# A METHOD FOR CLASSIFICATION OF POWER QUALITY DISTURBANCES EXPLOITING HIGHER ORDER STATISTICS IN THE EMD DOMAIN

by

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The thesis entitled **"A METHOD FOR CLASSIFICATION OF POWER QUALITY DISTURBANCES EXPLOITING HIGHER ORDER STATISTICS IN THE EMD DOMAIN"** submitted by Faeza Hafiz, Student No.: 1009062023F, Session: October, 2009 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING on August 3, 2013.

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I, do, hereby declare that neither this thesis nor any part of it has been submitted elsewhere for the award of any degree or diploma.

Signature of the Candidate

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Faeza Hafiz

# Dedication

*To my parents.*

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# Abstract

Power quality has become a major concern recently because of increasing number of sensitive loads being connected to the power system. Degradation in power quality is normally caused by power-line disturbances, malfunctions, instabilities, short lifetime, failure of electrical equipments etc. In order to improve power quality, the sources and causes of power quality (PQ) disturbance events must be known apriori to take appropriate mitigating actions. However, to determine the causes and sources of PQ disturbances, it is important to detect, localize and classify them. For the classification of PQ disturbances, a wide range of signal processing methods have been reported in the literature. Since, PQ disturbance is a non-stationary signal, development of a PQ disturbances classification method, which is simple yet effective in handling practical conditions, such as multiclass PQ disturbances, random selection of increased training and testing dataset, and presence of noise, is still a challenging task. In this thesis, a new method for the classification of PQ disturbances exploiting higher order statistics in the Empirical mode decomposition (EMD) domain is proposed. A PQ disturbed signal is first analyzed in terms of intrinsic mode functions (IMFs) by using EMD operation. The Higher Order Statistics (HOS), such as variance, skewness and kurtosis of the first three extracted IMFs are then utilized to form the feature vector. The feature vector thus obtained when fed to the Probabilistic Neural Network (PNN) and $k$-Nearest Neighborhood ($k$NN) classifiers separately is found to be capable of classifying the multiclass PQ disturbance signals even in the presence of noise. Moreover, as expected, the classification accuracy is found to be enhanced using the proposed feature set while increasing the training and testing dataset. For the characterization of PQ disturbance signals, mathematical models of eleven classes of disturbances are used. Simulations are carried out to evaluate the performance of the proposed method in terms of efficiency derived from the confusion matrix and CPU time representing the computational burden. It is shown that the proposed method outperforms some of the state-of-the-art methods with superior efficacy in stringent conditions.

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# List of abbreviations

| | |
|---|---|
| **PQ** | Power Quality |
| **FT** | Fourier Transform |
| **HHT** | Hilbert Huang Transform |
| **EMD** | Empirical Mode Decomposition |
| $k$**NN** | $k$ Nearest Neighbour |
| **PNN** | Probabilistic Neural Network |
| **RBF** | Radial Basis Neural Network |
| **SVM** | Support Vector Machine |
| **RVM** | Relevance Vector Machine |

# Chapter 1

# INTRODUCTION

Power quality (PQ) 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. The highest power quality is achieved when voltage and current have purely sinusoidal waveforms containing only the power frequency and when the voltage magnitude corresponds to its reference value. Any deviation from this may negatively affect the function and/or life expectancy of equipment connected to the power system [1–4].

PQ is becoming a mounting concern in the electric power industry. The deregulation of the power industry and the proliferation of sensitive semiconductor equipment into almost all kinds of industrial machinery and consumer electronics generated the demand for power quality and techniques for the reduction in PQ disturbances. Most often a disturbance in voltage also causes a disturbance in the current and hence the term Power quality is used when referring to both voltage quality or current quality. These disturbances even though last only a fraction of a second can cause huge losses and hours of manufacturing downtime in case of industrial applications. Consequently, monitoring of PQ disturbances is essential to offer solutions to industrial and electrical areas. For this reason, in order to improve power quality, the interest of the research community in PQ disturbances has dramatically increased over the past decade.

## 1.1 Types of Power Quality Disturbance Signals

PQ issues in a power system include different types of electric disturbances, such as voltage sag, swell, harmonics, fluctuation, interruption, spike, notch, transients, sag

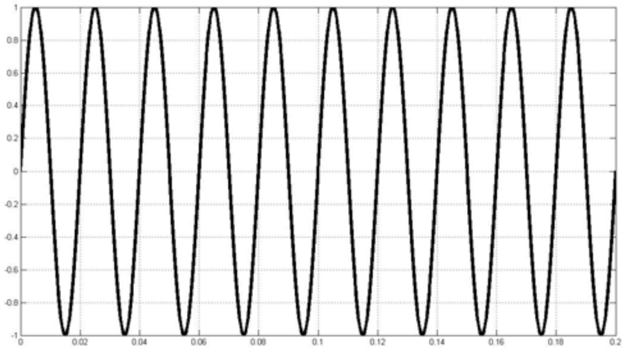



Figure 1.1: Normal Signal

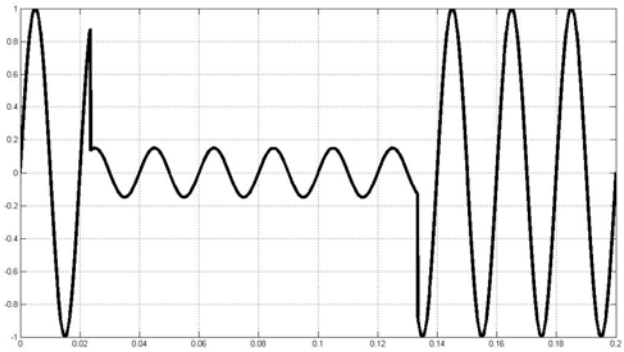



Figure 1.2: Sag

with harmonics, swell with harmonics etc. There are a number of different types of PQ disturbances and also a number of different ways to define and categorize them. Definitions of the different disturbance types as well as their usual causes and common negative effects of them are described below.

### 1.1.1 Voltage Sag

It is defined (ANSI std. 1100-1992) as the reduction in the AC RMS voltage, at the power frequency, for duration from half a cycle to a few seconds.

Main causes of voltage sag include energizing of heavy loads (e. g. arc furnaces), starting of large induction motors, single line-to-ground (SLG) faults, line-line and symmetrical faults, transference of load from one power source to another, animal contact or tree interference.

