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Power Quality Monitoring Using LabView

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ABSTRACT

In recent years, Power Quality becomes increasingly a major concern for both electric utilities and end users. Accordingly, the electrical engineering community has to deal with the analysis, diagnosis and solution of PQ issues using system approach rather than handling these issues as individual problems.

This project describes the analysis of PQ using advanced signal processing tools represented in Hilbert & Wavelet Transforms (HT-WT) and artificial intelligence tools represented in Artificial Neural Network & Support Vector Machine (ANN-SVM) for detection and classification of power quality disturbances respectively. These techniques were successfully simulated using LabVIEW software capabilities.

The results of simulation indicate that the proposed techniques are effective mechanisms to detect and classify power quality disturbances. At the end, the combination of WT as a tool of detection and features extraction with SVM as a classifier tool resulted as the best combination for PQ monitoring system.

DEDICATION

To our parents, brothers & sisters for their presence beside us always when needed

and for their continued support

To our colleagues, friends and everyone who shared with us moments of our lives

To our teachers for providing us with all the required knowledge

This modest work is dedicated to you

ACKNOWLDGEMENTS

First, all praise to ALLAH

We thank ALLAH for all His blessing & strength that He gave us to complete this project

Second, "Who did not thank people; did not thank ALLAH"

We would like to express our thanks and graduated to our supervisor Dr F.RECIOUI for Her encouragement, guidance & support during our work.

Finally, all the thank to everyone who support, helped or contributed in this project

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

PQ	Power Quality.
PQD	Power Quality Disturbances
PQM	Power Quality Monitoring
IEEE	Institute of Electrical & Electronic Engineers
ANSI	American National Standards Institute
WT	Wavelet Transform
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
DWC	Discrete Wavelet Coefficients
MRA	Multi Resolution Analysis
HT	Hilbert Transform.
NN	Neural Network
ANN	Artificial Neural Network
FFNN	Feed-Forward Neural Network
RNN	Recurrent Neural Network
SV	Support Vector
SVM	Support Vector Machine
ST	Stock well Transform
CZT	Chrip Z-Transform
FT	Fourier Transform
DT	Decision Tree
FL	Fuzzy Logic
HP & LP	High Pass & Low Pass Filters
RMS	Root Mean Square
THD	Total Harmonic Distortion

GENERAL INTRODUCTION

Power quality is known as one of the very serious issues in electric power transmission and distribution, manufacturers and end users because of its bad effects on electricity suppliers.

Power quality is a term of many meanings; each meaning relies on the reference to which it is attributed. For example, a utility may define power quality as reliability of its system. A manufacturer of load equipment may define power quality as those features of the power supply that enable the equipment to work properly. The end user's point of view of power quality is that any power problem manifested in voltage, current, or frequency deviations that result in failure or malfunction of customer equipment [**1**].

Power quality is generally meant to express the quality of voltage and/or the quality of current which can be defined as: the measure, analysis, and improvement of the bus voltage to maintain a sinusoidal waveform at rated voltage and frequency; This definition includes all momentary and steady-state phenomena [**2**].

All electrical devices are likely to fail or not work properly when exposed to one or more power quality problems; these devices react negatively to power quality issues, depending on the severity of problems. A simpler and may be more concise definition might state: “Power quality is a set of electrical boundaries that allows a piece of equipment to function in its intended manner without significant loss of performance or life expectancy.” This definition contains things needed from electrical devices which are performance and life expectancy [**3**].

It is common experience that electric power of poor quality has harmful effects on different equipment and systems. More than that, power system stability, continuity and reliability fall with the degradation of quality of electric power [**4**].

There are four main reasons for engineers to increase concern about the need for energy quality [**1**]:

1. Newer-generation load equipment, with microprocessor-based controls and power electronic devices, are more sensitive to power quality variations than was equipment used in the past.
2. The increasing focus on overall power system efficiency has resulted in continued growth in the use of devices such as high-frequency, adjustable-speed motor drives and shunt capacitors for power factor correction to reduce losses. This is resulting in increasing harmonic levels on power systems and has many people worried about the future effect on system abilities.
3. End users have an increased knowledge of power quality issues. Utility customers are becoming better informed about such issues as interruptions, sags, and switching transients and are challenging the utilities to improve the quality of power delivered.
4. Many things are now interconnected in a network. Integrated processes mean that the failure of any part has much more important results.

The common thread running through all these reasons for increased concern about the quality of electric power is the continued push for increasing productivity for all utility customers. Manufacturers want faster, more productive, more efficient machinery. Utilities encourage this effort because it helps their customers become more beneficial and also helps put off large investments in substations and generation by using more efficient load equipments. Interestingly, the equipment installed to increase the productivity is also often the equipment that suffers the most from common power disturbances. And the equipment is sometimes the source of adding more power quality problems. When whole processes are automated, the efficient operation of machines and their controls becomes more and more dependent on quality power [**1**].

The power system faces many issues; some of them shut it down causing a blackout of the network, the main problems that can cause harm to the power system are:

- Voltage sag or dip.
- Very short interruptions.
- Long interruptions.
- Voltage spike.

- Transient.
- Voltages swell.
- Harmonic distortion.
- Voltage fluctuation.
- Noise.
- Voltage unbalance.

Power quality disturbances have become a serious issue in power world, and this is because of the great damage that they caused to the system from the generation to the end users. For this reasons a power quality monitoring system must be included in the electrical network in order to: detect, classify and mitigate these problems.

Many researches have focused their attention on this goal, on how to create a monitoring system capable of detecting the disturbances the moment they appear and then classify them according to their parameters.

Detection techniques are numerous, each one distinct from the others; but the fastness time response to detect the disturbance is the major concern of all the studies.

Classification is also an important step in the monitoring, after the system detects a disturbance it must be recognized. The objective of the classifier is to identify the events and must have a perfect percentage of accuracy and precision.

In this project a power quality monitoring system is going to be presented, detection and classification techniques are introduced in order to solve part of power system problem. The work will be divided into the following sections: Chapter 1 gives definition of power quality problems and their causes and effects. Chapter 2 presents the detection and classification methods used in this project and explains them extensively: basics, advantages, and types of each method. Chapter 3 deals with the simulation part: proposed methods for simulating, results of the detection and classification of PQD and discussing these results. Finally, a general conclusion and future work are presented.

1.1 Introduction

Power quality involves voltage and frequency waveform, electricity need to travel from the generator to the transmission lines till it reaches the end users. In real life no electrical signal is pure; it must contain at least one of these disturbances that are frequently appearing in the voltage signal.

The Power Quality problems to be examined are transients, short term and Long-Duration Voltage Variations, harmonic distortion, Voltage unbalance, and Voltage Fluctuations. In this chapter each disturbance will be treated alone, definitions, causes and effects on the power system.

1.2 Types of power quality disturbances

1.2.1 Transients

The term transient in the point of view of an engineer is the short-duration oscillatory or non-oscillatory event which is undesirable and usually highly damped. Based on waveform shape of a current or voltage; Power system transients, can be classified into [**1**]:

a) Impulsive transients

An impulsive transient is a sudden non-power frequency change in the steady-state condition of voltage, current, or both that is unidirectional in polarity (primarily either positive or negative). Impulsive transients are usually characterized by their rise and decay times, which can also be showed by their spectral content [**1**]. Figure (1-1) illustrates a typical current impulsive transient caused by lightning.

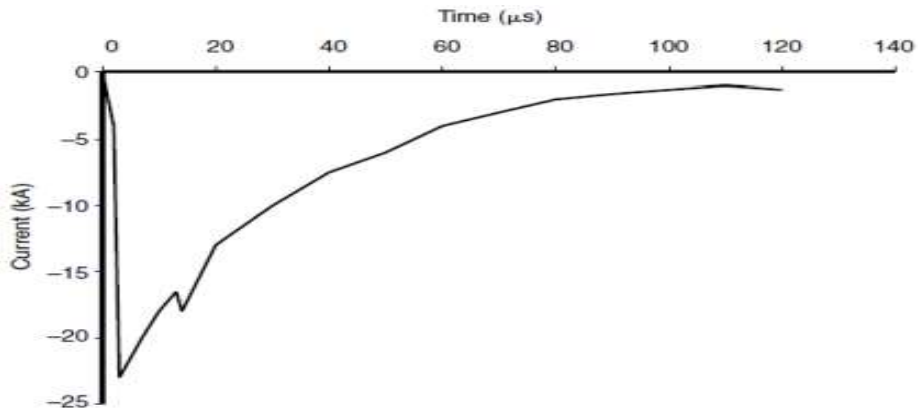


Fig 1-1 Typical current impulsive transient caused by lightning

b) Oscillatory transients

An oscillatory transient is a sudden, non–power frequency change in the steady-state condition of voltage, current, or both, that includes both positive and negative polarity values. An oscillatory transient consists of a voltage or current whose instantaneous value changes polarity rapidly. It is described by its spectral content (predominate frequency), duration, and magnitude [**1**]. Figure (1-2) illustrates an oscillatory transient current caused by back-to-back capacitor switching.

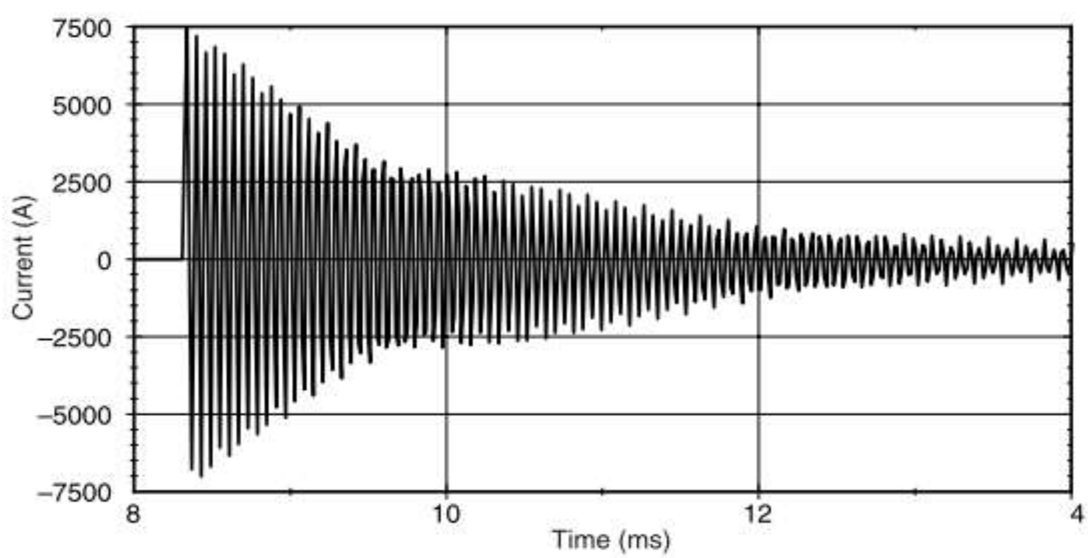


Fig 1-2 Oscillatory transient current caused by back-to-back capacitor switching.

There are different causes for power system transients. For example, lightning strokes to the wires in the power system or to ground and component switching either of network components or end user equipment. These transients can affect the power system either in operation or performance of different part of it, during a transient a high current passes in the circuit, this high current can burn out devices and instruments; Transients can cause mal-operation of relays and mal-tripping of circuit breakers. Frequent number of direct or indirectly induced oscillatory transients may change the magnetic properties of core materials used in electric machines [**5**].

1.2.2 Short-duration voltage variations

There are three types of short-duration voltage variations, namely, instantaneous, momentary and temporary, depending on its duration. Each category is divided into interruption, sag, and swell. Principal cases of short-duration voltage variations are large load energization, fault conditions, and loose connections [**2**].

a) Voltage Sag (Dip)

IEEE defines voltage sags as a reduction in voltage for a short time; this reduction is between 10 percent and 90 percent of the normal root mean square (rms) voltage. The duration of voltage sag is less than 1 minute but more than 8 milliseconds (0.5 cycles) [**4**]. Figure (1-3) shows a voltage sag signal.

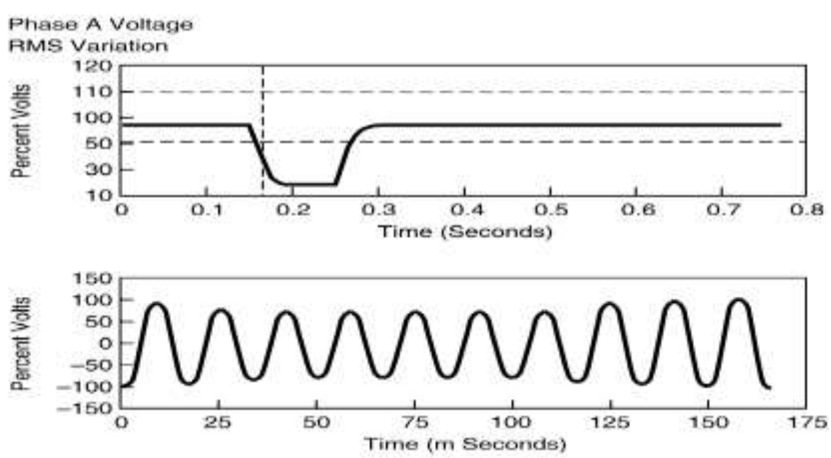


Fig 1-3 Voltage Sag signal

b) Voltage Swell

Voltage swells, or momentary overvoltages, are rms voltage variations that exceed 110 percent of the nominal voltage and last for less than 1minute [**4**]. Figure (1-4) shows a typical voltage swell signal.

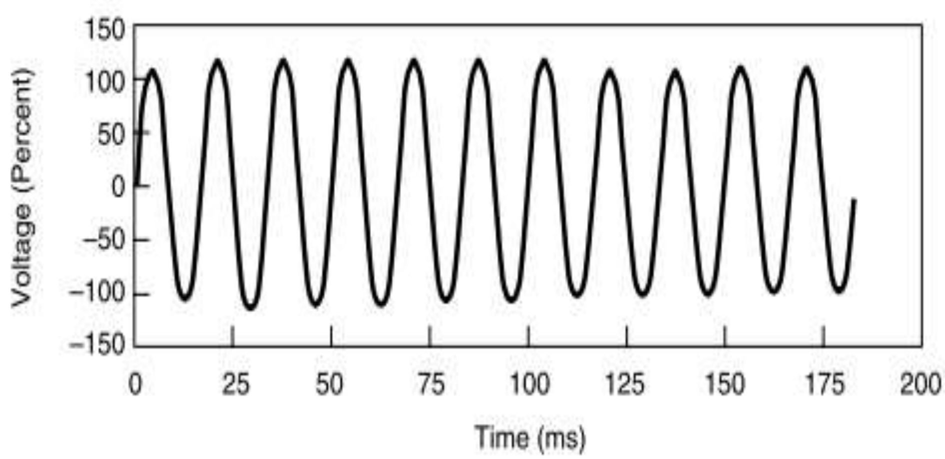


Fig 1-4 Typical voltage swell signal

There are many causes of voltage sags [**5**]:

- Energization of heavy loads.
- Starting of large induction motors.
- Single line-to-ground faults.
- Line-line and symmetrical fault.
- Load transferring from one power source to another.

As well as for voltage swells:

- Switching off of a large load.
- Energizing a capacitor bank.
- Voltage increase of the unfaulted phases during a single line-to-ground fault.

These causes affect the power system and their results are [**5**]:

- Voltage stability because of reduction of bus voltage for short duration.
- Electrical low-voltage devices will not work correctly.
- Malfunctions of uninterruptible power supply.

- Malfunction of measuring and control equipment.
- Interfacing with communication signals.

c) Interruptions

Interruptions are a complete loss of voltage (a drop to less than 10 percent of nominal voltage) in one or more phases. IEEE defines three types of interruptions according to the time of their occurrence: momentary, temporary, and long-duration interruptions. Momentary interruptions are the complete loss of voltage on one or more phase conductors for a time period between 8 milliseconds and 3 seconds. A temporary, or short-duration, interruption is a drop of voltage below 10 percent of the nominal voltage for a time period more than 3 seconds and less than 1 minute. Long-duration, or sustained, interruptions last longer than 1 minute [**4**]. Figure (1-5) shows the three interruptions types.

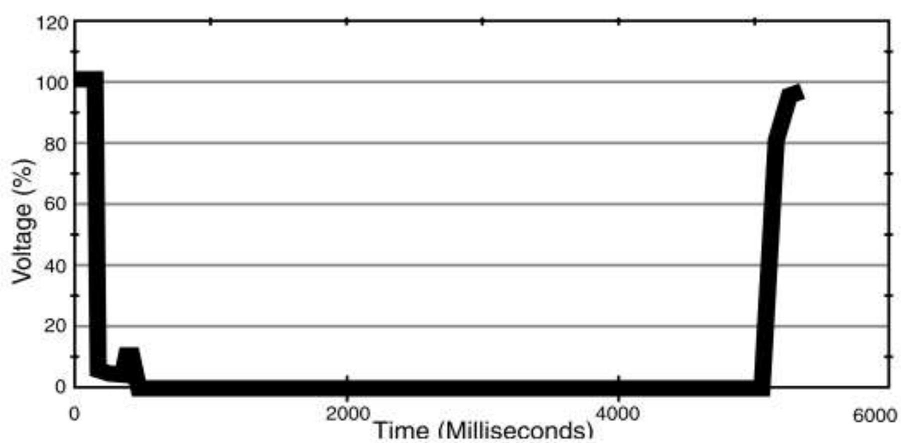


Fig 1-5 Interruptions types (momentary, temporary, and long-duration)

There are many reasons for power interruption. Some of the general causes of interruption are [**5**]:

- Equipment failures.
- Control malfunction.
- Blown fuse.
- Breaker opening.

Interruptions can cause a loss of production, for the factories loss of production is loss of money and loss of time will lead to bad results [**4**].

1.2.3 Long-duration voltage variations

Long-duration variations can be either overvoltages or undervoltages. They contain RMS deviations at power frequencies for a period of time longer than 1 min. They are usually not caused by system faults but system switching operations and load variations on the system [**1**].

a) Undervoltages

An undervoltage is a decrease in the rms ac voltage to less than 90 percent at the power frequency for duration longer than 1 min. Undervoltages are the result of switching events that are the opposite of the events that cause overvoltages. A load switching on or a capacitor bank switching off can cause an undervoltage until voltage regulation equipment on the system can bring the voltage back to within tolerances. Overloaded circuits can result in undervoltages also [**5**]. Figure (1-6) shows undervoltage plot.

