999.

5. Hamid E.Y., Mardiana R., Kawasaki Z.I., Wavelet-based compression of power disturbances using the minimum description length criterion, IEEE Power Engineering Society Summer Meeting 2002, Volume 3, 2001, 1772-1777.

6. El-Saadany E.F., Abdel-Galil T.K., Salama M.M.A., Application of wavelet transform for assessing power quality in medium voltage distribution system, Transmission and Distribution Conference and Exposition, 2001 IEEE/PES, Volume 1, 2001,

7. Pham V.L., Wong K.P, Antidistortion method for wavelet transform filter banks and nonstationary power system waveform harmonic analysis, IEE proceedings Generation, Transmission and Distribution, 148 (2), 2001,

8. Jensen A, La-Cour Harbo A, Ripples in Mathematics- The Discrete Wavelet Transform, Springler Verlag, Berlin, 2001.

9. Heydt G.T, Jewell W.T, Pitfalls of electric power quality indices, IEEE Transactions on Power Delivery, 13 (2), 1998, 570-578.

10. Beaulieu G, Bollen M.H.J, Malgarotti S, Ball R and other CIGRE working group 36-07 members, Power quality indices and objectives ongoing activities in CIGRE WG 36-07, IEEE Power Engineering Society Summer Meeting 2002, 2(21-25),789-794.

11. Heydt G.T., Problematic power quality indices, IEEE Power Engineering Society Winter Meeting, 4, 2000, 2838-2842.

12. Domijan A., Shaiq M., A new criterion based on the wavelet transform for power quality studies and waveform feature localization, ASHREA Transaction, 104, 1998, 3-16.

13. Gruzs T.M., Uncertainties in compliance with harmonic current distortion limits in electric power systems, IEEE Transactions on Industrial Applications, 27(4), 1991, 680-685.

14. Rosso O.A., Blanco S., Yordanova J., Kolev V., Figlioa A., Schurman M., Basar E., Wavelet entropy: A new tool for analysis of short duration brain electrical signals, Journal of Neuroscience Methods, 105, 2001, pp-65-75.

15. Gaouda A.M., Salama M.M.A., Sultan M.R., Chikhani A.Y., Power quality detection and classification using wavelet multi-resolution signal decomposition, IEEE Transactions on Power Delivery, 14(4), 1999, 1469-1475.

BIOGRAPHICAL SKETCH

Ajay Karthik Hari obtained his Bachelor of Technology degree in electrical and electronics engineering from Jawaharlal Nehru Technological University (JNTU), India, in June 2001. While working on his bachelor's degree, he was secretary of Electrical Technical Association (ETA). Starting from fall 2001, he is pursuing the Master of Science degree in electrical and computer engineering at the University of Florida. His research interests include advanced signal processing, power quality and power ICs. His other interests include politics, current affairs and quizzing. He was a member of Youth Parliament team in India, which won first prize for the year 1994.