Effects of voltage sag mainly include voltage instability and malfunctions in

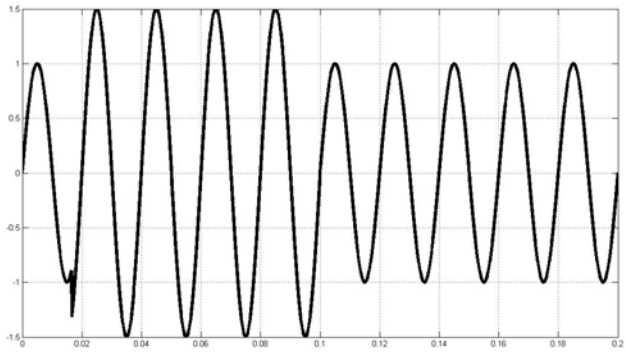


Figure 1.3: Swell

electrical low-voltage devices, uninterruptible power supplies, measuring and control equipments. Also, problems in interfacing with communication signals can arise. Lights may dim briefly and television pictures may, for a moment, shrink slightly. More sensitive equipment could be more noticeably affected.

### 1.1.2 Voltage Swell

It is the increase in the AC RMS voltage, at the power frequency, for duration from a half a cycle to a few seconds.

Main causes of voltage swells include energizing of capacitor banks, shutdown of large loads, unbalanced faults, transients and power frequency surges.

It causes problems with equipment that require constant steady-state voltage. Long-duration voltage variations can be seen in this case.

### 1.1.3 Voltage Interruption

It is the total loss of AC Power for typically a few seconds to as long as one minute. This could happen as a result of momentary short circuit on the line. This event could be very momentary or sometimes could be repeatitive for a short duration.

Planned interruptions are usually caused by construction or maintenance in the power system. Temporary interruptions are usually caused by faults and are generally unpredictable and random occurrences.

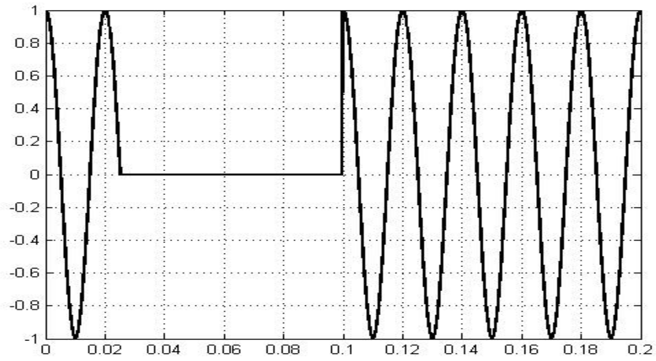



Figure 1.4: Interruption

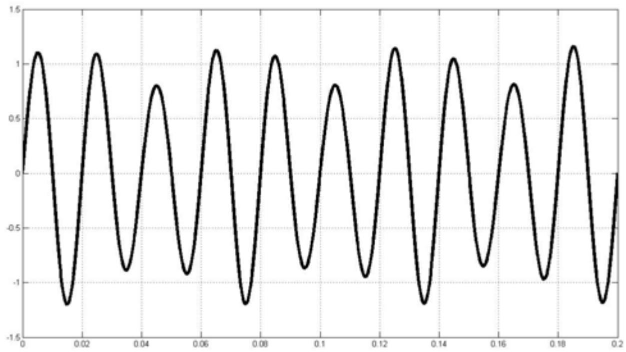


Figure 1.5: Flicker

### 1.1.4 Flicker

Flicker is generated from voltage fluctuations. The general way of describing the flicker level is the change in RMS voltage divided by the average RMS voltage. The instantaneous flicker level may vary with time depending on the length of the measure interval. If the interval is short compared to the flicker wavelength the flicker level will change periodically. To be able to estimate the flicker situation we must make a statistical analysis of the flicker level

Main causes of voltage flicker are startup of drives and drives with rapidly changing load or load impedance, as well as operation of arc furnaces, pulsed-power outputs, resistance welders and rolling mills.

This phenomenon can, when it reaches certain amplitudes (different amplitudes depending on the frequency of the flicker), cause discomfort for people exposed to the effects. However, flicker does not cause any malfunctions in the power system; the inducted discomfort is its only negative effect.

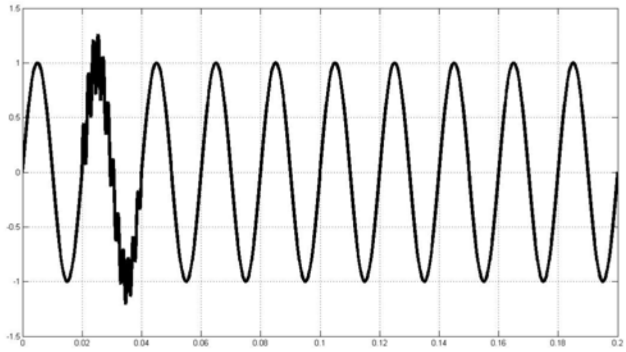


Figure 1.6: Transient

### 1.1.5 Voltage Transient

Transients, or transient over voltages, are short-duration either oscillating or impulsive voltage phenomena with a duration of usually a few milliseconds or shorter and normally heavily dampened. Though short in duration they often create very high magnitudes of voltage.

Main causes for transients are switching on secondary systems, Lightning-induced ringing, Local ferroresonance etc. Transients with high voltage magnitudes cause insulation breakdown in the power system and transients with high current magnitudes can burn out devices and instruments. Other effects of transients include mal-operation of relays, mal-tripping of circuit breakers, radiated noise may disrupt sensitive electronic equipment and Voltage magnification at customer capacitors.

### 1.1.6 Harmonics

Either voltage or current may be distorted by harmonics. When nonlinear loads are connected to normal sinusoidal voltage, the current waveform gets distorted. The distorted current waveform is made up of fundamental sine wave or first order 50 Hz current and multiple frequency currents such as 100 Hz, 150 Hz. The harmonic current will then travel upstream, away from the nonlinear loads that produced them and towards the utility source. This will distort the voltage at other nodes separated by appreciable impedance. If the voltage distortion is high, they may affect other

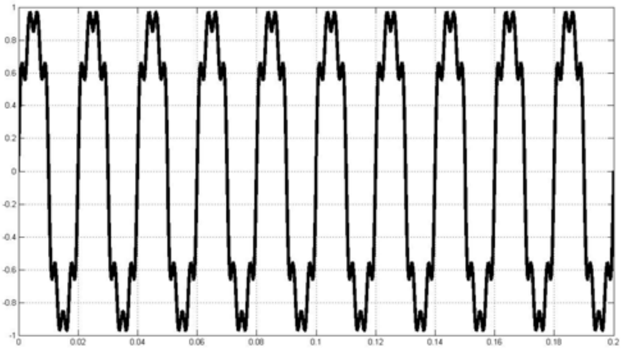


Figure 1.7: Harmonics

power consumers. At low voltage distortion, they will still affect other power system elements and other electrical circuits that are in parallel with the power circuits in the plant that generated them. Nonlinear loads such as computers, laser printers, welders, variable frequency drives, UPS systems, fluorescent lighting, etc., usually have diode-capacitor power supplies at the front end. They draw current in short pulses during the peak of the line voltage thus introducing harmonics.