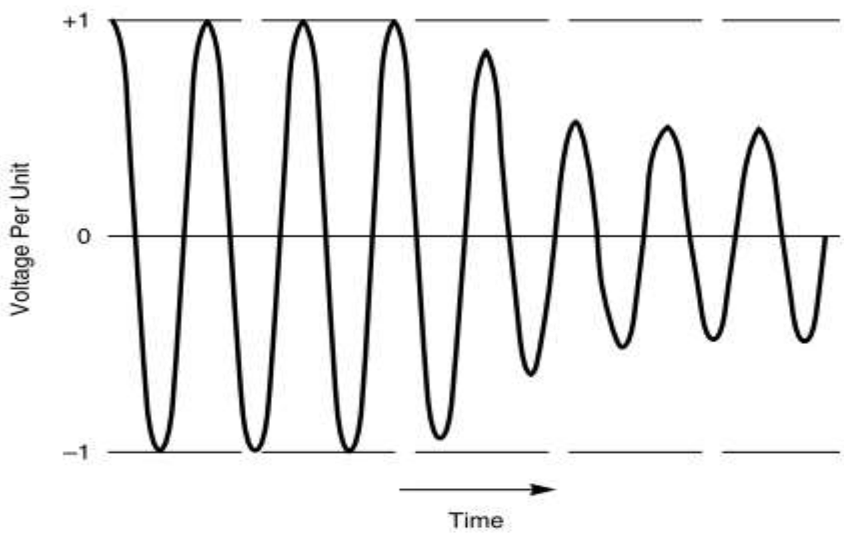


Fig 1-6 Undervoltage signal

b) Overvoltages

An overvoltage is an increase in the rms ac voltage greater than 110 percent at the power frequency for duration longer than 1 min. Overvoltages are usually the result of load switching. The overvoltages result because either the system is too weak for the desired voltage regulation or voltage controls are inadequate. Incorrect tap settings on transformers can also result in system overvoltages [**1**]. Figure (1-7) shows overvoltage plot.

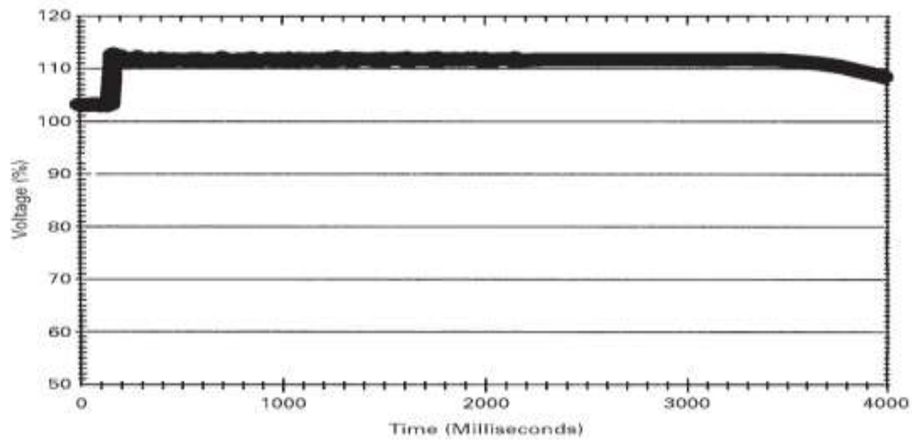


Fig 1-7 Overvoltage signal

The main reasons of undervoltages and overvoltages [**4**]:

- Capacitor switching.
- Load dropping.
- Missetting of voltage tap in transformers.
- Loss of transmission lines.
- Overloading.

Both disturbances undervoltages and overvoltages can have the following effects [**5**]:

- Over stress on insulation.
- Problems of voltage instability.
- High demand for reactive power.
- Drawl of high current by motors.

1.2.4 Harmonic distortion

Waveforms in a non-sinusoidal wave having frequencies other than fundamental frequency are called harmonics. The frequency of each harmonic component is known as harmonic frequency. In most of the cases of periodic and well defined waves, where waveform can be expressed by Fourier series, harmonic frequencies are integer multiple of fundamental frequency (however it may be fractional). The integer factor is known as the order of harmonic component [**5**].

Harmonic distortion is normally attributed to the application of nonlinear loads (i.e loads that when supplied by a sinusoidal voltage; do not draw a sinusoidal current). The current in these loads can be heavily distorted compared to a sine wave, and usually containing the odd harmonics, 3, 5, 7, 9, ….etc. These nonlinear loads not only have the potential to create problems within the facility that contains the nonlinear loads but also can adversely affect the neighboring facilities [6]. Figure (1-8) illustrates a sample of harmonic distortion event (a), and its frequency spectrum (b).

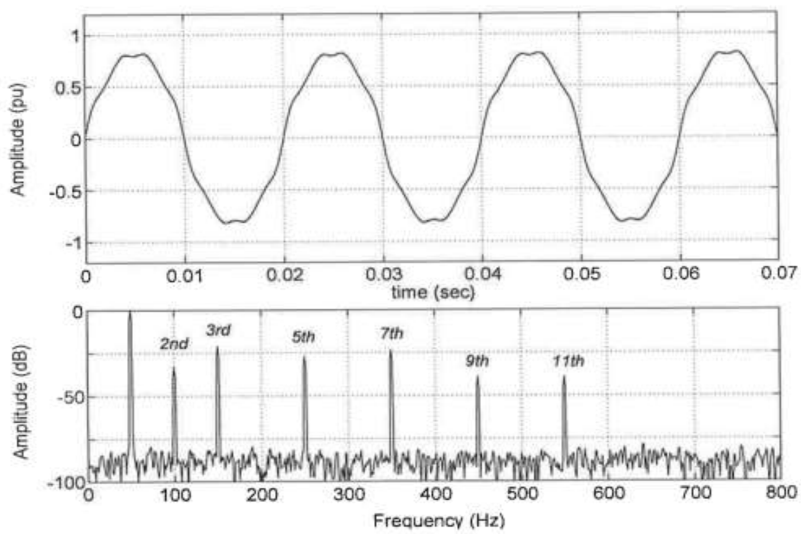


Fig 1-8 Harmonics (a) Harmonic distortion event, (b) frequency spectrum

Harmonics have many causes, some important causes are [**3**]:

- The non-linear loads like computers, rectifier banks, fluorescent lighting ….etc
- The non-uniformly distribution of coils around the generator stator slots.
- Current generated by end-user equipment's.

There are many effects of harmonics on the power system [**7**]:

- Overheating neutral conductors and transformers.
- Nuisance tripping of circuit breakers.
- Malfunction of different equipment and generator systems.
- Computer malfunctions.
- Overvoltage problems.

1.2.5 Voltage unbalance

This type of power quality disturbance is caused by unequal distribution of loads among the three phases. At three-phase distribution level, unsymmetrical loads at industrial units can result in voltage unbalance. Voltage unbalance is very significant for three-phase equipment such as transformer, motors and rectifiers, for which it results in overheating due to a high negative sequence current flowing into the equipment. The asymmetry can also have a bad effect on the performance of converters, as it results in the production of harmonic [**8**]. Figure (1-9) shows a typical three-phase unbalance voltage.

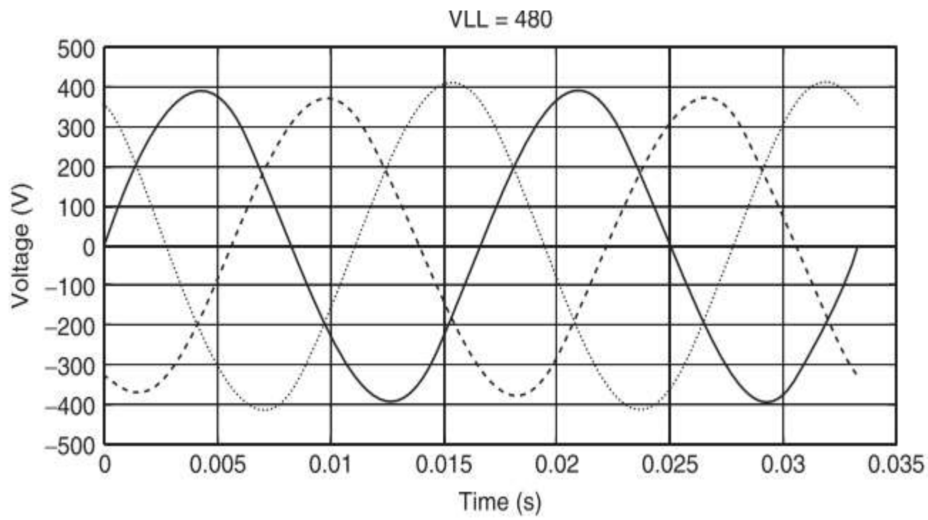


Fig 1-9 Typical three-phase unbalance voltage signal

The major causes of unbalance of the voltage are [**1**]:

- Single-phase loads on a three-phase circuit.
- Blown fuses in one phase of a three-phase capacitor bank.
- Single-phasing conditions.

The equipment use and efficiency is negatively influenced by voltage unbalance on the load side which is explained as follows [**9**]:

- Temperature rises in motor.
- The rotating machine in presence of voltage unbalance results in a reverse magnetic field, which results in decrease of useful torque due to machine windings heating.

- It also damages power supply wiring, transformers and generators.
- The unbalanced voltages across motor terminals causes phase current unbalance, 6-10 times the percent voltage unbalance for a fully loaded motor.
- It also reduces torque capability.

1.2.6 Voltage Fluctuations (Flicker)

Voltage fluctuations are defined as the cyclic variation of voltage with amplitude that does not exceed 10%. This variation in magnitude is usually much lower than the sensitivity threshold of most equipment and, consequently, operating problems are experienced only in rare cases. Except for these very particular cases, the main disturbing effect of voltage fluctuations is producing changes on the illumination intensity of light sources [**10**]. Figure (1-10) shows a Voltage Flicker event.

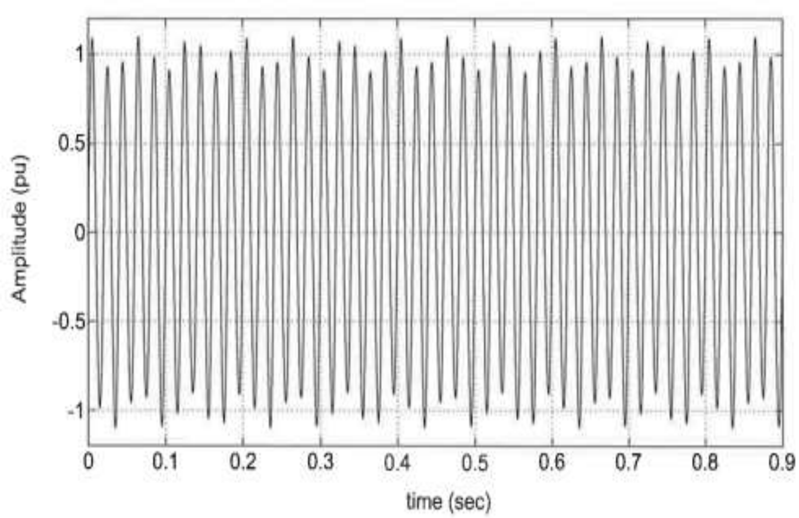


Fig 1-10 Voltage Flicker event

Voltage fluctuations can be attributed to various causes [**11**]:

- Pulsed power output where there is burst-firing control.
- Resistance welders.
- Start-up of drives.
- Pulsed power output with thermostat controls.
- Drives with steeply-changing loading.
- Arc furnaces.

Voltage Fluctuation can affect the power system [**11**]:

- Control actions for control system acting on the voltage angle.
- braking or acceleration moments from motors connected directly to the system
- impairment of electronic equipment where the fluctuation of the supply voltage passes through the power supply assembly to the electronic equipment.

1.3 Classification of power quality problems

The classification of power quality problems can be performed according to [**1**]:

- The source of the problem (e.g. converters, magnetic circuit nonlinearities…)
- Wave-shape of problematic signal (e.g. harmonic, flicker…)
- Frequency spectrum (e.g. radio frequency interference)

ANS1 C84.1- 1982 and other standards more specifically depict duration and other characteristics of different categories listed above. These phenomena listed above can be described further by listing appropriate attributes.

For steady-state phenomena, the following attributes can be used:

- Amplitude, Frequency.
- Spectrum, Modulation, Source impedance.
- Notch depth, Notch area.

For non-steady-state phenomena, other attributes may be required:

- Amplitude, Duration.
- Spectrum, Frequency.
- Rate of occurrence, Energy potential.
- Source impedance.

The following table summarizes all the disturbances with their parameters:

Table 1-1 Different types of PQD and their parameters

Categories	Spectral content	Typical duration	Voltage magnitude
1. Transients:			
• Impulsive			
- Nanosecond	5ns rise	<50ms	
- Microsecond	1µs rise	50ns-1ms	
- Millisecond	0.1ms rise	>1ms	
• Oscillatory			
- Low frequency	<5kHz	0.3-50ms	0-4pu
- Medium frequency	5-500kHz	20µs	0-8pu
- High frequency	0.5-5MHz	5µs	0-4pu
2. Short duration variations:			
• Instantaneous			
- Sag		0.5-30cyc	0.1-0.9pu
- Swell		0.5-30cyc	1.1-1.8pu
• Momentary			
- Interruptions		0.5-3s	<0.1pu
- Sag		0.5-3s	0.1-0.9pu
- Swell		0.5-3s	1.1-1.2pu
• Temporary			
- Interruptions		3s-1min	<0.1pu
- Sag		3s-1min	0.1-0.9pu
- Swell		3s-1min	1.1-1.2pu
3. Long duration variations:			
• Interruption,sustained		>1min	0.0pu
• Undervoltage		>1min	0.8-0.9pu
• Overvoltage		>1min	1.1-1.2pu
4. Voltage Imbalance		Steady state	
5. Waveform distortion			
• DC offset		Steady state	0-0.1%
• Harmonics	0-100th H	Steady state	0-20%
• Interharmonics	0-kHz	Steady state	0-2%
• Notching		Steady state	
• Noise	Broad-band	Steady state	0-1%
6. Voltage fluctuations	<25Hz	Intermittent	0.1-7%
7. Power frequency variations		<10s	

1.4 CONCLUSION

The previous set of disturbances could cause serious problems to the power system from the generation to the transmission ending with the end users. A pure energy delivery is a big issue for the power utilities worldwide. It could not happen that an electrical signal is without power quality disturbances, for these reasons a detection and classification processes must be done to handle the situation rapidly.

In the next chapter these methods of detection and classification of power quality disturbances will be treated and explained extensively.

2.1 Introduction

The important issues in power quality (PQ) problems are to detect and classify disturbance waveforms automatically in an efficient manner [**12**]. In order to improve electric power quality, the sources and causes of disturbances must be known before appropriate mitigating action can be taken, and continuous recording of disturbance waveforms is necessary [**13**]. Therefore, the monitoring equipment needs to firstly and accurately detect and identify the disturbance types.

Thus, the uses of new and powerful tools of signal analysis have enabled the development of additional methods to accurately characterize and identify several kinds of power quality disturbances [**14**]. Therefore, two methods of both detection and classification are introduced and used for power quality monitoring.

2.2 Detection methods

Detection methods are designed to identify the occurrences of disturbances. An effective method of detecting power quality events such as (sag, swell, harmonics, interruption, flicker and transient) is dependent on their accurate measurements in time which is still a challenge for researchers and engineers [**15**]. Signal processing techniques are widely used in analyzing PQ events to extract the most sensitive and interesting features concerning disturbances, these techniques are classified as using time domain, frequency domain, and time-frequency domain methods [**16**] [**17**]. Some examples are the fast Fourier Transform method, Fractal-Based method, S-Transform method (ST), Time-Frequency Ambiguity Plane method, Short Time Power and Correlation Transform method, Chirp-Z Transform (CZT), Wavelet Transform (WT) method, and Hilbert Transform (HT) [**17**], these two later have been proven to be effective signal processing tools for the detection and analysis of power signals.

2.2.1 Wavelet Transform

The Wavelet Transform (WT) has been found to be particularly useful for analyzing signal which is mostly non-stationary and can be best described as aperiodic, noisy, intermittent, transient and so on [**18**].Therefore, it represents one of the powerful signal processing algorithms that is used in the field [**19**]. It has the ability to analyze different power quality problems simultaneously in both time and frequency domains in a distinctly different way from the traditional tools such as Fourier Transform [**12**] [**18**], and this is why it overcomes the resolution limitation of FT. The main advantage of wavelets is that they have a varying window size, which is wide for slow frequencies and narrow for fast, thus leading to an optimal time frequency resolution in all frequency ranges [**20**].WT has two categories primarily called Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) [**21**], they will be described in the following sections.

a) Basic concepts of Wavelet

The Wavelet Transform procedure is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet $\psi(t)$ [**13**], This function has a mean of zero and sharply decays in an oscillatory fashion, i.e. it rapidly falls to zero either side of its central path [**22**] i.e. $\int_R \psi(t)dt = 0$. To be more flexible, each wavelet is created by scaling (stretching and squeezing) and translation (moving) operations in this mother wavelet [**23**] [**18**]. Some of the popular wavelet families such as: Haar, Daubechies, biorthogonal, Coiflet, Symlet, and Gaussian are shown in figure (2-1).

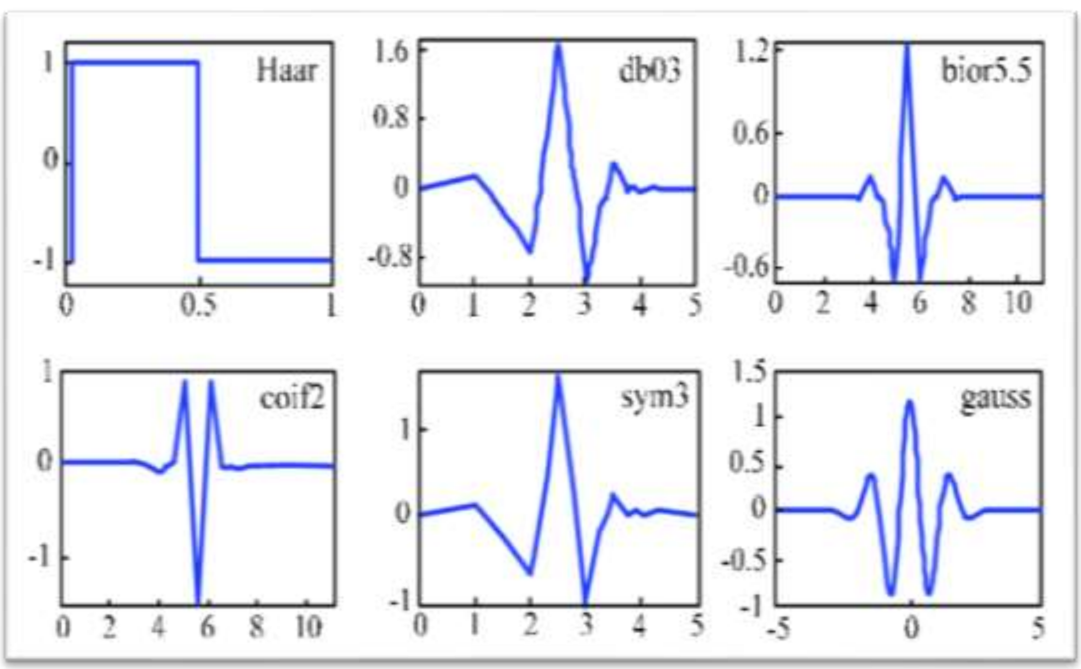


Fig 2-1 Examples of wavelet families

The selection of the mother Wavelet function is one of the main factors in the successful application of Wavelets. Shorter Wavelet functions of the Daubechies family being the most widely used in the detection and analysis of voltage events [**24**].