Harmonics in general are often caused by operation of rotating machines, arcing devices, semiconductor based power supply systems, converter-fed AC drives, thyristor controlled reactors, phase controllers, and AC regulators, as well as magnetization nonlinearities of transformers.

The general effects of harmonics include increased thermal stress and losses in capacitors and transformers, as well as poor damping, increased losses, and in other ways degraded performance of rotating motors. Furthermore, transmission systems are subject to higher copper losses, corona, skin effect, dielectric stress, interference with measuring equipment and protection systems. Harmonics also negatively affect consumer equipment such as television receivers, fluorescent and mercury arc lighting, and the CPUs and monitors of computers.

### 1.1.7 Sag with Harmonics

Sometimes sag and harmonics both may occur in a power system. This kind of event can be seen when the problems of sag and harmonics happen simultaneously. Disruption of operation can be seen for this distortion.

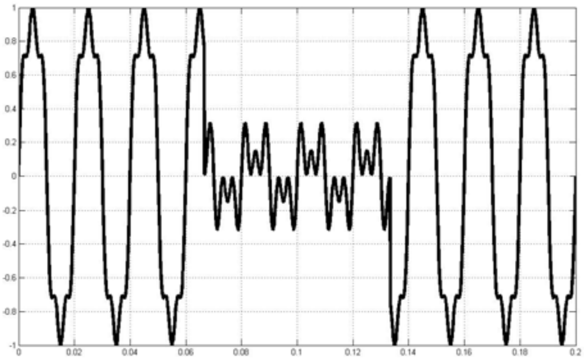


Figure 1.8: Sag with Harmonics

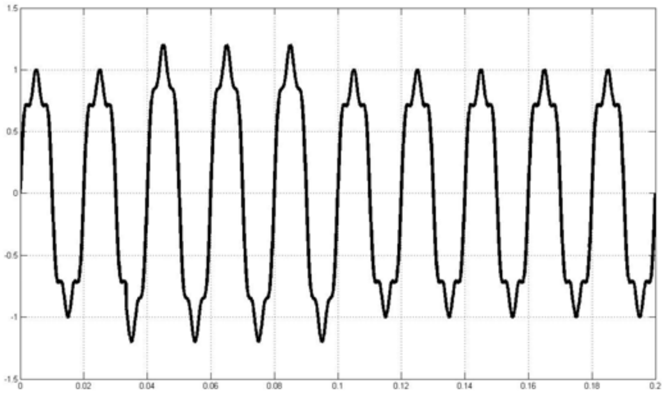


Figure 1.9: Swell with Harmonics

### 1.1.8 Swell with Harmonics

Swell and harmonics can be seen in a power system. Widespread use of shunt capacitor for the improvement of power factor and stability, solid state power converters for industrial furnaces etc. are the causes of this type of distortion. This causes production of heat that may reduce the operating life of equipments.

### 1.1.9 Spike

Spikes or surges normally are on the line for only 1/1000th of a second or less (less than 1 millisecond). They can be from a few to 10,000 volts-peak above or below the voltage sine wave. Voltage spikes normally last only for about 50 microseconds and current spikes last typically 20 microseconds ANSI C62.41-1991).

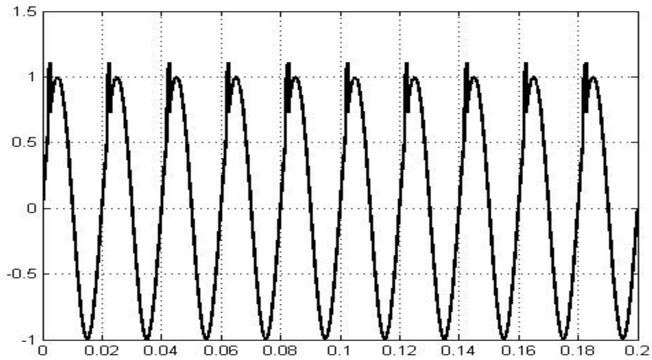



Figure 1.10: Spike

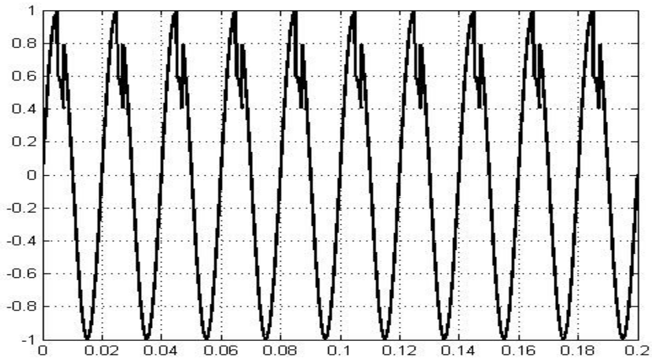



Figure 1.11: Notch

Lightning surges that come into your building by way of the wires power, telephone, cable TV or other; switching surges that occur when electrical loads are turned on or off either in your home (large motor-driven appliances) or on the electric system grid are the main causes of spike.

The effects of spike are damage to VCRs, televisions, computers and electronically controlled appliances. Susceptible appliances can usually be identified if they have electronic push buttons, electronic clocks, or digital displays.

### 1.1.10 Notch

Notching disturbances are non-sinusoidal, periodic waveform distortions and, as the name suggests, consist of notches in the fundamental sine wave component. This is caused by the commutation of current from one phase to another during the continuous operation of power electronic devices. Normal operation of electronic equipment may cause notch sometimes.

This event causes negative operational effects, such as signal interference introduced into logic and communication circuits. Also, when of sufficient power, the voltage notching effect may overload electromagnetic interference filters, and other similar high-frequency sensitive capacitive circuits.

## 1.2 Importance of the classification of Power Quality Disturbances

In early days, power quality issues were concerned with the power system transient arising due to switching and lightning surges, induction furnace and other cyclic loads. Increased interconnection, widespread use of power electronics devices with sensitive and fast control schemes in electrical power networks have brought many technical and economic advantages, but these have also caused degradation in power quality. Therefore, power quality may deteriorate due to a variety of reasons. Therefore, new challenges are introduced for the power engineer and they become more interested in PQ disturbances.

The main reasons for the increased interest in PQ disturbances can be summarized as follows:

- Modern electric appliances are equipped with power electronics devices utilizing microprocessor/microcontroller. These appliances introduce various types of PQ disturbances and moreover, these are very sensitive to the PQ disturbances.

- Industrial equipments such as high-efficiency, adjustable speed motor drives and shunt capacitors are now extensively used. The complexity of industrial processes results in huge economic losses if equipment fails or malfunctions.

- The complex interconnection of systems, resulting in more severe consequences if any one component fails. Moreover, various sophisticated power electronics equipments, which are very sensitive to the PQ disturbances, are used for improving system stability, operation and efficiency.

- There has been a significant increase in embedded generation and renewable energy sources which create new PQ disturbances, such as voltage variations, flicker and waveform distortions.

- In new electricity market scenarios, now electricity consumers can shift to the new service providers, if power quality is not good. Moreover, introduction of competitive electricity market gives right to the customers to demand high quality of power supply. The utilities or other electric power providers have to ensure a high quality of their service to remain competitive and to retain/attract the customers.

In order to maintain a reasonable level of quality, it is necessary to identify and classify the disturbance causing a particular type of power quality problem and to locate the sources of that disturbance in the power system so that corrective action can be taken.

## 1.3 Difficulties in classification of Power Quality Disturbances

Existing methods of analyzing and classifying power disturbances are laborious and time consuming since they are based on visual inspection of disturbance waveforms. Moreover, it is not always possible to extract important information from simple visual inspection. Due to the complexity of power quality problems and the lack of reliable techniques to analyze these problems, power utilities are unable to ensure the required level of power quality without a considerable increase in cost.

Accurate PQ disturbance classification, which depends on the several factors, is a difficult task. The following are the some of the major issues and challenges in classification of PQ disturbances.

- Performance of a classifier is highly dependent on the input extracted features. Deriving an effective feature for classifying PQ disturbances is a difficult task.

- The majority of classification techniques proposed is for single disturbance. Therefore, efforts need to be done for multiple disturbance classification like-sag with harmonics, swell with harmonics etc.

- Another issue of concern is the number of decomposition level required to avoid possible loss of some important information and to have accurate classifier since PQ disturbances cover a wide range of frequency.
- Effort should be aimed at incorporating knowledge and expertise of power system engineers in statistical classifiers also.
- To properly monitor the PQ events, the power quality monitors are installed in the system. Since, it is not possible to install the PQ monitor at all the nodes in the system due to technical and economical reasons, the optimal number of monitoring devices are to be placed in the system to get complete information about the PQ events.
- Most of the studies have done training and testing on synthetic data. Therefore, accumulation of a comprehensive standard PQ database similar to that of many other signal processing fields, for testing and comparisons of the state of the art techniques are also needed.
- Noise present in the signal has been a major hurdle in the accurate feature extraction and classification of PQ events.

## 1.4 Problem Definition

The increasing pollution of power signals and its impact on the power quality supplied by power plants to customers are pushing forward the development of signal processing tools to monitor and control of PQ disturbances.Recently, for the detection, localization and classification of PQ disturbances, researchers become interested to use efficient and appropriate signal processing methods that always try to model all information into a set of features from where decision making becomes easier and more accurate than the conventional methods of visual inspection [5–10]. Most of the signal processing techniques reported in the literature use time, frequency and time-frequency domain representation of the PQ disturbance waveforms, on the basis of which many specific features are derived in order to classify different types of PQ disturbances. The most difficult problem faced by today's PQ disturbances classification method is the large variation in the morphologies of PQ disturbance waveforms. It is to be noted that methods capable of classifying PQ disturbances in stringent conditions, such as multiclass PQ disturbances, and presence of noise have been limitedly reported. Thus, in order to handle the practical situations of real life applications as mentioned above, development of a method with an effective feature set for multiclass PQ disturbances classification that is capable of providing performance with greater accuracy with simplicity in computation is indeed a difficult problem.

## 1.5 Objective of the thesis

The objectives of this thesis are:

- To analyze the Intrinsic Mode Functions (IMFs) obtained by transforming the PQ disturbance signals in the Empirical Mode Decomposition (EMD) domain.

- To investigate the appropriateness of higher order statistics (HOS) of the extracted IMFs in distinguishing the multi class PQ disturbance signals through an extensive analysis.

- To develop a multi featured set using the HOS of the extracted IMFs for classifying PQ disturbance signals using different classifiers.

- To investigate the performance of the proposed feature set and that of different classifiers for the classification of multiclass PQ disturbance signals constructed from their corresponding model equations.

- To analyze the effectiveness of the proposed feature set and that of different classifiers for the classification of multiclass PQ disturbance signals in the presence of noise.

The outcome of this thesis is the development of an EMD based method exploiting a feature set derived from the HOS of the IMFs, which is able to classify multiclass PQ disturbance signals with greater accuracy in clean conditions, even in case of random selection of increased training and testing dataset as well as in noisy conditions.

## 1.6 Organization of the Thesis

This thesis is organized as follows:

- Different types of PQ disturbances, iimportance of the classification of PQ Disturbances, difficulties in classification of PQ Disturbances, objective of the thesis are introduced in Chapter 1.
- Chapter 2 provides a comprehensive review for the state-of-the-art methods for PQ Disturbances classification.
- Chapter 3 describes the proposed method of extracting features from the Higher Order Statistics (HOS) in the empirical mode decomposition (EMD) domain and that of using Probabilistic Neural Network (PNN) and k Nearest Neighborhood (kNN) classifiers for PQ disturbances classification.
- Simulation results and quantitative performance comparison of the proposed method are shown in detail in Chapter 4.
- Finally, concluding remarks, contribution and suggestions for future works of the thesis are highlighted in Chapter 5.

# Chapter 2

# LITERATURE REVIEW

## 2.1 Introduction

Degradation in quality of electric power due to various disturbances has become a major concern in recent times. There are many references which dealt with the various guidelines regarding monitoring power quality disturbances [11–17]. The basic introduction to all the various power quality disturbances possible in power distribution scenario is provided in [13]. A survey of various distribution sites concluded various interesting observations about the various disturbance occurrence statistics which includes that the majority of the voltage sags have a magnitude of around 80% and a duration of around 4 to 10 cycles and that the total harmonic distortion on harmonic disturbances is around 1.5 times the normal value [11] . These surveys provide basic introductory information about the occurrence and cause of the disturbances. However, for improving power quality by taking appropriate mitigating actions, it is essential to determine the causes and sources of disturbances. For this purpose, it is important to detect, localize and classify them.