The signal can be represented in terms of wavelet function and scaling function. Basically, it is represented by one set of scaling coefficients, and one or several sets of wavelet coefficients:

$$f(t) = \sum_{n} Aj(n)\phi(t-n) + \sum_{n}\sum_{j} Dj(n)2^{j/2}\psi(2^{j}t-n) \tag{2.1}$$

Where:

A j: Represents level scaling coefficient,

D j: Represents j level wavelet coefficient,

ϕ: Represents scaling function,

$\psi(t)$: Represents wavelet function,

j: Can be any higher level wavelet transform and *t* is time.

b) Continuous Wavelet Transform (CWT)

CWT algorithm uses the window function or the Wavelet function to compute individually each part of the time-domain signal according to the length of the window. The advantage of the CWT is that the window length is changed as the window function translating the entire signal [**25**], and it divides a continuous time signal into an equal time intervals and equal frequency intervals [**26**]. The expression of CWT of a continuous signal is given by:

$$\text{CWT}\{x(a,b)\} = \int_{-\infty}^{\infty} x(t)\,\psi^{*}_{a,b}(t)\,dt \quad a,b \in R \quad a \neq 0 \tag{2.2}$$

Where,

ψ^{*} a,b(t):is the dilated and translated mother wavelet expressed as :

$$\psi^{*}\, a,b(t) = \frac{1}{\sqrt{a}}\,\psi^{*}\left(\frac{t-b}{a}\right) \tag{2.3}$$

x(*t*): is signal to be analyzed,

a is scaling or dilation parameter and *b* is translation parameter.

The transformed signal is a function of variables “a” and “b”, the scaling parameter “a”, or window length is varied according to the signal frequency with low scale for high frequency and high scale for low frequency. Translation parameter "b" can be described as the location of the wavelet function as the wavelet function window shifted through the signal to acquire time information of the signal [**25**]. Thus, the set of all wavelet coefficients CWT (a,b) associated with a particular signal are the wavelet representation of the original signal *x(t)* with respect to the mother wavelet $\psi(t)$ [**22**]. CWT is not frequently used in power quality detection because of its computation complexity [**26**].

c) Discrete Wavelet Transforms (DWT)

The equation of CWT has great theoretical interest for the development and comprehension of its mathematical properties. However, its discretization is necessary for practical applications [**23**]. This is because the possibility of reconstruction the original signal using infinite summation of discrete wavelet coefficients rather than continuous integral, and this leads to a fast wavelet transform for the rapid computation of DWC and its inverse [**18**]. The discretization means using discrete values of the scaling parameter a = $a_0{}^m$ and translation parameter b = $nb_0a_0{}^m$. Then the mathematical expression for DWT can be given as:

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_0{}^m}}\,\psi\left(\frac{t - nb_0a_0{}^m}{a_0{}^m}\right) \tag{2.4}$$

Where, m and n are integers correspond to the control parameters of the wavelet dilation and translation respectively.

a_0: is a fixed dilation step parameter which should be always greater than one.

b_0: is the position parameter, it's value should be more than zero.

The wavelet transform of a continuous signal, x(t), is using DWT is then:

$$\mathrm{DWT}\{x(m,n)\} = \int_{-\infty}^{\infty} x(t)\frac{1}{a_0{}^{\frac{m}{2}}}\,\psi(a_0{}^{-m}t - nb_0)dt \tag{2.5}$$

The idea of the discrete wavelet transform is that filters with different cut-off frequencies are utilized to analyze the signal at different scales [**16**].

The high pass filter g(n) used to analyze high frequency and the low pass filter h(n) used to analyze low frequency of the signal. At every decomposition level, the filtering process will reduce the signal sample by half [**25**]. This is done through a process called "sub-band codification", which is done through digital filter techniques as shown in Fig (2-2).

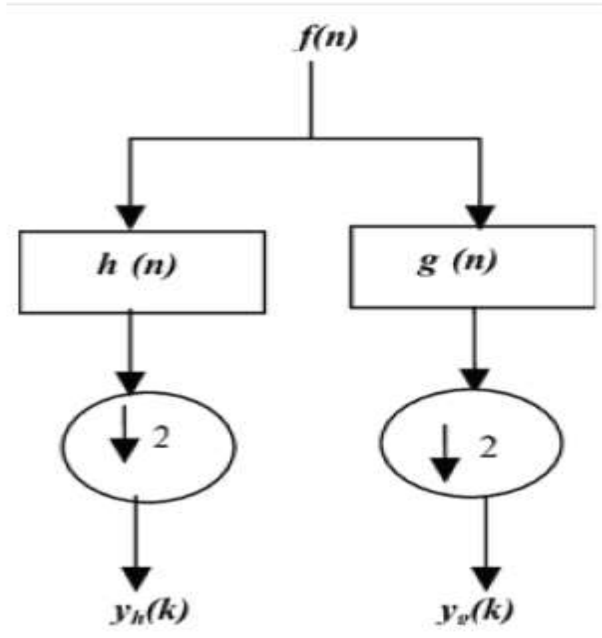


Fig 2-2 Sub-band Codification of signal

DWT evaluation has two stages and involves two steps. In first step the "wavelet coefficients "are determined. These obtained coefficients represent the signal in the wavelet domain. In the next step, the obtained wavelet coefficients are used for calculating "approximation" as well as the "detailed" version of original signal, in different levels of resolutions, in the time domain is done [**26**].

d) Multi Resolution Analysis (MRA)

The wavelet Multi-Resolution Analysis is a tool that utilizes DWT for the analysis of waveforms and images. In power quality, MRA can be used for detection as well as for distortion features extraction. The goal of MRA is to develop representations of a signal at various levels of resolution by decomposing the time domain signal [**16**] [**23**]. Wavelet functions and scaling functions are used as building blocks to decompose and reconstruct the signal at different resolutions in MRA [**26**]. They are associated with high pass g(n) and low pass h(n) filters respectively, so that :

$$\psi(t) = \sqrt{2}\sum_{n} g(n)\,\psi(2t-n) \tag{2.6}$$

$$\phi(t) = \sqrt{2}\sum_{n} h(n)\phi(2t-n) \tag{2.7}$$

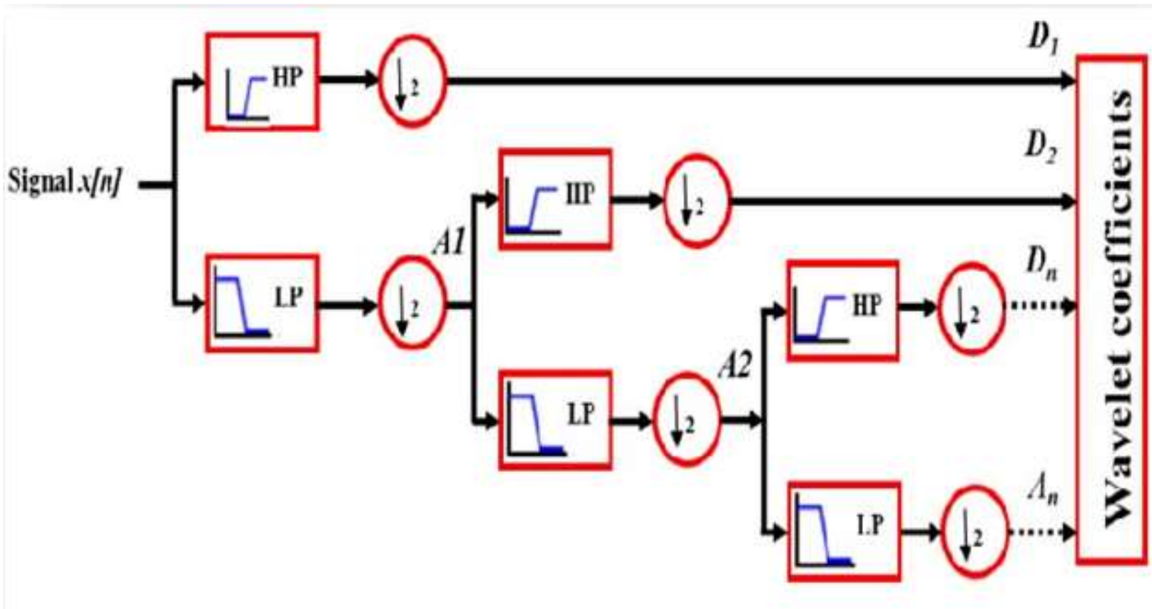


Fig 2-3 Signal decomposition using Multi Resolution Analysis

At the first level of decomposition, the original signal x[n] which is supposed to be discrete time signal scattered in various levels. This signal is filtered into high frequency component level 1 (D1(n)) by using HP filter (g(n)) and low frequency component level 1 (A1 (n)) by using LP filter (h(n)). This signal is then passed through down sampling this can be shown by the relation given in equation (2.8)(2.9):

$$D1\ (n) = \sum_k g(k-2n)x(k) \tag{2.8}$$

$$A1\ (n) = \sum_k h(k-2n)x(k) \tag{2.9}$$

The low frequency component obtained after level MRA analysis level 1 (A1 (n)) will be initial signal for MRA level 2. This signal is then passed through HP and LP filters. The filters' output are the high frequency component in level 2 (D2(n)) and the low frequency component in level 2 (A2 (n)) as relation in equations (2.10)(2.11) and this represent the second level of decomposition:

$$D2\ (n) = \sum_k g(k-2n)\mathrm{A1}(k) \tag{2.10}$$

$$A2\ (n) = \sum_k h(k-2n)\mathrm{A1}(k) \tag{2.11}$$

This process will continue up to "n-1"in order to calculate the "n" level high pass and low pass components [**26**]. At every level of decomposition, the filtering and dawnsampling will result in half the number of samples (half the time resolution) and half the frequency band (double the frequency resolution) [**16**].

2.2.2 The Hilbert Transform

The Hilbert Transform (HT) has been used widely in the telecommunication research for signal modulation and demodulation, and in various medical image processing applications. In power quality signal analysis, the HT has not been investigated, although it shows an accurate tracking of the changes in the power quality signals.

a) Basic concepts of Hilbert

The Hilbert Transformation of a 1-D real signal (function) u(t) is defined by the integral

$$v(t) = \frac{-1}{\pi} P \int_{-\infty}^{\infty} \frac{u(\eta)}{\eta - t}\, d\eta = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{u(\eta)}{t - \eta}\, d\eta \qquad (2.12)$$

And the inverse Hilbert Transformation is:

$$u(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{v(\eta)}{\eta - t}\, d\eta = \frac{-1}{\pi} P \int_{-\infty}^{\infty} \frac{v(\eta)}{t - \eta}\, d\eta \qquad (2.13)$$

Where P is the principal value of the integral.

The above definitions of Hilbert Transformations are frequently written in terms of the convolution notations [**27**]:

$$v(t) = u(t) * \frac{1}{\pi t} \qquad (2.14)$$

$$u(t) = -\, v(t) * \frac{1}{\pi t} \qquad (2.15)$$

The functions $u(t)$ and $v(t)$ are called a pair of Hilbert Transforms and in short are denoted [**28**]:

$$u(t) \overset{\mathbf{H}}{\Longleftrightarrow} v(t)$$

The Hilbert Transform of a signal is equivalent to a ±90° phase shift in all frequency components of the signal [**29**].

Hilbert Transform is used to generate a complex signal from a real signal. And it is a multiplier operator. Unlike other transform techniques, the HT of time-domain function is still in time domain [**30**].

According to mathematical reason, it is confirmed: H[x(t)] has the effect of shifting the phase of the negative frequency components by +90° (π/2 radians) and the phase of the positive frequency components by −90°. And H[x(t)] has the effect of restoring the positive frequency components while shifting the negative frequency ones an additional +90°, resulting in their negation [**31**].

The HT in frequency domain can be expressed as: [using x(f) instead of u(f)]

$$X^h(f) = X(f)H(f) \tag{2.16}$$

Because the Fourier Transform of h(t) is:

$$F[h(t)] = H(f) = -jsgn(f) = -j \begin{cases} -1, & f < 0 \\ 1, & f > 0 \end{cases} \text{ (sgn is the sign function).} \tag{2.17}$$

The HT result can be deduced from FT, hence

$$X^h(f) = x(t) * h(t) = F^{-1}[X(f)H(f)] \tag{2.18}$$

As an example $x(t) = \sin(2\pi f_i t)$ is input signal, after the Hilbert Transform the result is just a shift of –j (or 90°) to the input signal as figure (2-4) shows.

$$H[\sin(2\pi f_i t)] = -\cos(2\pi f_i t) \tag{2.19}$$

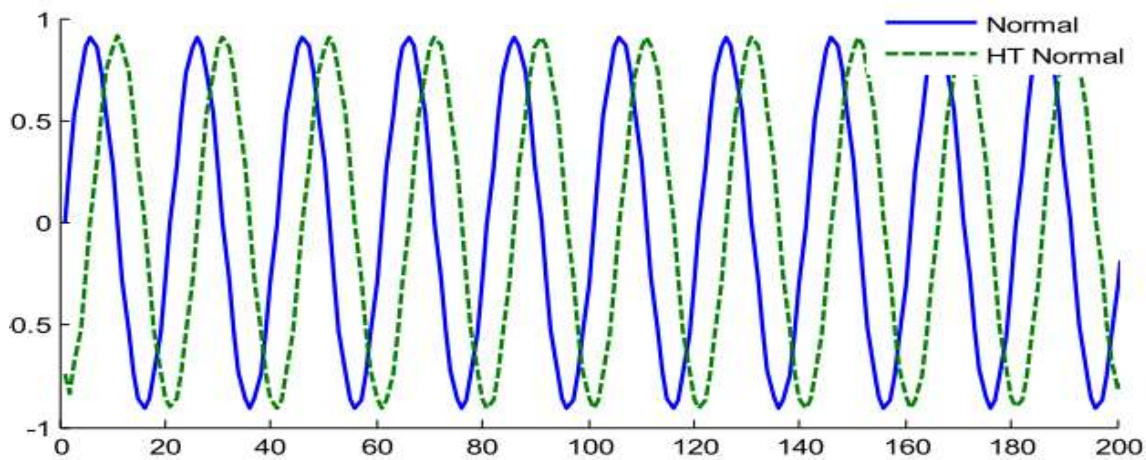


Fig 2-4 Hilbert signal of Sine function

HT can provide 90° phase-shifting and not influence the amplitude of the frequency–spectrum components [**32**].

b) The phase-Shifting

The ideal signal of power system is the pure sine waveform:

$$u(t) = A\sin(2\pi f_0 t + \varphi_0) = A\sin(\omega_0 t + \varphi_0) \tag{2.20}$$

Where: A is the voltage amplitude; f_0 is the basic frequency 50Hz, φ_0 is the initial phase.

The detection output y(t):

$$y(t) = u^2(t) + u^2(t - T/4) - A^2 \tag{2.21}$$

In ideal conditions, the properties of u(t) are:

$$u^2(t) + u^2\left(t - \frac{T}{4}\right) = [A\sin(\omega_0 t + \varphi_0)]^2 + \left[A\sin\left(\omega_0\left(t - \frac{T}{4}\right) + \varphi_0\right)\right]^2 = A^2 \quad (2.\ 22)$$

Apparently, if input signal is the ideal waveform, the detection output is 0.

However, when the input signal contains disturbances, the expression is:

$$u(t) = A\sin(\omega_0 t + \varphi_0) + e(t) \tag{2.23}$$

After 90° phase-shifting to the u(t):

$$u_2(t) = u\left(t - \frac{T}{4}\right) = A\sin(\omega_0 t + \varphi_0 - 90°) + e(t - 90°) \tag{2.24}$$

The detection output y(t):

$$u^2(t) + u^2\left(t - \frac{T}{4}\right) - A^2 = 2A\ \sin(\omega_0 t + \varphi_0) * e(t) + 2A\ \cos(\omega_0 t + \varphi_0) * e(t - 90°) + e^2(t) + e^2(t - 90°) \tag{2.25}$$

In the above formula, $A\ \sin(\omega_0 t + \varphi_0)$ and $A\ \cos(\omega_0 t + \varphi_0)$ are known, so:

$$y(t) = \xi(e(t)) \tag{2.26}$$

Hence, when there are disturbances in the input signal, the detection output $y(t)$ certainly cannot be 0, furthermore e(t) is different when the disturbances input are different, and $y(t)$ will have different waveform characteristic, if it is corresponding to the time when disturbances take place, it can assure the detection's real-time characteristic [**33**].

2.3 Classification methods

The main task of power quality (PQ) disturbance recognition is to accurately identify the disturbance type, and provide the references for parameter estimation and control strategies of power system [**34**]. Therefore continuous monitoring and classification are required for these disturbances due to increasing demand of pure power [**35**].To perform the classification of these disturbances different algorithms have been defined in order to relate the signal characteristics with the group they belong to: Decision Trees (DTs), Fuzzy Logic (FL), Neural Networks (NNs), and Support Vector Machine (SVM), among others. These methodologies play an important role on the disturbance classification because their performance depends on the extracted features and the classifier utilized; if the disturbance characteristics are not accurately captured, the performance is also limited [**36**].

2.3.1 Artificial neural network

Artificial Neural Networks have been developed as generalizations of mathematical models of human cognition or neural biology. A neural network is characterized by [**37**]:

- Its pattern of connections between the neurons (called architecture).
- Its method of determining the weights on the connections (called training or learning algorithm).
- Its activation function.

All definitions of Artificial Neural Networks emphasize the idea of highly interconnected units comprising simple nonlinear elements [**38**].

Neural Networks have been extensively used for the classification because of their large data handling capability. They are used to recognize and classify complex fault patterns without much knowledge about the system they deal with. The neural networks are described by the transfer function of their neurons, by training algorithm and by the connecting formula [**39**].

Artificial Neural Networks (ANNs) have attracted a great deal of attention because of their pattern recognition capabilities, and their ability to handle noisy data; however, its ability to perform well is greatly influenced by the weight adaptation algorithm and the amount of noise in the data [**40**].

a) Artificial Neural Network Applications

ANNs are among the oldest Artificial Intelligence techniques; they have been around the power research arena for quite some time. Neural networks have been applied extensively in PQ. Main applications include [**41**]:

- Identifying PQ events from non-power quality ones.
- Modeling the patterns of harmonic production from individual fluorescent lighting systems.
- Estimating harmonic distortions and PQ in power networks.
- Identifying and recognizing PQ events using the wavelet transform in conjunction with neural networks.

- Identifying high-impedance fault, fault-like load, and normal load current patterns.
- Analyzing harmonic distortion while avoiding the effects of noise and sub harmonics.
- Developing a screening tool for the power system engineer to use in addressing PQ issues.

b) Neural network principle work

A neuron is a real function of the input vector ($y_1 \ldots . y_k$), the output is obtained as [**42**]:

$$f(x_j) = f\left\{a_j + \sum_{i=1}^{k} w_{ij} y_j\right\} \tag{2.27}$$

where f is a function.

Figure (2-5) shows a graphical representation of a neuron.

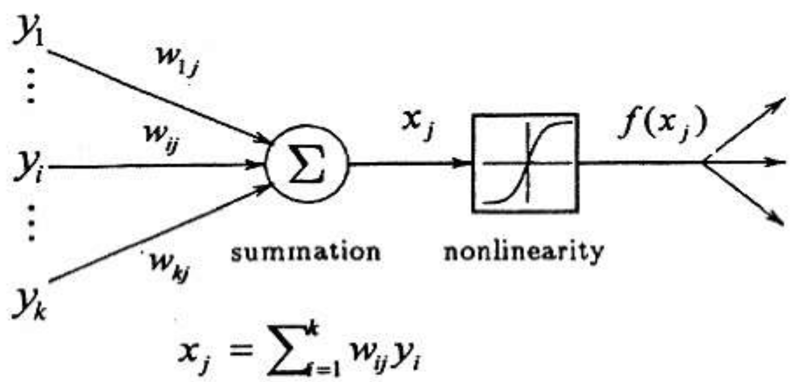


Fig 2-5 Graphical representation of a neuron

c) Elements of neural network

Weight, threshold and activation function are the basic elements that include in neural network.