It is a very time consuming to analyze PQ disturbance waveforms based on visual inspection. Moreover, it is not always possible to extract important information from simple visual inspection due to large variation in morphologies of PQ disturbance waveforms. Since PQ disturbance signals are non-stationary, the general methods of frequency analysis are not satisfactory for classification purposes. Therefore, many signal processing techniques have been utilized that try to extract feature from a PQ disturbance signal based on time or frequency or time-frequency domain and then use different classifiers for classification. The main principles of such methods are based on pattern recognition techniques that involve:

- signal processing methods for feature selection
- signal processing methods for disturbance classification.

This Chapter presents review on the literature survey of the different PQ disturbances classification methods.

## 2.2 Signal Processing Methods for Feature Extraction

More frequently, features extracted from the signals are used as the input of a classification system instead of the signal waveform itself, as this usually leads to a much smaller system input. Selecting a proper set of features is thus an important step toward successful classification. It is desirable that the selected set of features may characterize and distinguish different classes of PQ disturbances. This can roughly be described as selecting features with a large interclass (or between-class) mean distance and a small intraclass (or within-class) distance. Furthermore, it is desirable that the selected features are uncorrelated and that the total number of features is small. Other issues that could be taken into account include mathematical definability, numerical stability, insensitivity to noise, invariability to affine transformations, and physical interpretability. In signal decomposition using various parametric models of signals, the extraction of signal characteristics (or features, attributes) becomes easier in some Transform domain as compared with directly using signal waveforms in the time domain. The conventional signal processing methods for feature extraction of PQ disturbance signals use the following transform domains:

- Fourier Transform
- Short time Fourier Transform
- Wavelet Transform
- Hilbert Transform
- Hilbert-Huang Transform
- S Transform

### 2.2.1 Fourier Transform based Methods

Power system disturbance data is often available as a sampled time function which is represented by a time series of amplitudes. To deal with such data, among different signal processing approaches, Fourier transform (FT) is commonly used [18]. But the effectiveness of FT is limited to stationary signals only.

### 2.2.2 Short Time Fourier Transform based Methods

Brief time frequency information related to disturbance waveforms can be obtained by using the Short Time Fourier Transform (STFT) [19].The STFT as time-frequency analysis technique depends critically on the choice of the window. When a window has been selected for the STFT, the frequency resolution is unique at all frequency. However, the transient signals cannot be adequately described using STFT due to a fixed window size.

In [5], the spectral content as a function of time by using discrete STFT is obtained. Discrete STFT detects and analysis transients in the voltage disturbances by suitable selection of window size. Since the STFT has a fixed resolution at all frequency the interpretation of it terms of harmonics are easier. The band-pass filter outputs from discrete STFT are well associated with harmonics and are suitable for power system analysis. Also the STFT method is compared to wavelet in [5]. The Authors of [5] believes that the choice of these methods depends heavily on particular applications. Overall it appears more favorable to use discrete STFT than dyadic wavelet and Binary-Tree Wavelet Filters (BT-WF) for voltage disturbance analysis.

### 2.2.3 Wavelet Transform based Methods

The main advantages of wavelets is that they have a varying window size, being wide for slow frequencies and narrow for the fast ones, thus leading to an optimal timefrequency resolution in all the frequency ranges. Wavelet transform (WT) is widely being used for disturbance detection in PQ recently [20–24]. Wavelets can provide accurate frequency resolution and poor time localization at low frequencies and the vice versa at high frequencies. The property that the wavelets integrate to zero shows the ability of the standard deviation of different resolution levels to represent the distribution of the distorted signals. This capacity is used to classify and quantify the short duration variations within the power signals.

Olivier Poisson, Pascal Rioual, and M.Meunier [25], proposed a method of using continuous WTs to detect and analyze voltage sags and transients. The characteristics of the analyzed signals are measured on a time-frequency plane and are compared with the standard benchmark values. Any inconstancy will imply that there is a disturbance in the signal. This algorithm enabled accurate time localization, magnitude measurement of voltage sags and transient identification. Papers in [6, 25–30] present the properties of WTs and their use to scenarios similar to power quality disturbance classification. Most of them are based on WT, wavelet packet transform and wavelet multi resolution analysis, but these methods tend to be over sensitive to noise signals. Also, proper selection of mother wavelet and the level of decomposition are crucial for effective recognition of disturbance signals in the wavelet domain. Approaches like combining FT with various WT functions and similar methods depending on the type of disturbances can also be investigated [31].

Multi-resolved analysis (MRA) is based on Wavelet. The signal being analysed is first decomposed into distinct representations: one rich in high frequencies and the other in low frequencies, by processing the signal through high- and low-pass filters. This process is repeated as the signal is filtered at succeeding levels of detail; the filtering is accompanied by a down-sampling operator, which reduces the amount of information passed to subsequent levels [32]. This type of methodology MRA is widely used in various non-stationary signal analyses for different electrical problems such as rotating machines [33]. Sometimes a filter is applied to remove the fundamental frequency component so that the remaining signal, attributed to disturbance events, can be analyzed. In [34], this methodology is used to detect PQ disturbance and evaluate PQ disturbances.

Similar to the MRA, band-pass filters will be able to extract the high-frequency signals representing sudden changes in power systems as: transients caused by power system faults or power system switching operations, as well as the rapid rises or falls of the system voltage [35]. On the other hand, low-pass filters can extract

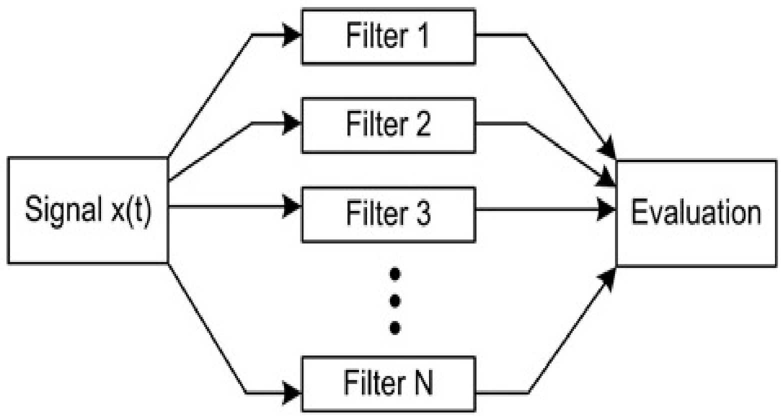



Figure 2.1: Block diagram of PQ disturbance detection based on a multi-channel filter system

slower signals, such as steady-state distortions like power system harmonics [36]. Therefore an appropriate combination of several bandpass filters will be able to obtain the necessary information to identify the PQ problems. To illustrate the general concept of a filter bank, the diagram in Fig. 2.1 shows a block diagram, where the signal under analysis $x(t)$ is divided into frequency bands. These bands are determined by the coefficients of each filter for being evaluated afterwards. In [37], a self-organizing learning array based on wavelet transform is introduced for power quality classification.

### 2.2.4 S Transform based Methods

STFT is commonly used in time-frequency signal processing. However, one of its drawbacks is the fixed width and height of the analyzing window. This causes misinterpretation of signal components with period longer than the window width; also the finite width limits time resolution of high-frequency signal components. One solution is to scale the dimensions of the analyzing window to accommodate a similar number of cycles for each spectral component, as in wavelets. This leads to the S-transform introduced by Stockwell, Mansinha and Lowe [38]. Like the STFT, it is a time-localized Fourier spectrum which maintains the absolute phase of each localized frequency component. Unlike the STFT, though, the S-transform has a window whose height and width frequency varying.

The S-transform was originally defined with a Gaussian window whose standard deviation is scaled to be equal to one wavelength of the complex Fourier spectrum. It can be considered as an extension of WT [39–41]. The Stockwel transform produces a time-frequency representation of a signal that uniquely combines a frequency dependent resolution and simultaneously localizes the real and imaginary spectra. Here, the modulating sinusoids are fixed with respect to time axis while the Gaussian window scales and moves. The S-transform has an advantage that it provides multi-resolution analysis while retaining the absolute phase of each frequency [9, 42–45]. But it requires the selection of a suitable window to match with the specific frequency content of the signal. Standard S Transform suffers from poor energy concentration in the time-frequency domain. It gives degradation in time resolution at lower frequency and poor frequency resolution at higher frequency.

The output of S Transform is a N×M matrix with complex values and is called the S-Matrix whose rows pertain to frequency and whose columns pertain to time.Important information in terms of magnitude, phase and frequency can be extracted from the S-matrix. Feature extraction is done by applying standard statistical techniques to the S-matrix. Many features such as amplitude, slope (or gradient) of amplitude, time of occurrence, mean, standard deviation and energy of the transformed signal are widely used for proper classification [42].

### 2.2.5 Hilbert Transform based Methods

A pattern recognition system has been proposed based on Hilbert Transform (HT). The output of the Hilbert Transform is 90 degree phase shift of the original signal. The envelope of the power quality disturbances are calculated by using Hilbert Transform. The type of the power quality events is detected by the shape of the envelope. In [43] and [46], authors have used Hilbert transform for feature extraction of distorted waveform that generates a quadrature signal and thereby an analytical signal. From these signals, the instantaneous amplitude and phase can be easily evaluated.

Some statistical information from the coefficients of Hilbert Transform are used for the formation of feature vector. Mean, standard deviation, peak value and energy of the Hilbert Transform coefficient are employed as input vector of the neural network classifier. The method in [47], shows that the Hilbert Transform features are less sensitive to noise level. But Hilbert Transformer gives a better approximate of a quadrature signal only if the signal approaches a narrow band condition. A combination of Prony analysis and Hilbert transform is also performed, where a signal is reconstructed using linear combination of damped complex exponential [48]. A prediction model is developed in this case which estimates the different modes of a signal and hence the signal as combination of these modes. The estimated signal best fits with the original signal only if condition of minimization of least square error between the original signal and estimated signal is satisfied. The Hilbert transform applied on the estimated signal then gives the envelope of the voltage waveform which is informative about the severity of voltage flicker. The technique employed is well capable of detecting a voltage envelope of distorted waveform. One limitation that the Prony technique suffers is the selection of number of modes. The accuracy of the estimation depends upon the number of modes, based on which a prediction model is developed. There are no rules which can guide in the selection of this number and generally it is chosen randomly.

### 2.2.6 Empirical Mode Decomposition based Methods

As a multi-resolution signal decomposition technique, Empirical Mode Decomposition (EMD) has the ability to detect some features of PQ disturbances [49]. The key task here is to identify the intrinsic oscillatory modes by their characteristic time scales in the signal empirically, and accordingly, decompose the signal into intrinsic mode functions (IMFs). Feature selection is always the key element among the process. Previous studies may have overlooked some essential features and some nonessential features may be inappropriately regarded [50], [51]. Any resulting combination of inappropriate attributes would add to the difficulty of classification.

Since, PQ disturbance is a non-stationary signal, EMD can perform better than the conventional S-transform analysis methods for the classification of PQ disturbances. But, the use of a feature set comprising of standard deviation, norm, maximum and minimum of instantaneous frequency and instantaneous amplitude of Intrinsic Mode Functions (IMFs) resulting from the EMD operation shows less efficiency while classifying multiclass PQ disturbances.

The combination of Empirical Mode Decomposition (EMD) and HT are suggested in [52]. The HT is applied to first three IMF extracted from EMD to assess instantaneous amplitude and phase which are then employed for feature vector formation. The pattern recognition system used Probabilistic Neural Network (PNN) classifier for classifying the various PQ events.

## 2.3 Signal Processing Methods for Classification

Classification of disturbance signals requires the use of pattern recognition techniques. Pattern recognition is a process of perceiving a pattern of a given object based on the knowledge already possessed. It is reported in the literature that for the classification of PQ disturbance signals, pattern recognition uses various artificial intelligence techniques, such as artificial neural networks (ANN), Radial Basis Function (RBF) Neural Network, Probabilistic Neural Network (PNN), fuzzy logic (FL), Support Vector Machine and Relevance Vector Machine.

### 2.3.1 Artificial Neural Network Based Classifiers

Neural network is a non-linear, data driven self adaptive method and is a promising tool for classification. These can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model. The neural network recognizes a given pattern by experience which is acquired during the learning or training phase when a set of finite examples is presented to the network. This set of finite examples is called the training set, and it consists of input patterns (i.e., input vector) along with their label of classes (i.e., output). In this phase, neurons in the network adjust their weight vectors according to certain learning rules. After the training process is completed, the knowledge needed to recognize patterns is stored in the neurons weight vectors. The network is, then, presented to another set of finite examples, i.e., the testing data set, to assess how well the network performs the recognition tasks. This process is known as testing or generalization. ANN is a universal function approximator i.e. this can approximate any function with arbitrary accuracy. All the above mentioned attributes make artifical neural lnetwork (ANN) flexible in modeling real world complex problems [53]. ANNs are good at pattern-matching and classification, function approximation, optimization and data clustering [54], [55]. The back-propagation algorithm is the most widely used algorithm for training multi-layered feed forward networks.