- *Weighting factor*

The values w_1, w_2, w_3 …… w_k are weight factors associated with each node to determine the strength of input vector, each input is multiplied by the associated weight of the neuron connection, depending upon the activation function, if the weight is positive commonly excites the node output, whereas for negative weights, tends to inhibit the node output [**42**].

- *Threshold*

The node's internal threshold θ is the magnitude offset that affects the activation of the node output [**42**].

- *Activation function*

An activation function performs a mathematical operation on the signal output depending upon the type of problem to be solved by the network many sophisticated activation functions can be used such as: the linear function, the step function, the sigmoidal function [**42**], the most used in the studies is the sigmoidal function. Figure (2-6) shows these three activation functions.

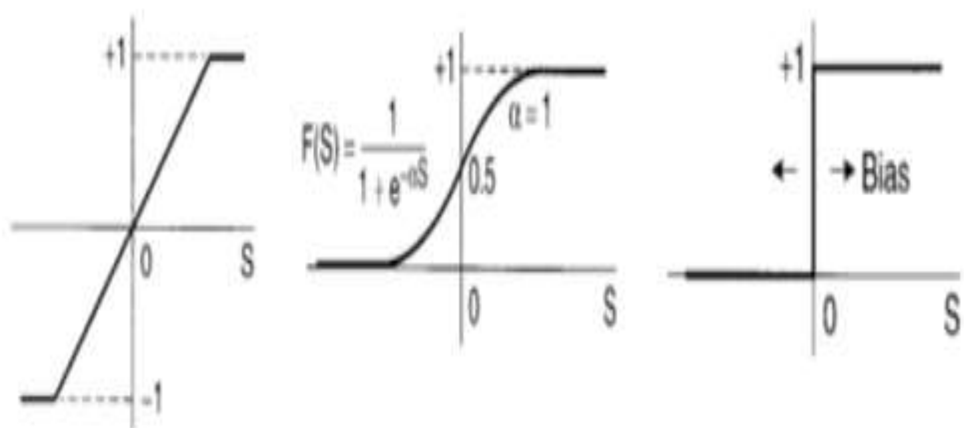


Fig 2-6 Activation functions: (Linear, Sigmoidal and Step)

d) Types of Artificial Neural Network

ANNs can be viewed as weighted directed graphs in which artificial neurons are nodes and directed edges (with weights) are connections between neuron outputs and neuron inputs. Based on the connection pattern (architecture), ANNs can be grouped into two categories [**43**]:

1. Feed-forward networks, in which graphs have no loops.
2. Recurrent (or feedback) networks, in which loops occur because of feedback connections.

Figure (2-7) presents the typical network of each category.

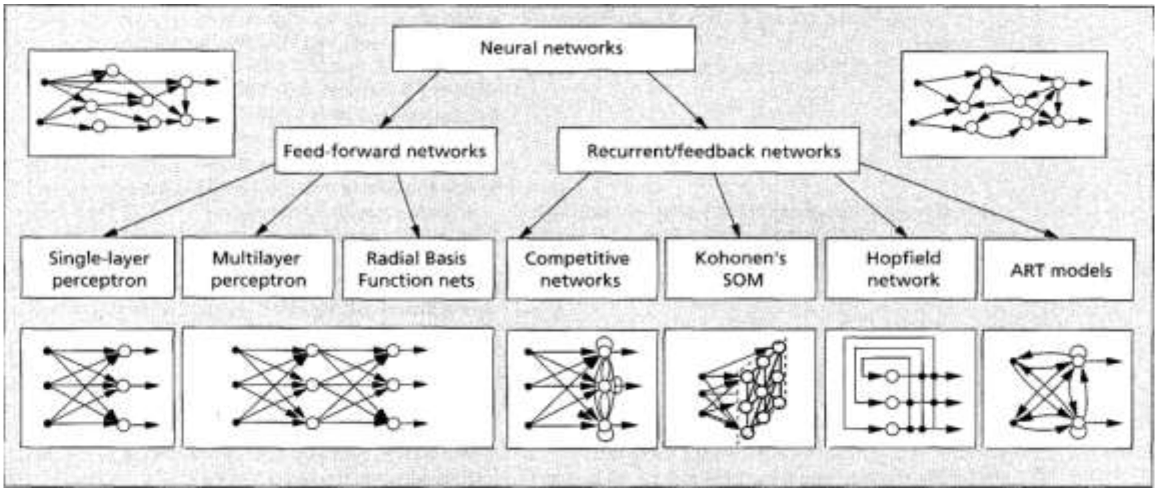


Fig 2-7 Types of ANN and their typical networks

- **Feed-forward networks**

With a neural model of computation, one must determine the order in which computation should proceed. Feed-forward neural networks are a restricted class of neural networks which forbade cycles in the graph. Thus all nodes can be arranged into layers. The outputs in each layer can be calculated given the outputs from the lower layers [**44**]. In this type there is no feedback from the outputs of the neurons toward the inputs throughout the network; Feed-forward neural networks divided into two categories depending on the number of the layers, either "Single layer" or "Multi-layer" [**45**]. Figure (2-8) shows these two types of connections.

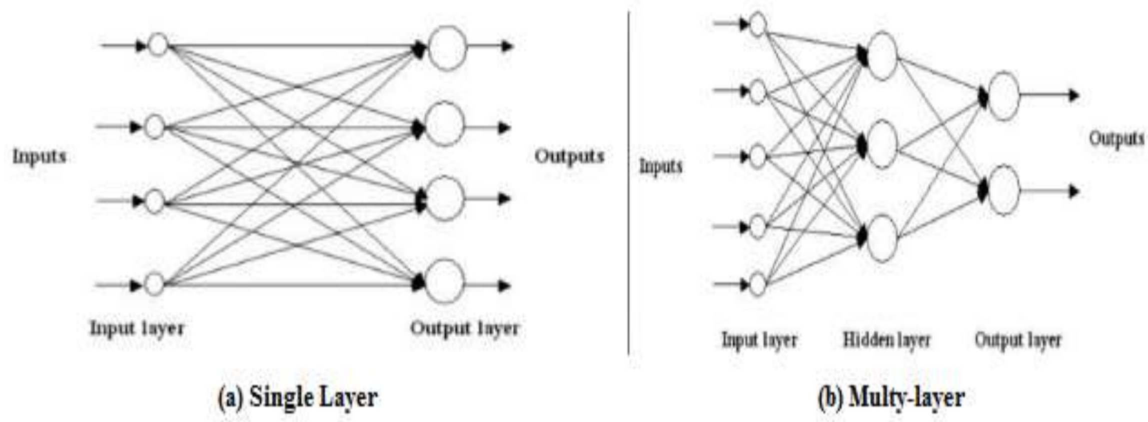


Fig 2-8 Types of FFNN

- **Recurrent (Feedback) networks**

Recurrent Neural Networks (RNNs) form an expressive model family for sequence tasks. They are powerful because they have a high-dimensional hidden state with nonlinear dynamics that enable them to remember and process past information [**46**]; and there exist a synaptic connection from the outputs towards the inputs (either their own inputs or the inputs of other neurons) [**45**]. Figure (2-9) represents a recurrent neural network [**47**].

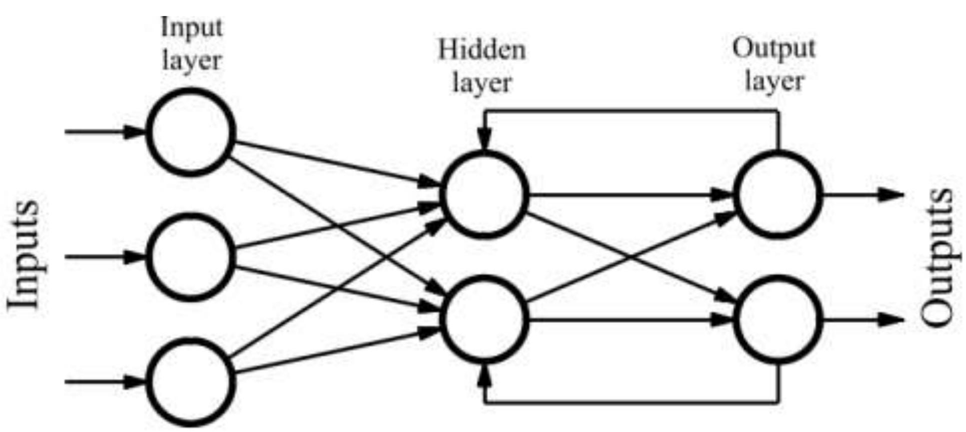


Fig 2-9 Recurrent Neural Network

2.3.2 Support Vector Machine

The Support Vector Machine (SVM) is one of the most prominent techniques in supervised machine learning that have attracted a significant amount of attention in the field of machine learning over the past decade by proving themselves to be very effective in a variety of real-world pattern classification and regression estimation tasks [**48**]. It has been applied to the problems of dependency estimation, forecasting, and constructing intelligent machines [**49**].

SVM is a statistical learning technique based on structural risk minimization method. Its main objective is building a model with the use of training set, where each sample belongs into one of the two possible classes, class 1 or class 2. With the trained SVM, a prediction model can be achieved [**50**], which can deal with linear and nonlinearly separable models using a hyperplane based on theoretical results from the statistical learning theory [**51**].

a) Advantages of SVMs

SVM is an algorithm with great advantages for classification developed from Statistical Learning Theory by Vapnik; Firstly, it provides accurate classifier with support vectors, which is robust to noise [**52**] [**17**]. Secondly, SVMs have the potential to handle very large feature spaces, because the training of SVM is carried out so that the dimension of classified vectors does not have as a distinct influence on the performance of SVM as it has on the performance of conventional classifiers [**53**]. Also, SVM-based classifiers are claimed to have good generalization properties compared to conventional classifiers, because in training the SVM classifier, the so-called structural misclassification risk is to be minimized, whereas traditional classifiers are usually trained so that the empirical risk is minimized [**48**] [**53**]. Finally, SVM is capable to solve nonlinear problems without constructing a feature space with explicit high dimension and to be applied for both binary and multiclass classification [**52**].

b) Construction of a Support Vector Machine

The SVM algorithm builds a model to classify samples. The model represents the samples in a multi-dimensional space where the samples are separated by the maximum possible distance. The following figure (2-10) shows a general form for an application that involves linearly-separable two classes [**54**].

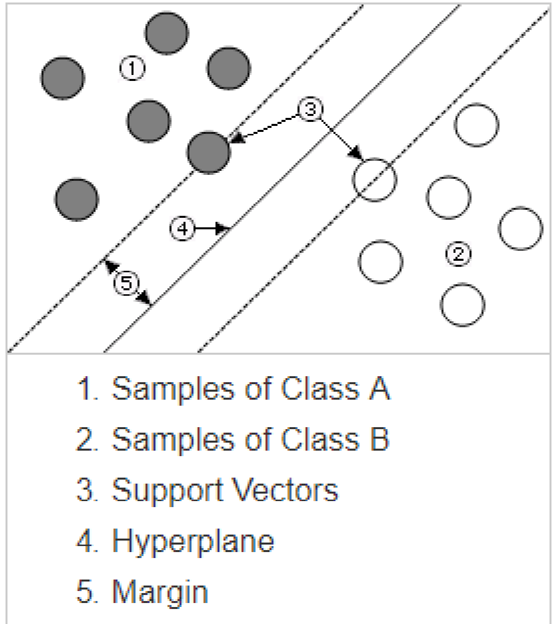


Fig 2-10 Application involves linearly-separable two classes represented in a two-dimensional space

As shown in Figure (2-10); a Support Vector (SV) is a sample in one class that is closest to another class. Also, a hyperplane is a subspace that separates the support vectors of each class, whereas, the margin is the distance between the support vector and the hyperplane.

SVMs employed for two-class problems are based on hyperplanes to separate the data [**51**]. Therefore, SVM implements a special training algorithm that maximizes the separating margin between two classes, given by a set of data pairs (input vector, class) [**55**]. Hence, an optimal separating hyperplane is a separating hyperplane that creates the maximum margin between the plane and the nearest data [**53**]. By finding this hyperplane, it is intuitively expected that the classifier will have better generalization ability [**51**]. In the following sections, the construction of optimal hyperplanes of the simple case of linearly separable patterns is discussed, followed by considering the more difficult case of non-separable patterns, also the Kernel functions are introduced.

- **Optimal Hyperplane for Linearly Separable Patterns**

Although the theory can be extended to accommodate multiple classes, without loss of generality let first consider a binary classification task assuming we have linearly separable set of data samples [**48**], by considering a training set of N data points Tr = { x_i,y_i }, where

x_i is a real valued -dimensional input vector (i.e. $x_i \in \Re^n$) and $y_i \in \{+1, -1\}$ is a label that determines the class of x_i and (i = 1,2,…,N). a suitable classifier could then be defined as:

$$f(\boldsymbol{x}) = sign(\langle \boldsymbol{w}, \boldsymbol{x} \rangle + \boldsymbol{b}) \tag{2.28}$$

Where:
x is input vector,
w is adjustable weight vector,
b is bias or offset from the origin,
$\langle \boldsymbol{w}, \boldsymbol{x} \rangle = w^T x_i$ is the inner product of the vectors $\boldsymbol{w}$ and $\boldsymbol{x}$.
So that $\boldsymbol{w}$ and $\boldsymbol{b}$ are determined to correctly classify the training examples and to maximize the margin [**51**].

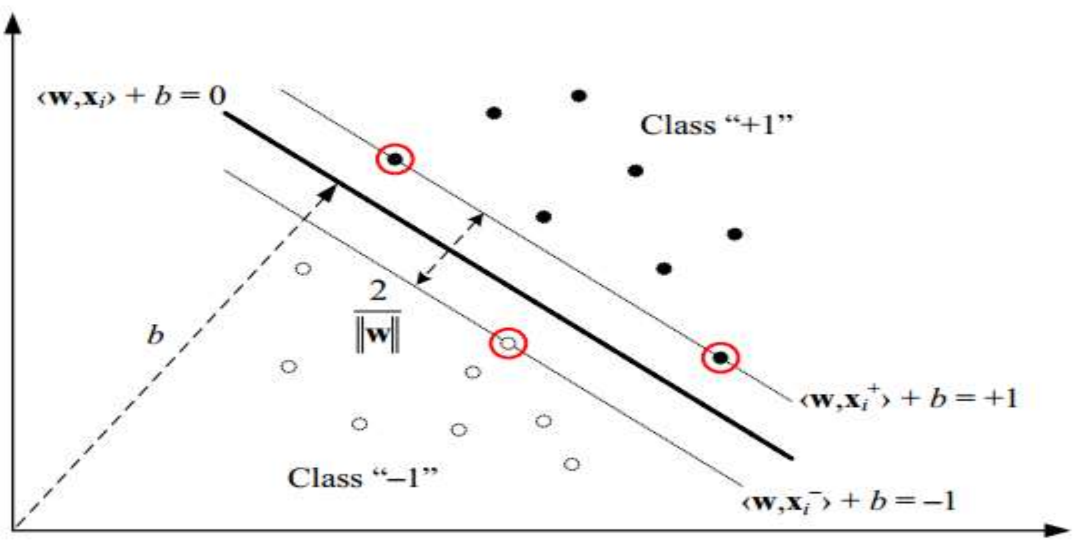


Fig 2-11 Maximum-margin classifier with no errors showing optimal separating hyperplane (solid line) with canonical hyperplanes on either side (dotted lines)

The separating hyperplane is given by:

$$f(x) = w^T x + b = \sum_{i=1}^{N} w_i x_i = 0 \tag{2.29}$$

This separating hyperplane satisfies the constraints:

$$f(x_i) \geq 1 \text{ if } y_i = +1 \text{ and } f(x_i) \leq -1 \text{ if } y_i = -1$$

And this results in Equation (3.30):

$$y_i\, f(x_i) = y_i(w^T x_i + b) \geq +1 \quad \text{for (i = 1,2,..N)} \tag{2.30}$$

As it is mentioned before, the goal of a SVM is to find the optimal hyperplane for which the margin of separation denoted by "ρ" is maximized. Mathematically to find the expression of the maximum margin, consider the fact that it is always possible to scale ***w*** and ***b*** so that for SVs that are encircled in the Figure (3-11) and denoted as x_1 and x_2:

$$w^T x + b = \pm 1 \tag{2.31}$$

And for non-SVs:

$$w^T x + b \geq +1 \text{ or } w^T x + b \leq -1 \tag{2.32}$$

The margin ρ as shown in the figure can be calculated as follow:

$$\rho = \frac{w^T}{\|w\|}(x_1 - x_2) = \frac{2}{\|w\|} \tag{2.33}$$

Maximizing ρ is equivalent to minimizing

$$\frac{1}{2}\|w\| = \frac{1}{2} w^T w \tag{2.34}$$

And by considering the constraint in equation (2.30), and by using the method of Lagrange Multiplier, this problem leads to minimization of the Lagrange function [**56**]:

$$J(w, b, \alpha) = \frac{1}{2} w^T w - \sum_{i=1}^{N} \alpha_i [y_i (w^T x_i + b) - 1] \tag{2.35}$$

Where α_i are called Lagrange multipliers.

Equation (2.35) can be transformed to its dual problem, which is easier to solve. The solution to the problem is given by [**17**]:

$$\alpha^* = \arg min_\alpha = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle - \sum_{k=1}^{N} \alpha_k \tag{2.36}$$

With constraints:

$$\alpha_i \geq 0 \quad \text{and} \quad \sum_{j=1}^{N} \alpha_j y_j = 0 \tag{2.37}$$

Solving (2.36) with constraints (2.37) determines the Lagrange multipliers, and the optimal separating hyperplane is given by:

$$w^* = \sum_{i=1}^{N} \alpha_i{}^* y_i x_i \tag{2.38}$$

And

$$b^* = -\frac{1}{2}\langle w^*, x_r + x_s \rangle \tag{2.39}$$

Where x_r, x_s are any support vectors (SV) from each class satisfying:

$$\alpha_r, \alpha_s > 0\,, \;\; y_r = -1\,, \qquad y_s = +1$$

The final decision function is given by:

$$f^*(x) = sign\,\Big(\sum_{i\,\in\,SVs} \alpha_i{}^* y_i\,\langle x_i{}^*, x\rangle + b^*\Big) \tag{2.40}$$

The unknown data sample x is then classified as [**53**]:

$$x \in \begin{cases} class\ 1 & if\ f(x) \geq 0 \\ class\ 2 & otherwise \end{cases} \tag{2.41}$$

- **Optimal Hyperplane for Non-Separable Patterns**

More often than not, however, real-world data sets are typically not linearly separable in input space, it is not possible to construct a separating hyperplane without encountering classification errors, meaning that the maximum margin classifier model used in the linearly separable patterns is no longer valid and a new approach must be introduced [**48**]. This approach is called the soft-margin classifier.

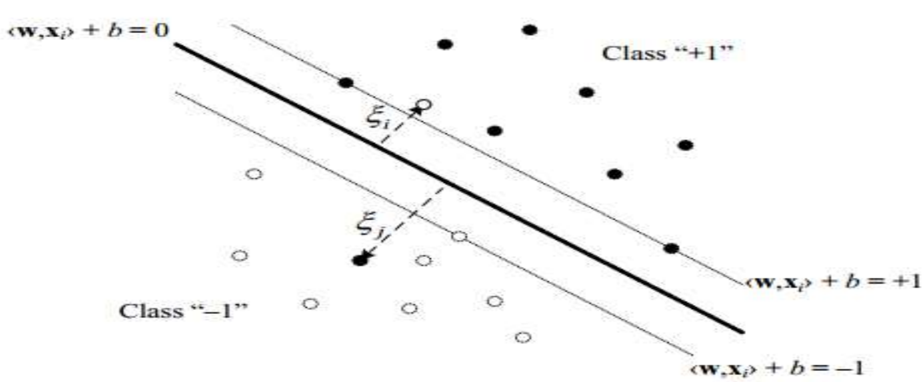


Fig 2-12 Soft-margin classifier with some errors denoted by the slack variables ξ which represent the errors

A new set of nonnegative scalar variables ξ_i called slack variables and an upper bound of α denoted by C are introduced where ξ_i are measures of the misclassification errors. Hence, the constraints of Equation (2.30) are modified to:

$$y_i\, f(x_i) = y_i(w^T x_i + b) \geq\ 1 - \xi_i \quad \text{for (i = 1,2,..N)} \tag{2.42}$$

Where $\xi_i \geq 0$. The new optimal separating hyperplane is determined by the vector w that minimizes the functional:

$$\Phi(w, \xi) = \frac{1}{2}\, w^T w + C \sum_{i=1}^{N} \xi_i \tag{2.43}$$

The solution to the problem is:

$$\alpha^* = \arg min_\alpha = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \langle\, x_i, x_j \rangle - \sum_{k=1}^{N} \alpha_k \tag{2.44}$$

With the constraints:

$$0 \leq \alpha_i \leq C \quad \text{ and } \quad \sum_{\mathrm{j=1}}^{\mathrm{N}} \alpha_j y_j = 0 \tag{2.45}$$

C must be chosen to reflect the knowledge of the noise on the data.

- **Kernel Functions**

For highly complicated data, the SVM can be extended to work in the high dimensional feature space formed by the nonlinear mapping of the N-dimensional input vector into a K-dimensional feature space, where the linear classification is possible through the use of a kernel function instead of the inner product $\langle x_i, x \rangle$ [**51**]. The change of optimization problem of Equation (2.44) is $\langle x_i, x_j \rangle$ to $K(x_i, x_j)$ where the constraints in Equation (2.45) are not changed.

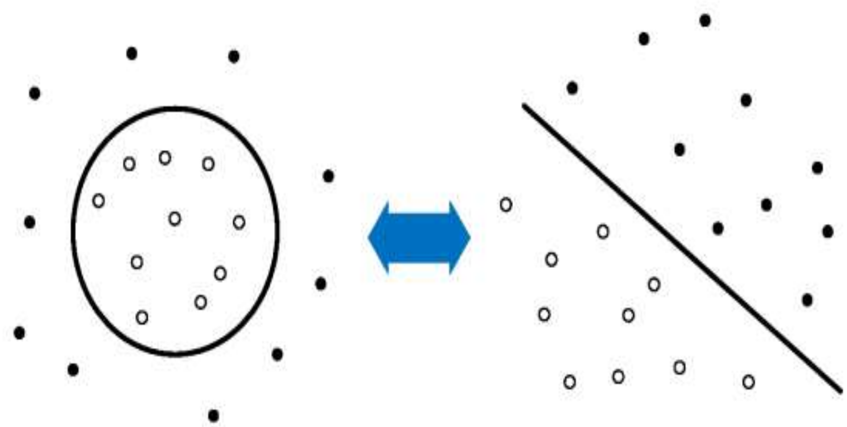


Fig 2-13 Kernel functions generate implicit nonlinear mappings, enabling SVMs to operate on a linear separating hyperplane in higher dimensional feature space

There are a number of different Kernel functions available; few popular types are Linear function, Polynomial function, Gaussian radial basis function, and Spline function [**48**].

c) Multi-class SVM

SVM classification typically involves two classes. For applications that involve more than two classes, multi-class SVM classifiers are obtained by combining two-class SVMs. The SVM algorithm uses two approaches [**57**]:

- One-versus-all approach: it is the most fundamental approach and it utilizes *(P-1)* classification models (with P is the number of classes). Each machine is trained as a classifier of one class against all other classes.
- One-versus-one approach: in this approach, ($P \times (P-1)/2$) classification models so that each machine is trained as a classifier for one class against other class. In order to evaluate the classifier, pair wise competition between all the machines is performed; each winner competes against another winner until a single winner remains. This final winner determines the class of the test data.

2.4 Conclusion

The selected detection and classification methods have been described, giving their basics, types and principal of work. WT and HT are the chosen advanced signal processing tools used for detection, whereas, SVM and ANN are introduced as the artificial intelligence tools used for classification.

3.1 Introduction

Simulation studies have been performed to investigate the performance of the power quality detection and classification methods. In this section, the description of the methods shown in the block diagram, simulated circuits and their results are discussed including the fastness (time response) of the detection methods and the precision of the classification ones. Two methods for detection and four combinations for classification were simulated.

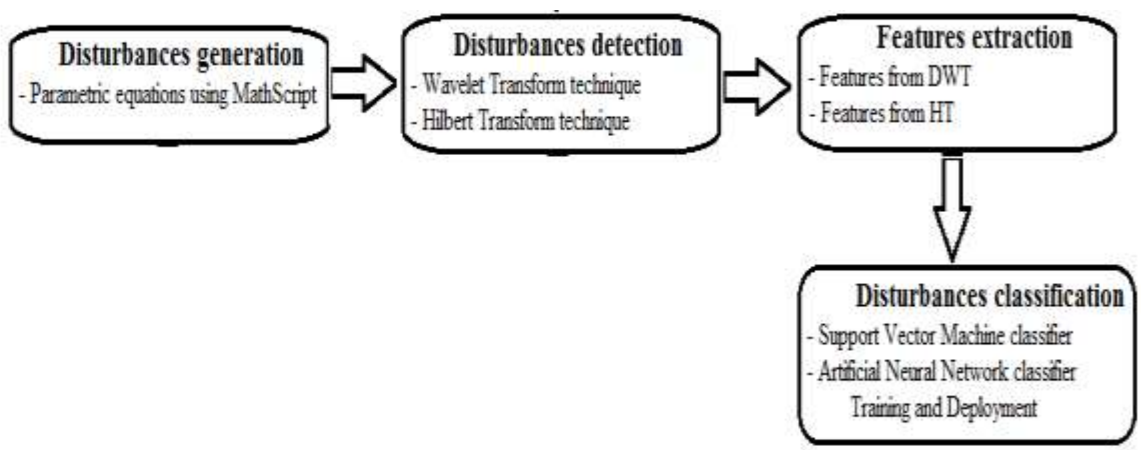


Fig 3-1 Block diagram of PQDs detection & classification

The software used for the simulation is the Laboratory Virtual Instrument Engineering Workbench (LabVIEW). It is a development environment based on the graphical programming language G. LabVIEW programs are called Virtual Instruments, or VIs. LabVIEW contains a comprehensive set of tools for acquiring, analyzing, displaying, and storing data. A VI contains the three components: the front panel, the block diagram, and the icon and connector pane; The front panel serves as the user interface whereas the block diagram contains the graphical source code that defines the functionality of the VI, The icon and connector pane identifies the VI so that a VI can be used in another VI [**58**].

3.2 Disturbance generation

The generation of power quality events was performed using the parametric equations represented in Table (3-1) through a program written in the Matlab language called by a Matlab Script node which offered in LabVIEW. In addition to a pure sine wave with amplitude of 230V and frequency of 50Hz, eight types of PQDs that are commonly occur in power system were generated including sag, swell, interruption, harmonics, transient, flicker, sag with harmonics, and swell with harmonics. The different parameters of signals represented in the starting time, duration and distortion magnitude were generated randomly. Signals simulated that way are very close to reality because none of these are fixed for real power system events. On the other hand, different signals belonging to the same class give the opportunity to estimate the generalization ability of classifiers. During the detecting and classifying of PQ disturbances, 100 different cases for every type of PQ disturbance waveforms are generated.

Table 3-1 Signal Modeling of Power Quality Events

PQEs	Equations Models	Parameters
Sine	$(t) = A \sin(\omega t)$	$A = 230$ $f = 50Hz$
Sag	$(t) = (1 - ((t - t1) - (t - t2))) \sin(\omega t)$	$0.1 \leq \alpha \leq 0.9$ $T \leq$ t2-t1 $\leq 9T$
Swell	$(t) = A(1 + \alpha(u(t - t1) - u(t - t2))) \sin(\omega t)$	$0.1 \leq \alpha \leq 0.8$ $T \leq$ t2-t1 $\leq 9T$
Interruption	$(t) = (1 - ((t - t1) - (t - t2))) \sin(\omega t)$	$0.9 \leq \alpha \leq 1$ $T \leq$ t2-t1 $\leq 9T$
Harmonics	$(t) = [\sin(\omega t) + \alpha 3 \sin(3\omega t) + \alpha 5 \sin(5\omega t) + \alpha 7 \sin(7\omega t)]$	$0.05 \leq \alpha 3 \leq 0.15$ $0.05 \leq \alpha 5 \leq 0.15$ $0.05 \leq \alpha 7 \leq 0.15$
Transient	$f(t) = A[\sin(\omega t) + \alpha \exp(-(t-t1)/\tau)] \sin(\omega tr(t-t1))$	τ = 0.008--0.04 sec ωtr = 100--400Hz $0.1 \leq \alpha \leq 0.9$
Flicker	$(t) = A \sin(\omega t) (1 + \beta \sin(\gamma \omega t))$	$0.1 \leq \beta \leq 0.2$ $0.1 \leq \gamma \leq 0.2$
Sag & harmonics	$f(t) = A[1 - \alpha(u(t - t1) - u(t - t2))][\sin(\omega t) + \alpha 3 \sin(3\omega t) + \alpha 5 \sin(5\omega t) + \alpha 7 \sin(7\omega t)]$	$0.1 \leq \alpha \leq 0.9$ $0.05 \leq \alpha 3 \leq 0.15$ $0.05 \leq \alpha 5 \leq 0.15$ $0.05 \leq \alpha 7 \leq 0.15$
Swell & harmonics	$f(t) = A[1 + \alpha(u(t - t1) - u(t - t2))][\sin(\omega t) + \alpha 3 \sin(3\omega t) + \alpha 5 \sin(5\omega t) + \alpha 7 \sin(7\omega t)]$	$0.1 \leq \alpha \leq 0.8$ $0.05 \leq \alpha 3 \leq 0.15$ $0.05 \leq \alpha 5 \leq 0.15$ $0.05 \leq \alpha 7 \leq 0.15$

3.3 Detection methods

After generating the disturbed signals, the event detection is performed via Discrete Wavelet Transform VI and Fast Hilbert Transform VI for the DWT and HT's detection methods respectively.

For DWT, the mother wavelet chosen is fourth-order Daubechies (db4) and the MRA is of 5 levels. The detection is made using the third level detailed coefficient signal (D3). The simulated circuit is shown in Figure (3-2) below.

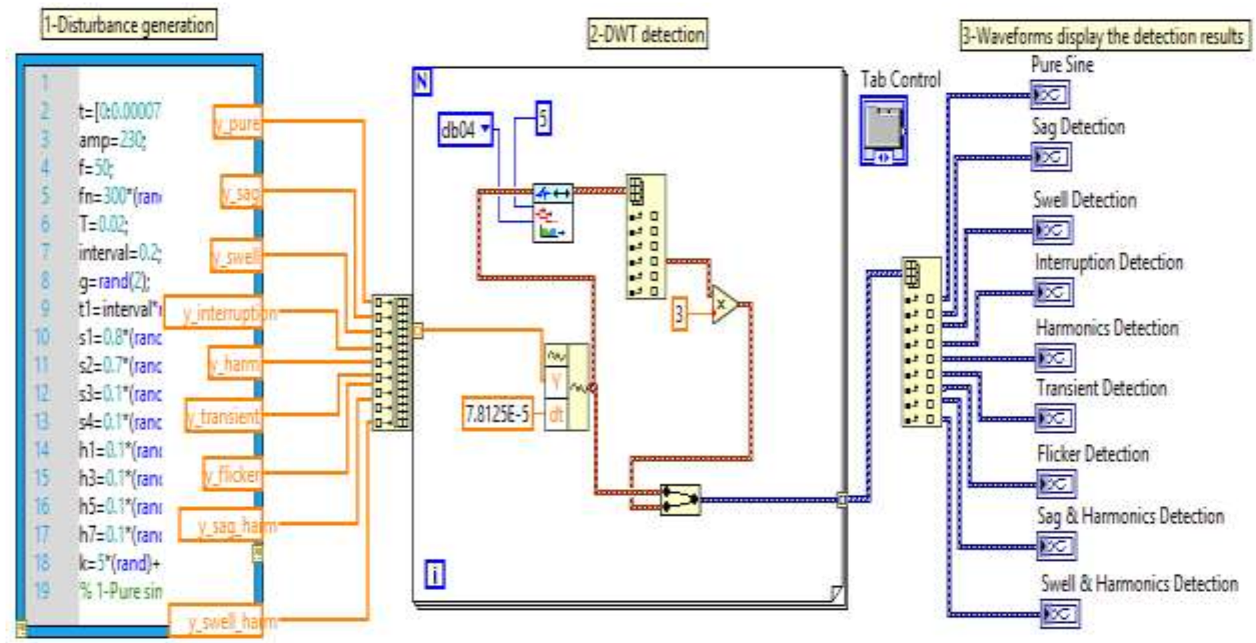
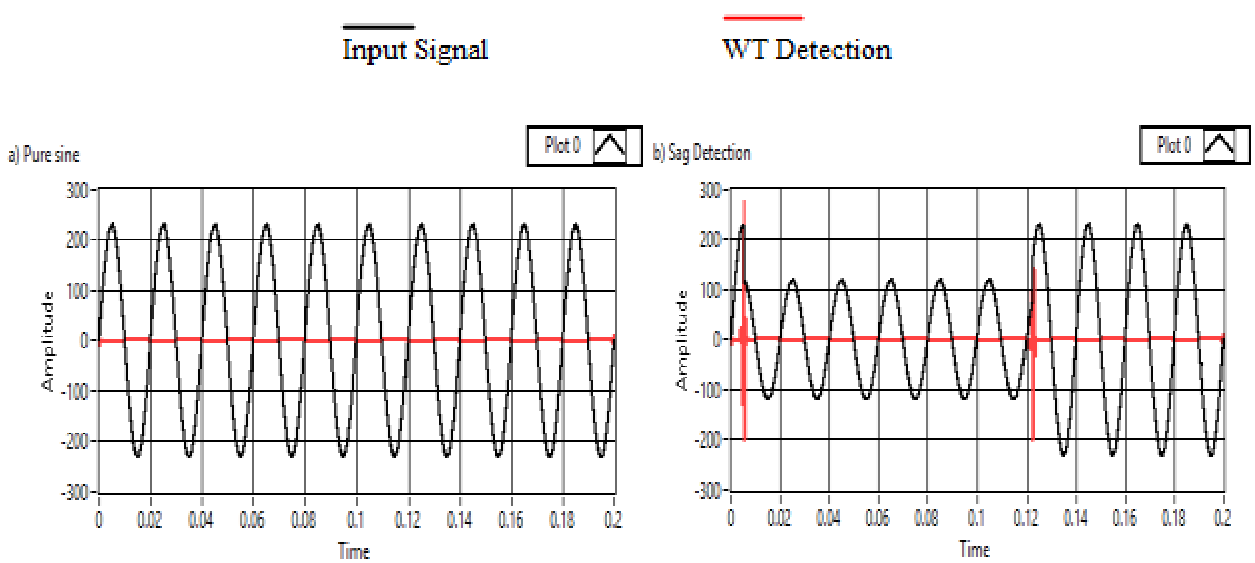


Fig 3-2 Detection circtuit of the DWT

The results of detection are shown in the Figure (3-3).



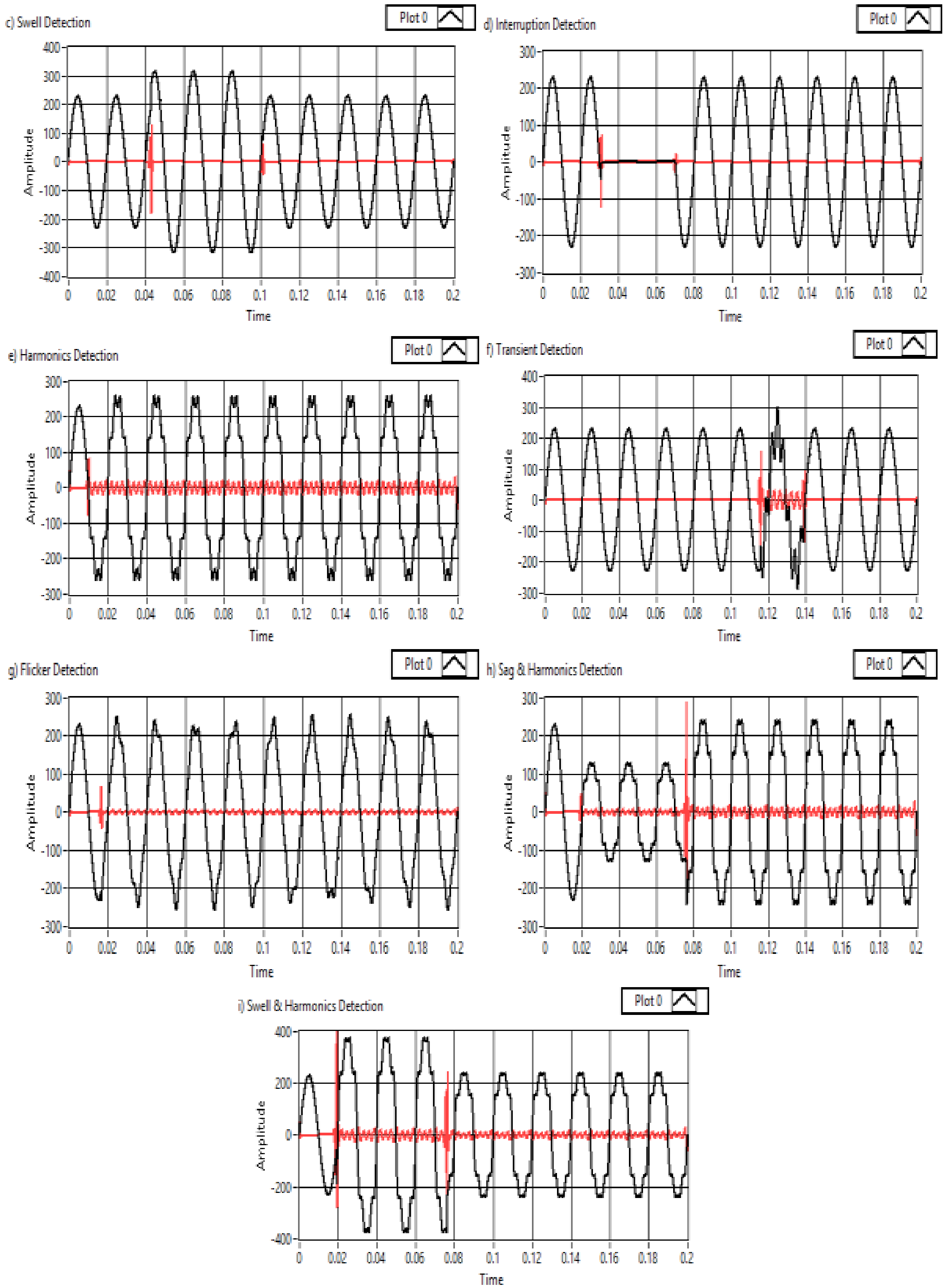


Fig 3-3 Detection results of DWT

And for HT, the phase shifting algorithm has been applied to the different disturbances using the envelope of the transform as shown in Figure (3-4).