An ANN architecture commonly used for data classification is the multi-layer perceptron (MLP) [56]. MLP networks are ANN formed up by cells simulating the low-level functions of neurons [57]. MLP is well known for their learning and recognition ability where the signals cannot be defined mathematically. However, MLP has difficulties on determining a proper architecture, such as the number of hidden layers and nodes. Training an MLP is time consuming and very slow without guaranteeing a global minimum.

ANNs are the oldest among the pattern recognition tools [58]. They are defined as software algorithms that can be trained to learn the relationships that exist between input and output data. The disadvantage of using artificial neural networks is that they require a lot of time to train them, before they are fully functional. The advantage of using neural networks is that they do not make any assumptions regarding the underlying distribution. They recognize the patterns by experience acquired during the training session. The network adjusts its internal parameters by prescribed rules during the training session. The main drawbacks of ANN for PQ classifications are-

- There is no rule to determine the data required for the training of each disturbance types. More data available for training will give better accuracy but will increase time to train the network. A classifier trained with a small data set is very accurate in identifying the training data set, but it is potentially unable to identify other data sets.

- The generalization performance of ANN is not guaranteed and could be poor on selection of training data. The performance is heavily dependent on the selection of training data set and the structure (or topologies) of neural networks (e.g. the number of hidden layers, neurons, the interconnection of sub neural networks if employed).

### 2.3.2 Radial Basis Function Neural Network

A radial basis function (RBF) neural network is a class of single hidden layer feed forward Neural Network. The network has an input, a hidden and an output layer [47]. RBF networks can be viewed as an alternative tool for learning in Neural Networks. While RBF networks exhibit the same properties as back propagation networks such as generalization ability and robustness. They also have the additional advantage of fast learning and the ability to detect outliers during estimation [50].

Choosing the spread of the RBF depends on the pattern to be classified. The learning process undertaken by a RBF network may be visualized as follows. The linear weights associated with the output units of the network tend to evolve on a different time scale compared to the nonlinear activation functions of the hidden units. Thus, as the hidden layers activation functions evolve slowly in accordance with some nonlinear optimization strategy, the output layers weights adjust themselves rapidly through a linear optimization strategy. The important point to note is that the different layers of an RBF network perform different tasks, and so it is reasonable to separate the optimization of the hidden and output layers of the network by using different techniques, and perhaps operating on different time scales. There are different learning strategies that can be followed in the design of an RBF network, depending on how the centers of the radial basis functions of the network are specified. Essentially following three approaches are in use:

- Fixed centers selected at random
- Self-organized selection of centers
- Supervised selection of centers

### 2.3.3 Probabilistic Neural Network

The Probabilistic neural network (PNN) was first proposed in [59]. The development of PNN relies on the Parzen window concept of multivariate probability estimates. The PNN combines the Bayes strategy for decision-making with a non-parametric estimator for obtaining the Probability Density Function [60]. The PNN architecture includes four layers; input, pattern, summation, and output layers. The input nodes are the set of measurements. The second layer consists of the Gaussian functions formed using the given set of data points as centers. The third layer performs an average operation of the outputs from the second layer for each class. The fourth layer performs a vote, selecting the largest value. The associated class label is then determined. The input layer unit does not perform any computation and simply distributes the input to the neurons. The most important advantages of PNN classifier are as below:

- Training process is very fast
- An inherent parallel structure
- It converges to an optimal classifier as the size of the representative training set increases
- There are not local minima issues
- Training patterns can be added or removed without extensive retraining

### 2.3.4 Fuzzy Logic

Fuzzy logic with rule based expert system has emerged as a powerful categorization tool for PQ events that is computationally simple and fairly accurate [61]. Fuzzy logic system (FLS) has strong inference capabilities of expert system as well as power of natural knowledge representation. It was developed from the fact that human brain does not make decisions based on sharp decision boundaries. Fuzzy logic uses exactly the same concept. Unlike the classical digital logic which uses either a 0 or 1, fuzzy logic uses a decision boundary which smoothly transitions between stages. The membership function sets this smooth transition between the decision boundaries. Classification of signals is made by using a fixed set of fuzzy rules which consists of fuzzification, inference, composition and defuzzification. The basic block diagram of fuzzy logic system is shown in Fig. 2.2.

Approaches which combine both neural networks and fuzzy logic are recently being published in [62–65]. Liao Y and Lee J.B presented a novel approach of using a fuzzy-expert system for automated detection and classification of power quality disturbances [66]. Fuzzy logic is used for the classification of PQ disturbance signals. A combination of Fourier and wavelet based techniques is used to the

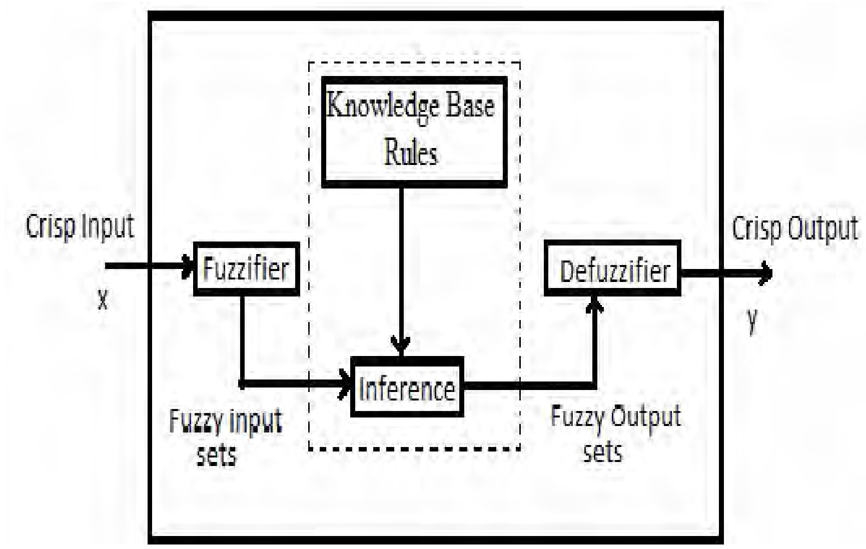



Figure 2.2: Block diagram of Fuzzy logic system

detection of signals. They compared the classification results with those of using ANN and proved that fuzzy logic is an efficient tool for the classification of power signal disturbances in terms of computational efficiency and accuracy.