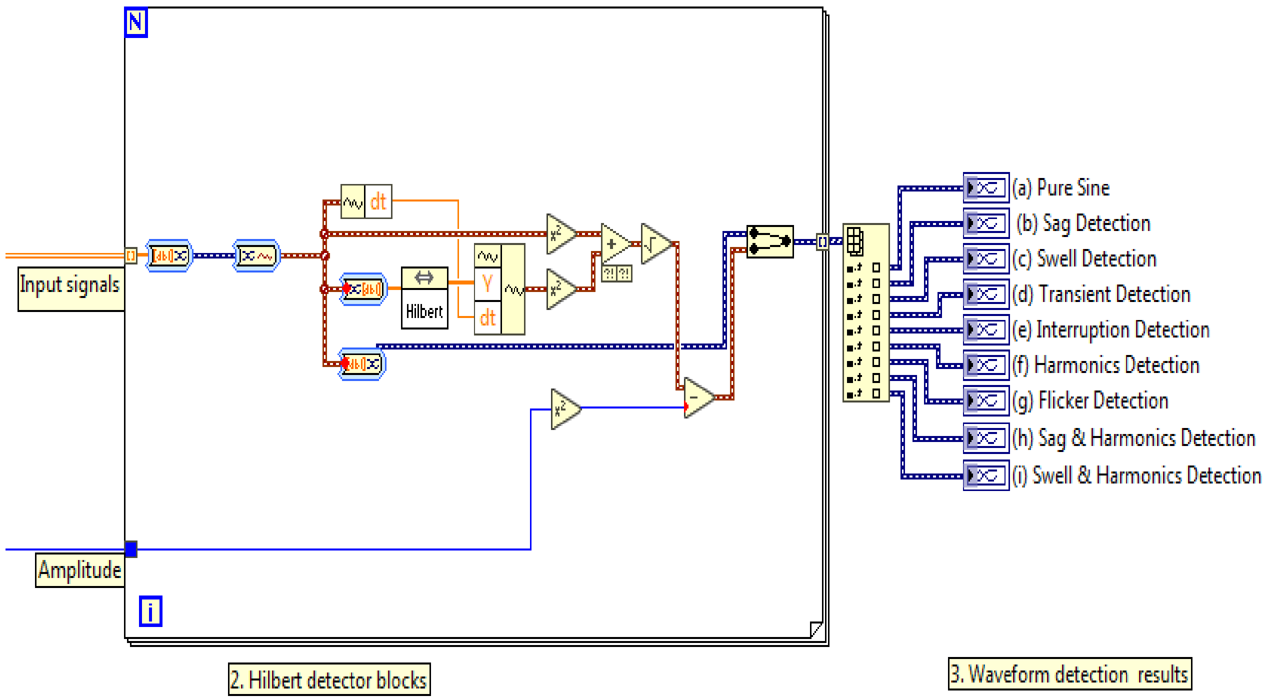
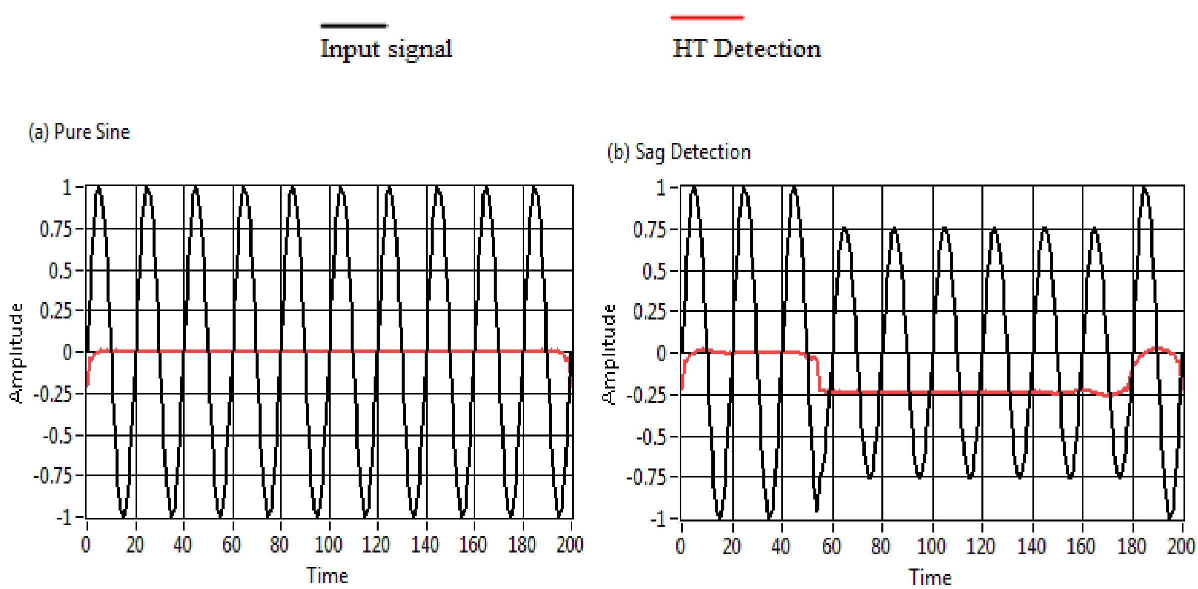


Fig 3-4 Detection circuit of HT

The disturbances have been successfully detected the results are illustrated in Figure (3-5).



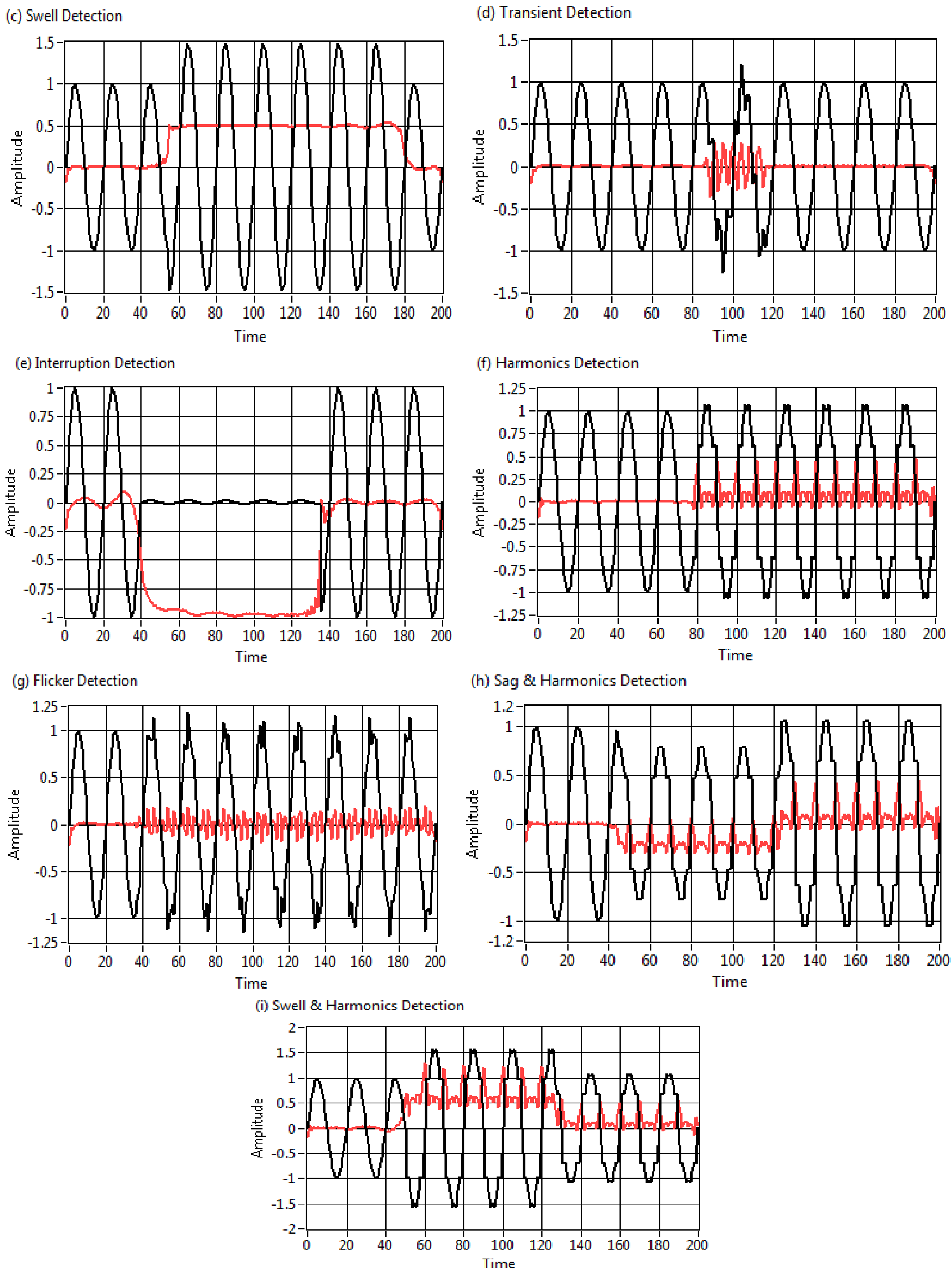


Fig 3-5 Detection results of HT

In order to measure the time response for both techniques, the starting time was identified using the waveform peak detection VI by passing the signal used for detection (D3) through the VI as illustrated in Figure (3-6).

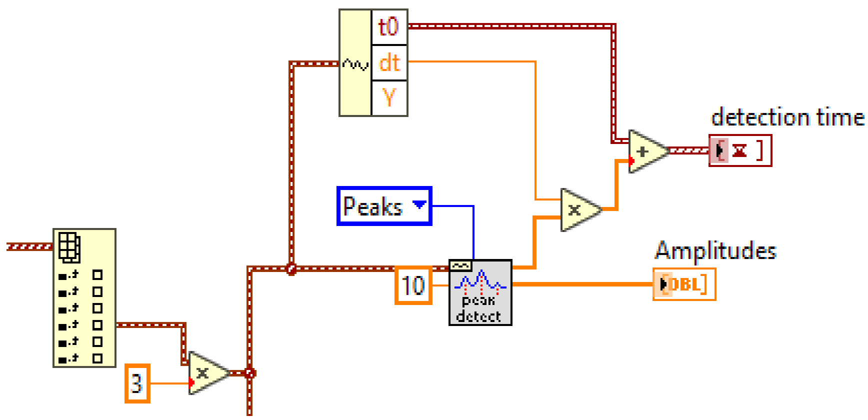


Fig 3-6 Time response identification for DWT method

Next, the measured time was compared to the real starting time used in the disturbance generation program. This was repeated for the eight disturbances and the results recorded in Table (3-2).

Table 3-2 Detection time for DWT and HT

Disturbance	Detection of starting time for DWT			Detection of starting time for HT		
	Actual time (ms)	Measured time (ms)	**Time delay(ms)**	Actual time(ms)	Measured time (ms)	**Time delay(ms)**
Sag	22.671	22.758	**0.087**	54.42	55.2	**0.78**
Swell	116.967	117.043	**0.076**	31.18	32.1	**0.92**
Interruption	59.141	59.601	**0.46**	14.56	15.5	**0.94**
Harmonics	46.040	46.612	**0.572**	60.24	61.14	**0.90**
Transient	95.187	95.247	**0.06**	106.66	107.23	**0.57**
Flicker	42.263	42.682	**0.419**	45.6	46.33	**0.73**
Sag & harmonics	77.945	78.358	**0.413**	87.14	88.02	**0.88**
Swell & harmonics	35.859	35.888	**0.029**	137.88	138.5	**0.62**

Discussion

- As it is mentioned in Figure (3-4) and Figure (3-5), the two proposed methods detected the eight disturbances successfully and for the pure sine signal the detector signals stayed a straight line along the x-axis to indicate the absence of any disturbance.
- For DWT method, the detection is made by spikes at the starting and ending time of disturbance. Therefore in addition to detect the disturbance, it measures the period of disturbance occurrence and that is an advantage for it.
- For HT method, the detection is made by reshaping the envelope according to the shape of disturbance depending on its magnitude. Therefore the advantage of this method is giving information about the amplitude of disturbance.
- For the detection of starting time, the Wavelet detection has a higher time response than the Hilbert detection which has also an acceptable time response. This is due to the spikes generated by DWT.

3.4 Features extraction

Before the classification stage takes place, a stage of feature extraction stage must be done. The input of the classifier is a preprocessed signal generated from this stage. Feature extraction is the key for pattern recognition so that it is the most important component of designing the intelligent system based on pattern recognition since even the best classifier will perform poorly if the features are not chosen well. In this work, the preprocessed signal was generated using features of DWT and HT once a time.

For the WT, the wavelet coefficients obtained from discrete wavelet and multiresolution analysis of the disturbance signal represented in 1^{st} level detailed coefficient (D1), 5^{th} level detailed coefficient (D5), and 5^{th} level approximated coefficient (A5) were used for the construction of feature vector by calculating the three features based on DWT for each coefficient. The three features are Energy, Shannon Entropy and Kurtosis and they; their expressions are shown in Table (3-3).

Table 3-3 Expression of the Wavelet based features

Feature	expression
Energy	$$E_i = \sum_{j=1}^{N} \lvert C_{ij} \rvert^2$$ Were "i" denotes level of decomposition,
Shannon Entropy	$$SE_i = -\sum_{j=1}^{N} {C_{ij}}^2 Log({C_{ij}}^2)$$
Kurtosis	$$KRT_i = \sqrt{\frac{N}{24}}\left(\frac{1}{N}\sum_{j=1}^{n}\left(\frac{C_{ij}-\mu_i}{\sigma_i}\right)^4 - 3\right)$$ Where μ_i is the means and σ_i in the standard deviation

The number of features is than 3*3 = 9 features for each disturbance signal; Figure (3-7) represents the block diagram for the feature extraction.

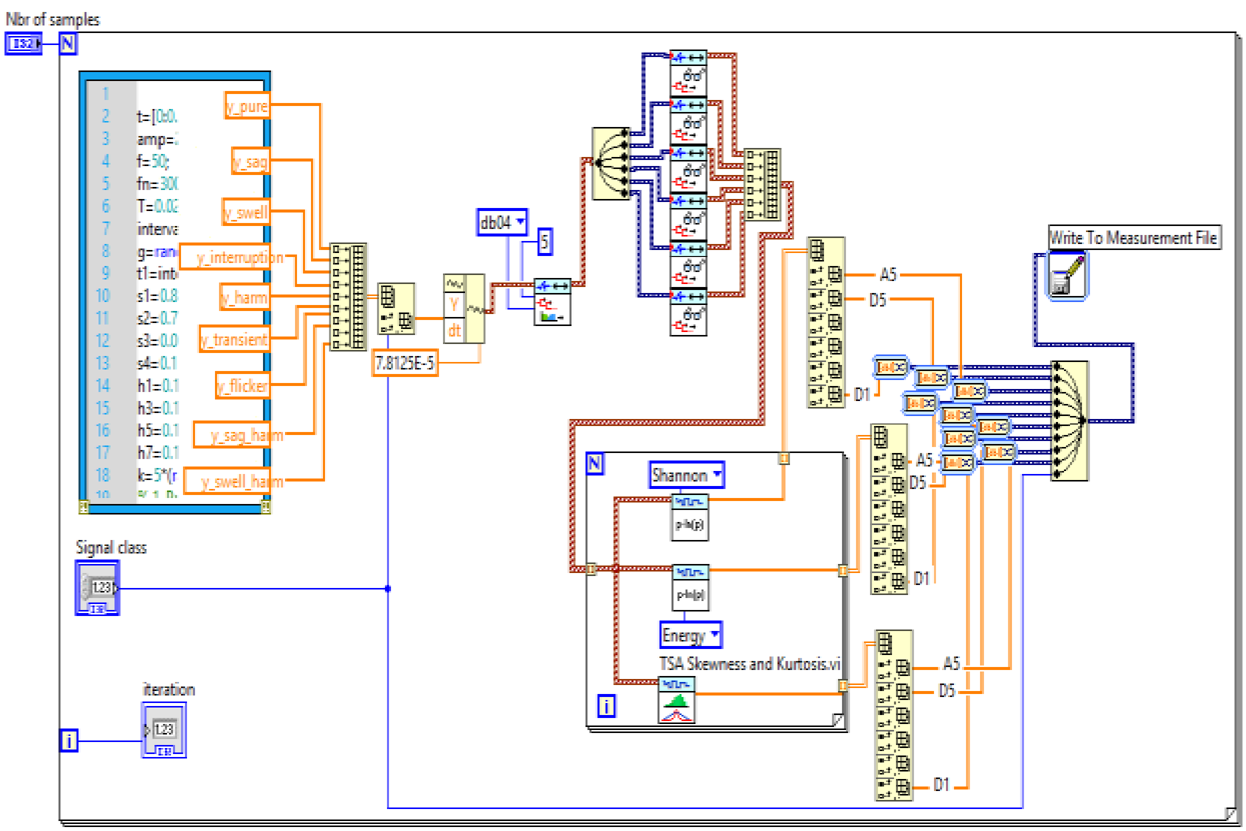


Fig 3-7 Feature extraction circuit based on DWT

1000 samples of each disturbance class were randomly generated. Hence the size of the training data is 1000*9 = 9000 data samples per class.

For HT, nine extracted features were calculated for the envelope of the transform. The features are Mean value, RMS, Standard deviation, Variance, Maximum and Minimum Values, THD, and Duration. Table (3-4) shows the features' expressions.

Table 3-4 Expression of features used in HT

Feature	Expression
Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$
Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$
Variance	$\mu(x^2) - [\mu(x)]^2$
RMS	$rms = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2}$
THD	$thd = \frac{\sqrt{\sum_{i=2}^{N} {x_n}^2}}{x_i}$

Also 1000 disturbances for each class were randomly generated and the size of training data is then 1000*9 = 9000 data samples per class. The block diagram is shown in Figure (3-8)

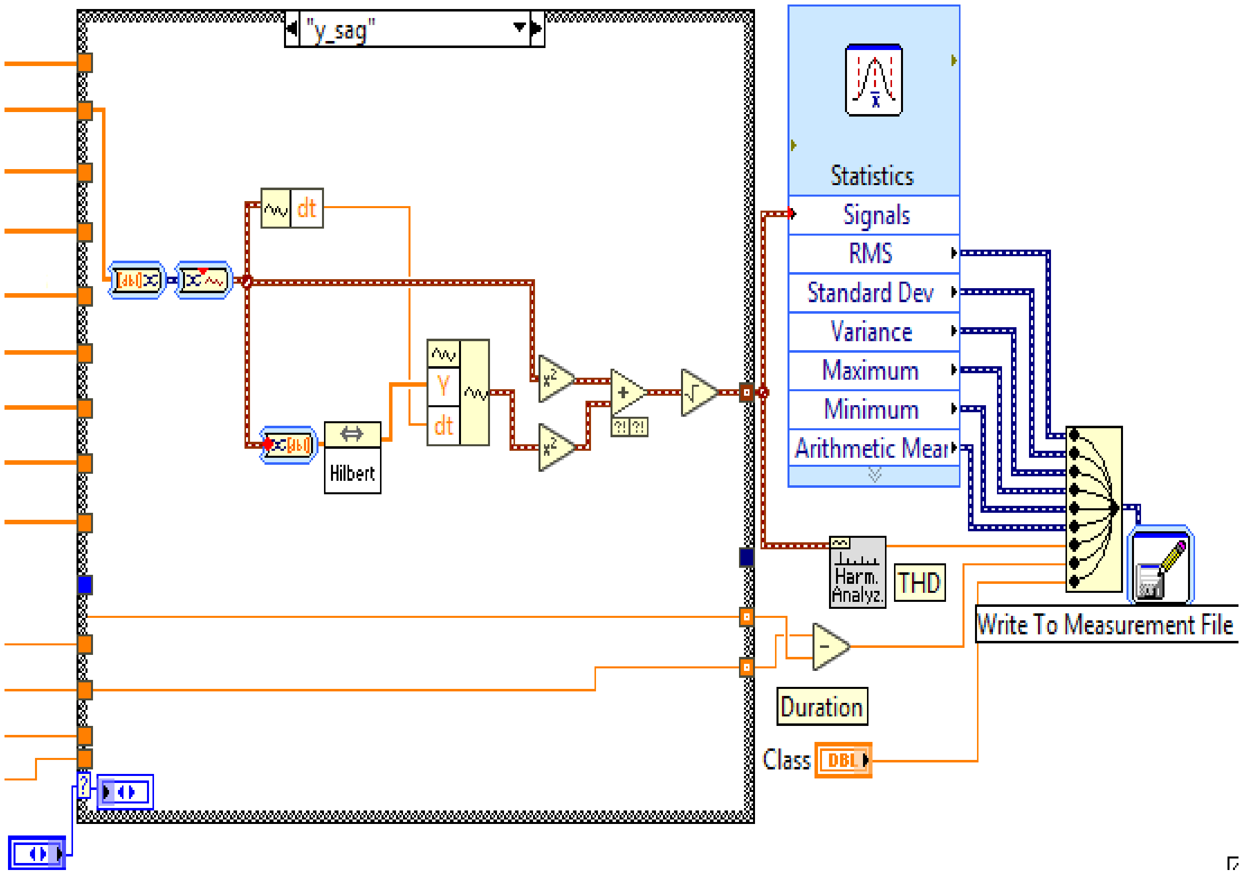


Fig 3-8 Features extraction from the Envelope of HT

3.5 Classification methods

After preparing two different training data, they were utilized as the inputs of the untrained models SVM and ANN. These two late are available blocks in LabVIEW. Four proposed methods resulted from the possible combination between training data and classifiers. The methods are:

- Training data obtained from DWT as trained data for SVM classifier denoted as DWT-SVM.
- Training data obtained from HT as trained data for SVM classifier denoted as HT-SVM.
- Training data obtained from HT as trained data for ANN classifier denoted as HT-ANN.
- Training data obtained from DWT as trained data for ANN classifier denoted as DWT-ANN.

The training process of the two classifier are shown in the next two Figures (3-9) (3-10), where the test data file in the figures is the CSV file contains the training data obtained from the features extraction.

SVM Classifier:

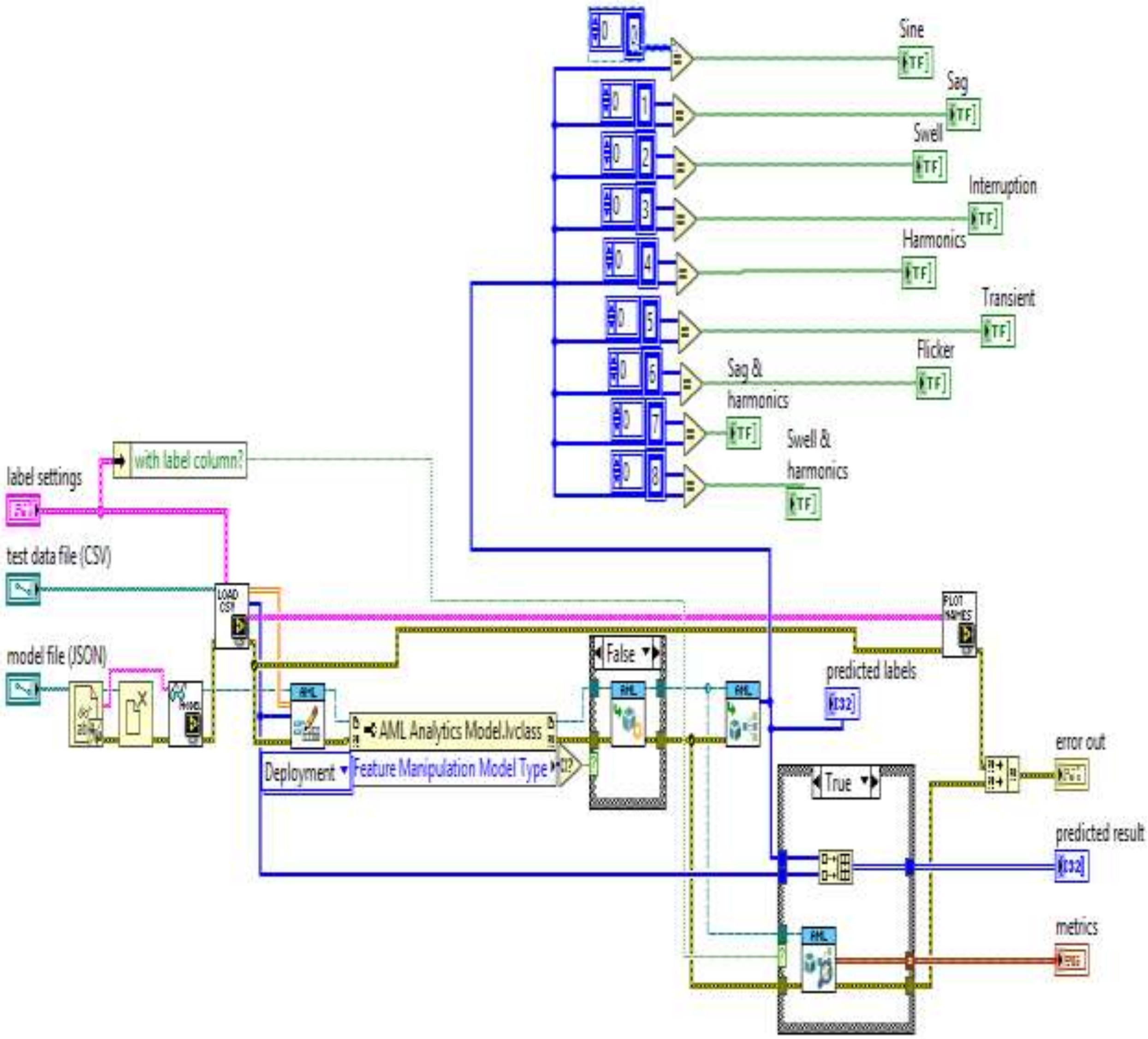


Fig 3-9 Testing circuit of SVM classifier

ANN classifier:

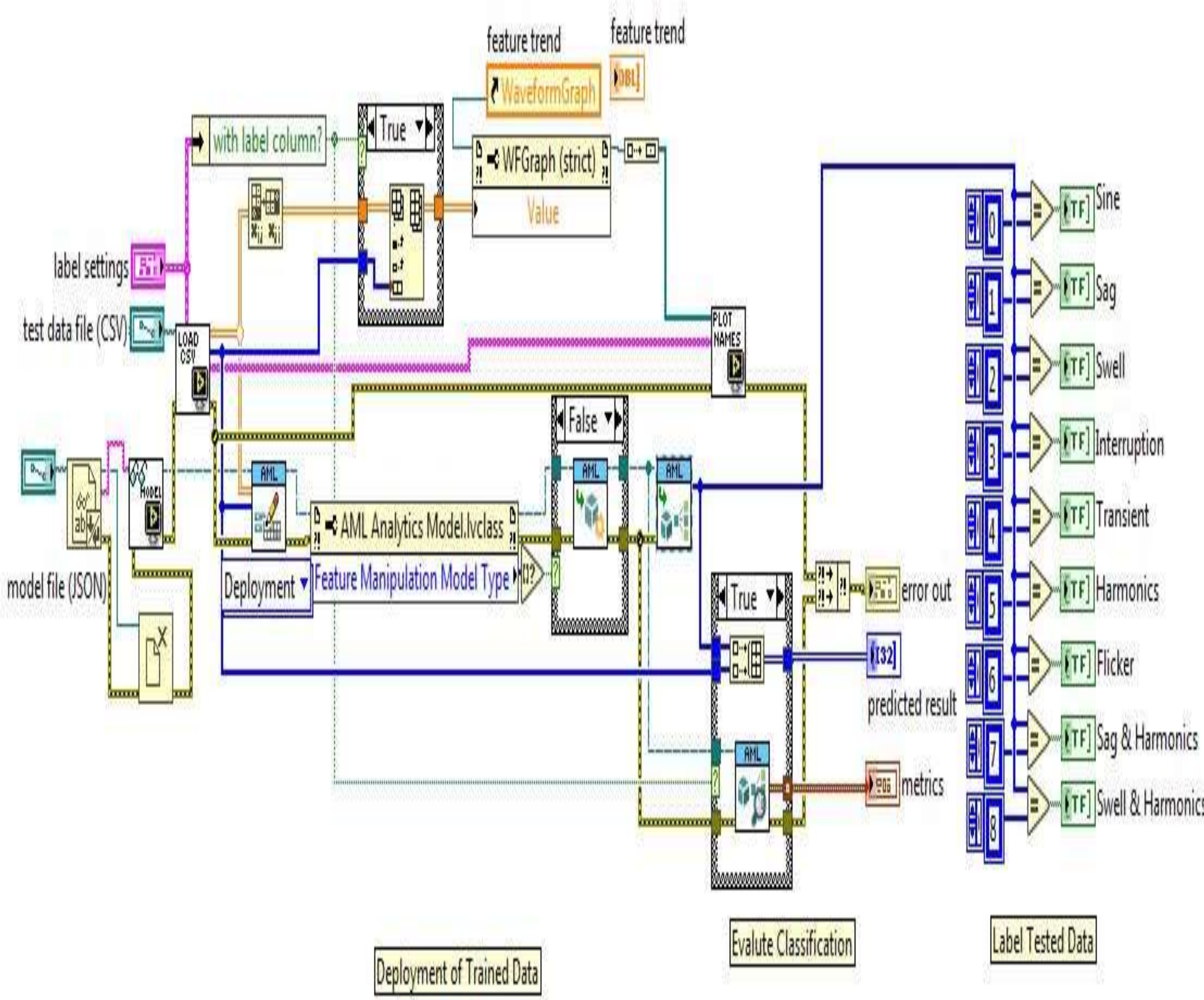


Fig 3-10 Testing circuit of ANN classifier

The classification model parameters were set automatically by the model itself using cross validation techniques as shown in Figure (3-11).

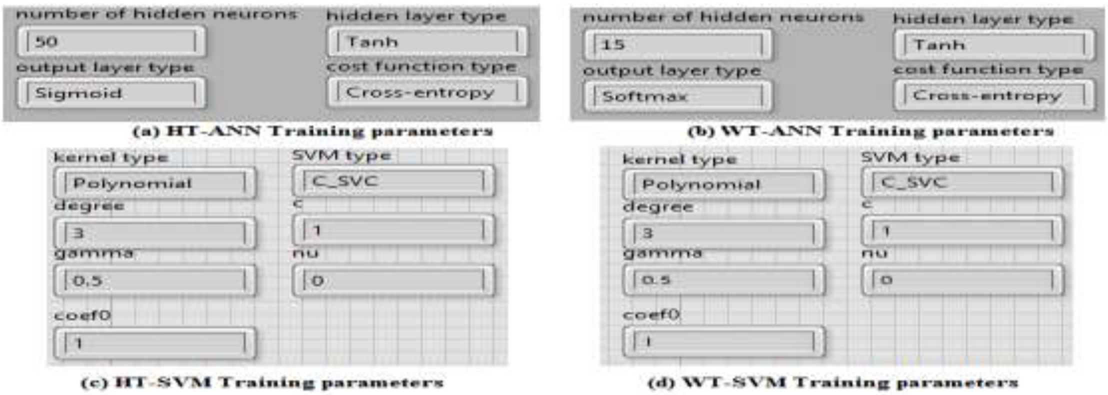
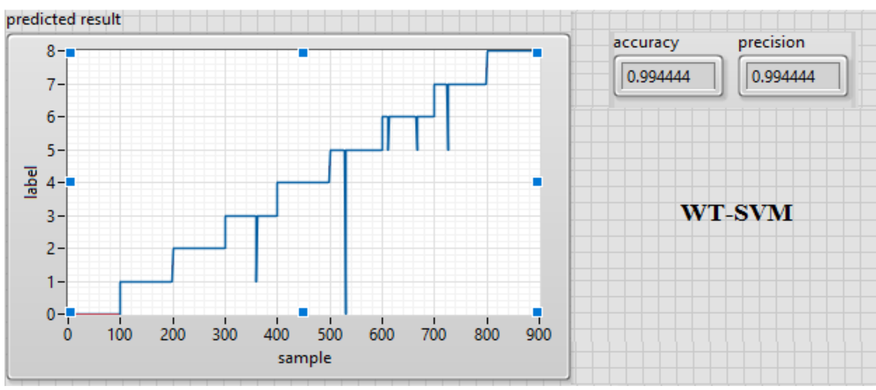
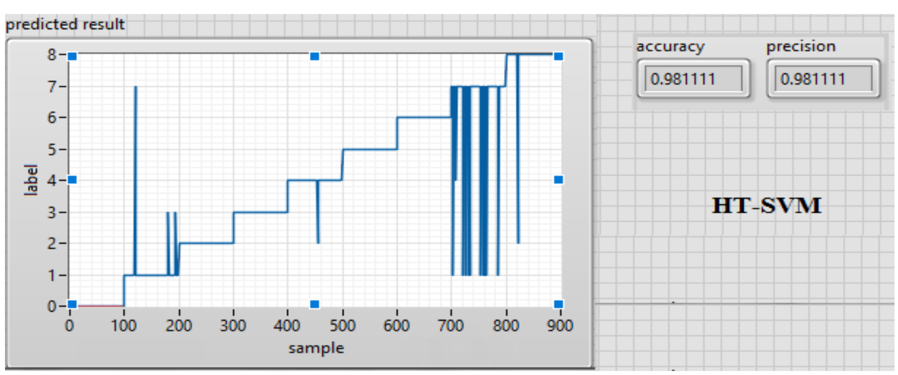


Fig 3-11 Parameters of training Classifiers

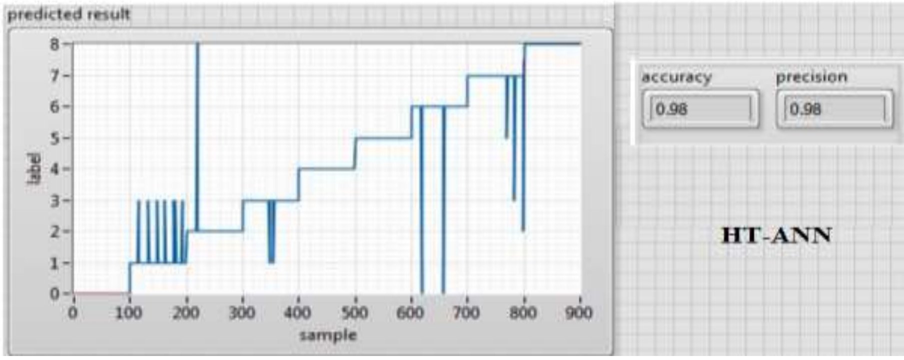
100 testing data sample for each class were used to test the performance of each method. The classification results are shown in Figure (3-12).



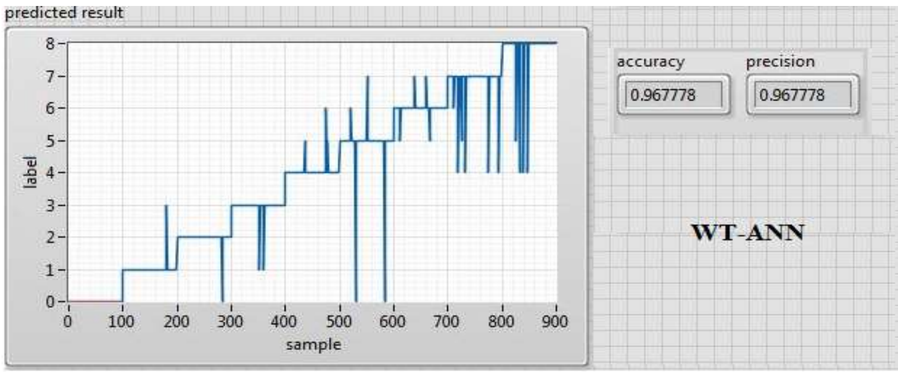
(a)



(b)



(c)



(d)

Fig 3-12 Testing results of the four proposed methods (a) WT-SVM,(b) HT-SVM,(c) HT-ANN,(d) WT-ANN

The following tables illustrate the results including the number of correct classified and misclassified events and the accuracy.

- First, DWT- SVM which has the higher value of precision over all the used methods.

Table 3-5 Classification results using the proposed WT-SVM classifier

Signals	Tested Samples	Correctly identified	Fault identified	Precision (%)
Pure Sine	100	100	0	100
Sag	100	100	0	100
Swell	100	100	0	100
Transients	100	99	1	99
Interruptions	100	99	1	99
Harmonics	100	100	0	100
Flicker	100	98	2	98
Sag & Harmonics	100	99	1	99
Swell & Harmonics	100	100	0	100
Total	***9000***	***895***	***5***	***99.44***

- Second, HT-SVM also has acceptable results.

Table 3-6 Classification results using the proposed HT-SVM classifier

Signals	Tested Samples	Correctly identified	Fault identified	Precision (%)
Pure Sine	100	100	0	100
Sag	100	97	3	97
Swell	100	100	0	100
Transients	100	100	0	100
Interruptions	100	100	0	100
Harmonics	100	99	1	99
Flicker	100	100	0	100
Sag & Harmonics	100	88	12	88
Swell & Harmonics	100	99	1	99
Total	***9000***	***883***	***17***	***98.11***

- Third, HT-ANN almost has as the previous method.

Table 3-7 Classification results using the proposed HT-ANN classifier

Signals	Tested Samples	Correctly identified	Fault identified	Precision (%)
Pure Sine	100	100	0	100
Sag	100	90	10	90
Swell	100	99	1	99
Transients	100	100	0	100
Interruptions	100	98	2	98
Harmonics	100	100	0	100
Flicker	100	98	2	98
Sag & Harmonics	100	97	3	97
Swell & Harmonics	100	100	100	100
Total	***900***	***882***	***18***	***98.00***

- Finally, DWT-ANN which has the lowest value of precision between the used methods.

Table 3-8 Classification results using the proposed WT-ANN classifier

Signals	Tested Samples	Correctly identified	Fault identified	Precision (%)
Pure Sine	100	100	100	100
Sag	100	99	1	99
Swell	100	99	1	99
Transients	100	95	5	95
Interruptions	100	98	2	98
Harmonics	100	97	3	97
Flicker	100	96	4	96
Sag & Harmonics	100	91	9	91
Swell & Harmonics	100	96	4	96
Total	***9000***	***871***	***29***	***96.78***

The last Table (3-9) indicates the accuracy of the four proposed methods.

Table 3-9 Accuracy results of all simulated methods

Method	DWT-SVM	HT-SVM	HT-ANN	DWT-ANN
Accuracy (%)	99.44	98.11	98.00	96.78

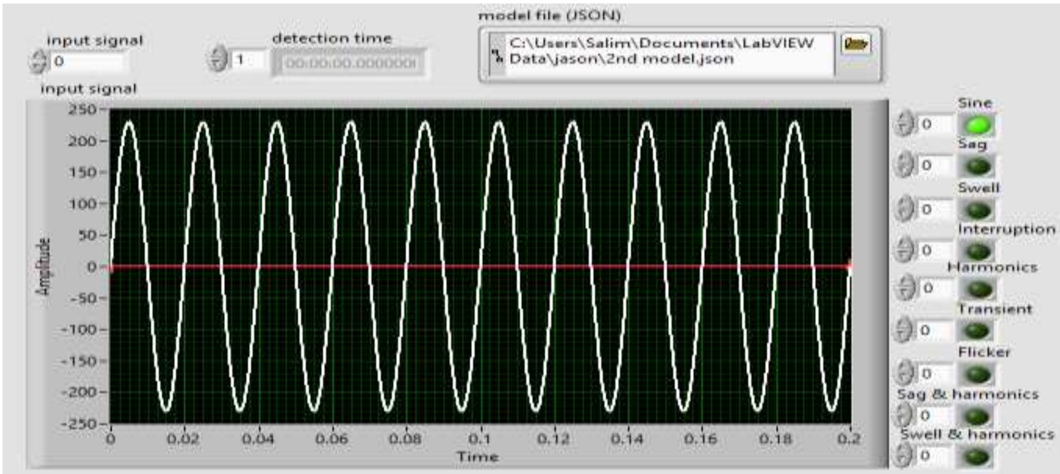
Discussion

- All the proposed classification methods give good accuracy results that are between 96.7% and 99.4%.
- These results show the effectiveness of the features chosen for both DWT and HT.
- The features extracted from DWT are more suitable for SVM classifier whereas the features extracted from HT are more suitable for ANN.
- The lowest accuracy was resulted in DWT-ANN, and this indicates that the DWT features utilized are not much suitable for the ANN classifier.
- ANN classifier had low accuracy in classifying Sag & Harmonic events with DWT (91%).
- SVM classifier had low accuracy in classifying Sag & Harmonic events with HT (88%).
- SVM classifier proves its robustness and efficiency over ANN.
- The method DWT-SVM expresses a very high accuracy that makes it to be the best one over the other methods, which proves the effectiveness of DWT features for SVM classifier.

3.6 Overall PQ monitoring system

From the previous results of detection and classification, a proposed method for a power quality monitoring system was deduced. The method utilizes the combination between DWT and SVM; DWT is used for detection and features extraction of disturbances, and SVM classifier is used for identifying the type of disturbances. The system had been successfully simulated and the resulted front panels for the nine events are shown in Figure (3-13).

Input Signal WT Detection



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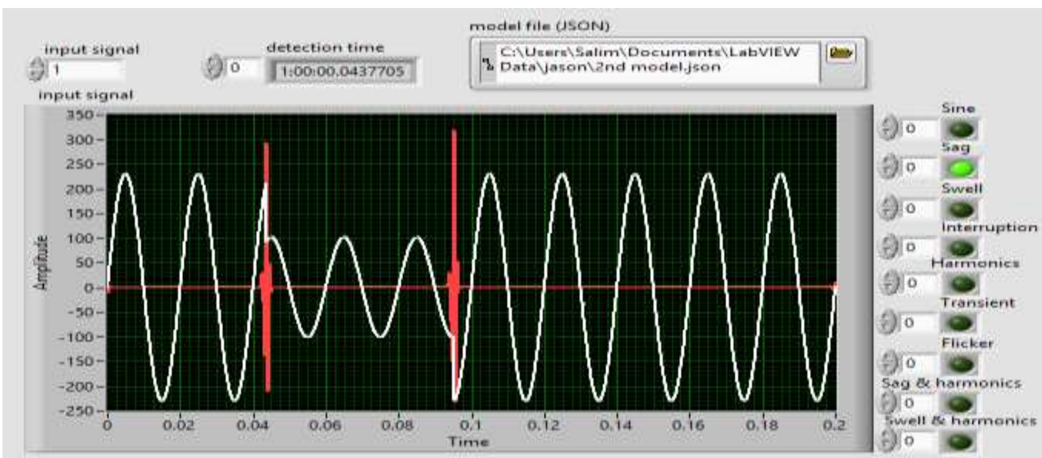

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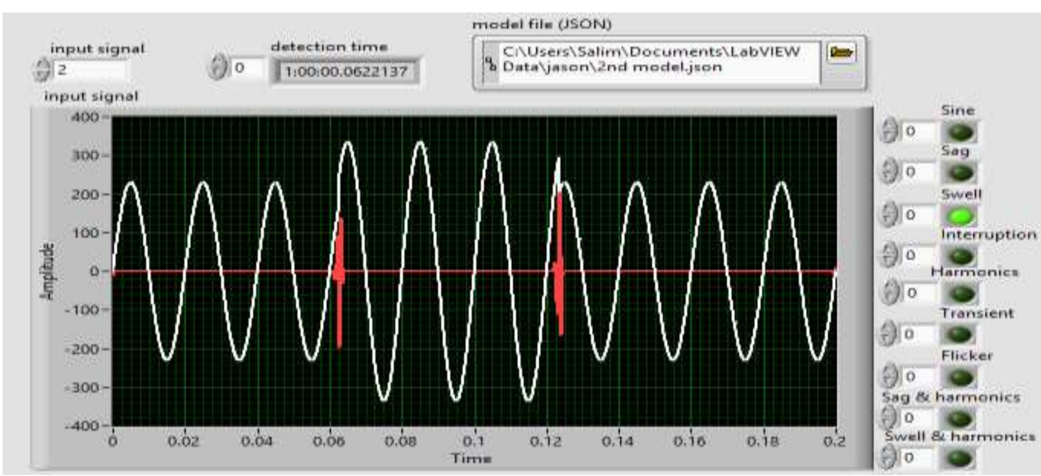

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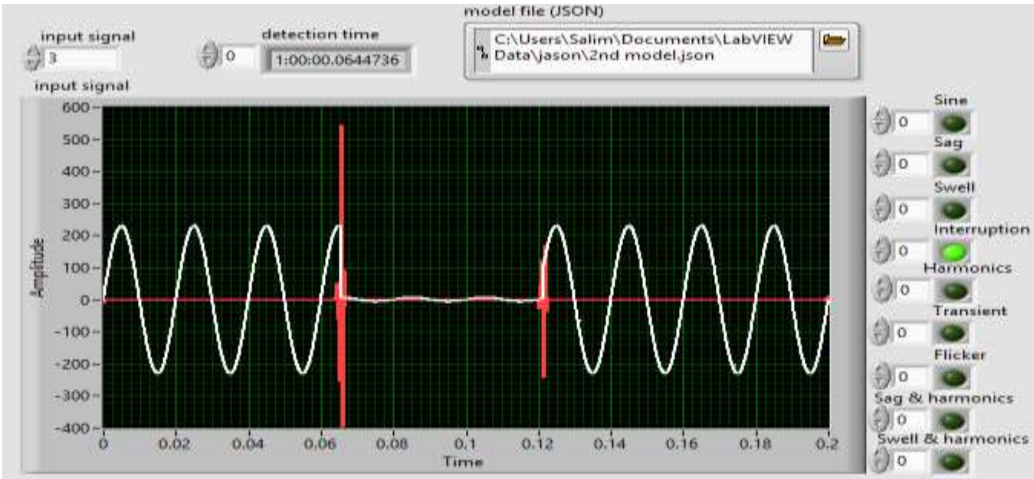
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input signal
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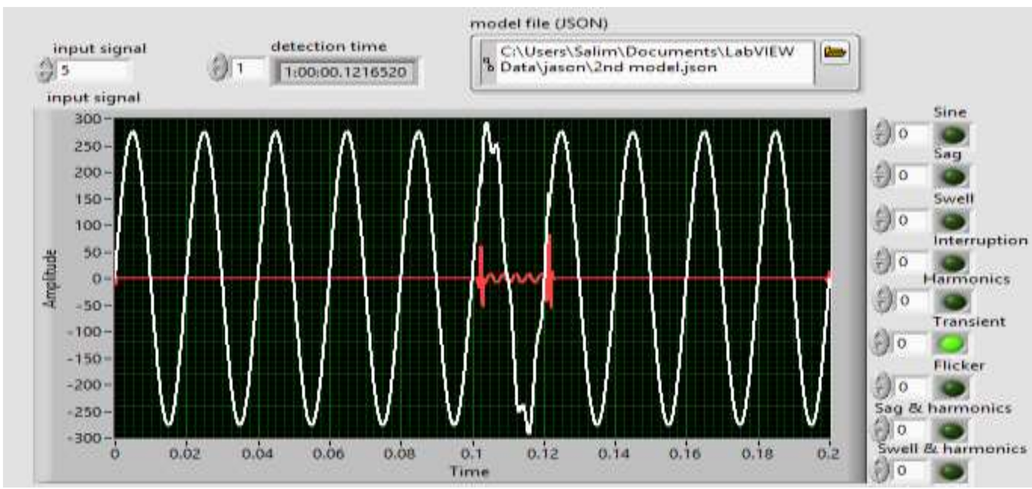
Time
Sine
Sag
Swell
Interruption
Harmonics
Transient
Flicker
Sag & harmonics
Swell & harmonics

(d)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Time
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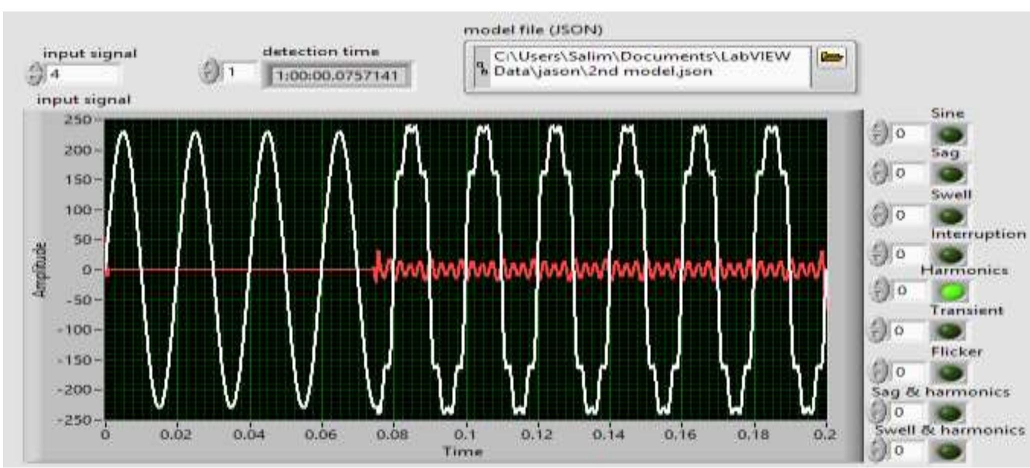
Sag
Swell
Interruption
Harmonics
Transient
Flicker
Sag & harmonics
Swell & harmonics

(e)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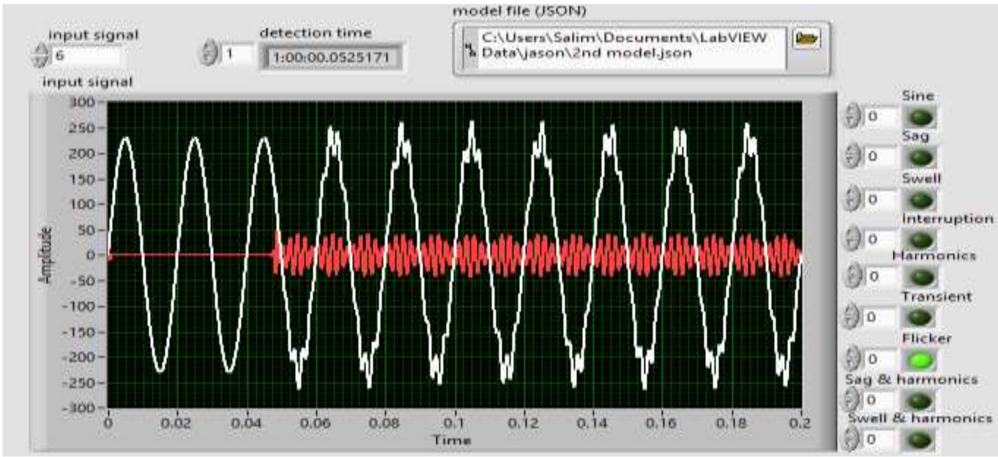
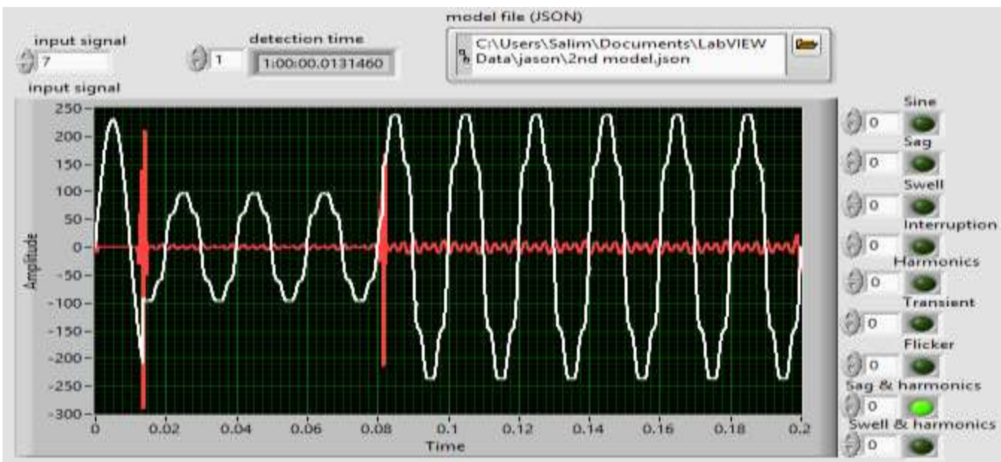
Sag
Swell
Interruption
Harmonics
Transient
Flicker
Sag & harmonics
Swell & harmonics

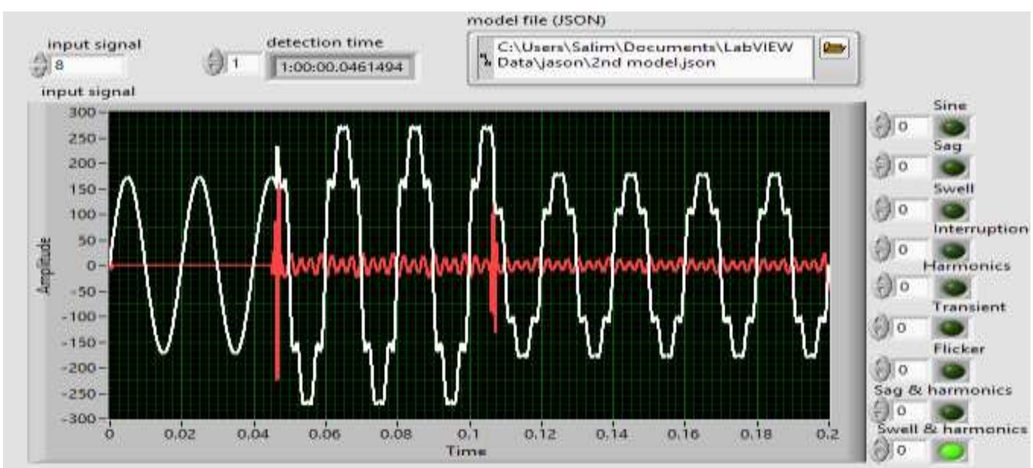
(f)



(g)



(h)



(i)

Fig 3-13 PQM Front Panel (a) Sine, (b) Sag, (c) Swell, (d) Interruption, (e) Transients, (f) Harmonics, (g) Flicker, (h) Sag & Harmonics, (i) Swell & Harmonics.

3.7 Conclusion

In this chapter, different types of disturbances were simulated to test and evaluate the performance of proposed detection and classification methods. For detection, both DWT and HT show fast time response to detect the disturbance the time that is occurs with advantage for DWT. For classification, combinations between signal processing & machine learning methods were utilized to successfully classify power quality disturbances. The combination DWT-SVM was the best one with great amount of accuracy.

GENERAL CONCLUSSION

The objectives of this project were to develop a PQM system that had the ability to detect power quality disturbances at the minimum possible of time and to correctly identify them with high precision, which is the major area of research in power system field.

To do that, WT and HT were introduced as signal processing tools used for detecting and characterizing PQDs and they have proved their efficiency and flexibility in detecting different disturbances, either the amplitude variation disturbances or the frequency variation ones. Also the machine learning tools ANN and SVM were proposed in the literature to classify the different PQDs, as a result, the accuracy of the classifiers was encouraging by more than 96% that shows their effectiveness. From the analysis done in the literature, it may be concluded that:

- One of the main purposes in the power quality field is the development of high speed-accuracy automatic system for the identification, detection and classification of disturbance.
- DWT with MRA technique is an effective tool for analyzing non-stationary signals as the ones of PQDs and detect any type of them at a faster rate (0.029ms ~ 0.572ms) by choosing suitable mother wavelet and multi-resolution level.
- Feature extraction is the key for pattern recognition to design the best performance classifier.
- Features extracted from HT and DWT are more efficient for a classifier than the ones extracted directly from the disturbed signal.
- ANN and SVM classifier are efficient tools in automatic classification of disturbances (96.78% ~ 99.44%), for best accuracy results; features that are the training data for the classifier must be well chosen by trying different sets of features combination.
- The combination DWT-SVM proposed in the literature shows high robustness and accuracy (99.44%) for detection and classification of the nine PQDs.

- Virtual instrument represented in LabVIEW is a very good instrument for the detection and analysis of power quality, furthermore, PQM system designed using LabVIEW is economic, highly flexible, user-friendly and easily upgradable comes up as a revolutionary tool with its improved performance and more reliability than the traditional PQ analyzers which themselves may be tedious to handle and time consuming.

Future Work:

The scope of the future work that must take place and use the results drawn from this work can be listed as follow:

- The real time monitoring using the Data Acquisition Card (DAC) where real data of voltage waveform are collected from power system and then analyzed by the proposed PQM system; in this case and since the real time signal may be noised, de-noising step using WT capabilities should take place before starting the analysis of the signal.
- Extending the proposed method to analyze the maximum possible of disturbances occur in power system to increase the ability and efficiency of the monitoring system. This can be done by training the classifier for more signals.
- After detection and classification and to complete the monitoring cycle, mitigation stage should be developed by creating efficient mitigation techniques that are suitable to reduce the losses produced because of each disturbance.
- Developing hybrid model with other methods that are able to detect and classify non-distorted waveform disturbances like voltage imbalance occurred in phase angles.

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