In [64], the use of a Fourier linear combiner and a fuzzy expert system for the classification of signals is proposed. A Fourier linear combiner estimates the normalized peak amplitude of the voltage signal and its rate of change. These values are given as input to the fuzzy expert system which classifies the disturbances based on the rules formulated. Even though this system seems to be computationally simple compared with using WTs and ANN or FL, the authors have not provided the computational error efficiency or other comparison strategies which could prove its efficiency over the existing methods.

The main disadvantage of fuzzy classifier is that system time response slows down with the increase in number of rules. If the system does not perform satisfactorily, then the rules are reset again to obtain efficient results i.e. it is not adaptable according to the variation in data. The accuracy of the system is dependent on the knowledge and experience of human experts. The rules should be updated and weighting factors in the fuzzy sets should be refined with time. Neural networks, genetic algorithms, swarm optimization techniques, etc. can be used to for fine tuning of fuzzy logic control systems.

### 2.3.5 Support Vector Machine

Support vector machines (SVMs), which are relatively recent development, are a set of related supervised learning methods, introduced in the last decade, for pattern recognition and regression, and belong to a family of generalized linear classifiers [8, 67–70]. In another terms, SVM is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data. SVMs are based on minimization of the misclassification probability of unseen patterns with an unknown probability distribution of data and have solid theoretical foundation rooted in statistical learning theory. Real world problems often require hypothesis spaces that are more complex than those using linear discriminants. SVMs are able to find non-linear boundaries if classes are linearly non-separable.

The main issue of interest in using SVM for classification is its generalization performance. SVM performs better than neural networks in terms of generalization. Applications within power systems using SVM have been reported in [71–74]. In [69], a classifier based on radial basis function (RBF) network and SVM has been proposed and compared for classification of four classes of PQ disturbances. It is claimed that the SVM classifier is particularly effective in the automatic classification of voltage disturbances. The investigation revealed that the SVM network has satisfactory generalization ability and is able to recognize sags and other disturbances correctly, for the wide range of variable parameters. In another work, SVM based algorithm has been proposed for classification of common types of voltage sag disturbances [75]. The results have shown high classification accuracy which implies that the SVM classification technique is an attractive choice for classification of voltage sag and other PQ disturbances. It has also been found that the accuracy of the proposed method is also dependent on the features given to the classifier. The other advantage of SVM based system is that it is straight forward to extend the system when new types of disturbances are added to the classifier.

Bollen et al proposed a method based on statistical learning and SVMs for classification of five common types of voltage disturbances [76]. Here, the SVM classifier demonstrated high performance even when training data and test data originate from different networks. Using features from both time domain (RMS signatures) and frequency domain (harmonic magnitudes and total harmonic distortions), SVM can effectively characterize the disturbance classes. SVM has originally designed for binary classification and effectively extending it for multiclass classification is still an ongoing research issue. In [77], wavelets and fuzzy support vector machines are used to automatically and classify power quality (PQ) disturbances.

### 2.3.6 Relevance Vector Machine

Michael E. Tipping proposed Relevance Vector Machine (RVM) in 2001 [78]. It assumes knowledge of probability in the areas of Bayes' theorem and Gaussian distributions including marginal and conditional Gaussian distributions. RVMs are established upon a Bayesian formulation of a linear model with an appropriate prior that cause a sparse representation. Consequently, they can generalize well and provide inferences at low computational cost. The main formulation of RVMs is presented in [78]. New combination of WT and RVMs are suggested in employed the WT techniques to extract the feature from details and approximation waves. The constructed feature vectors as input of RVM classifier are applied for training the machines to monitoring the power quality events. The feature extracted from various PQ signals are as follow:

- Standard deviation of level 2 of detail.
- Minimum value of absolute of level n of approximation. ( n is desirable decomposition levels)
- Mean of average of absolute of all level of details.
- Mean of disturbances energy.
- Energy of level 3 of detail.
- RMS value of main signal.

In [79], it is seen that RVM offers an excellent compromise between accuracy and sparsity of the solution, and reveal itself as less sensitive to selection of the free parameters. Some disadvantages of RVM are also pointed, such as the unintuitive confidence intervals provided and the computational cost.

Furthermore in [80], a hidden Markov model (HMM) for classifying disturbances is presented. The rule based method classifies time-characterized-feature disturbances and the wavelet packet-based HMM is used for the frequency-characterized-feature power disturbances. The optimum way of classifying power disturbance events using the HMM is the ML method. On the other hand, in [19], the nearest-neighbour (NN) pattern recognition technique is implemented online to classify different disturbances and evaluate the efficiency of the extracted features. In [27], the following pattern recognition techniques: minimum Euclidean distance classifier, NN and ANN are compared. Inductive learning by using decision trees is introduced in [81]. In [82], dynamic time warping (DTW) algorithm is used and Higher Order Statistics (HOS) based method for PQ disturbance classification is reported in and [83].

## 2.4 Conclusion

In this chapter, a brief literature survey of the recent state-of-the-art PQ disturbance classification methods are presented. All the methods have their pros and cons. In order to handle the practical situations of real life application, a PQ disturbance classification method, apart from providing simplicity in computation, is needed to be capable of producing optimal results with improved overall classification accuracy for a multi class problem. Thus, the development of an effective feature set capable of classifying multi class PQ disturbances is still a challenging problem.

# Chapter 3

# A METHOD FOR CLASSIFICATION OF POWER QUALITY DISTURBANCES EXPLOITING HIGHER ORDER STATISTIC ANALYSIS IN EMD DOMAIN

## Introduction

For the purpose of classifying Different PQ disturbances, a training database is needed to be prepared consisting of template PQ signals of different classes. The classification task is based on comparing a test EEG signal with template data. It is obvious that considering PQ disturbance signals themselves would require extensive computations for the purpose of comparison. Thus, instead of utilizing the PQ disturbance signals, some characteristic features are extracted for preparing the template. It is to be noted that the classification accuracy strongly depends upon the quality of the extracted features.

In literature, there exist a numerous methods to extract feature vector, such as Fourier transform, Short time fourier transform, wavelet transform, S transform, Hilbert transform, Empirical mode decomposition etc. Designing a feature set which is capable of extracting distinguishable information to detect PQ disturbances data is not an easy task. Therefore, the main focus of this thesis is to develop an effective feature extraction algorithm.

Unlike FT or wavelet, EMD is intuitive and adaptive, with basic functions derived fully from the data. The computation of EMD does not require any previously known value of the signal. As a result, EMD is especially applicable for nonlinear and non-stationary signals, such as PQ disturbances. In this chapter, we endeavored

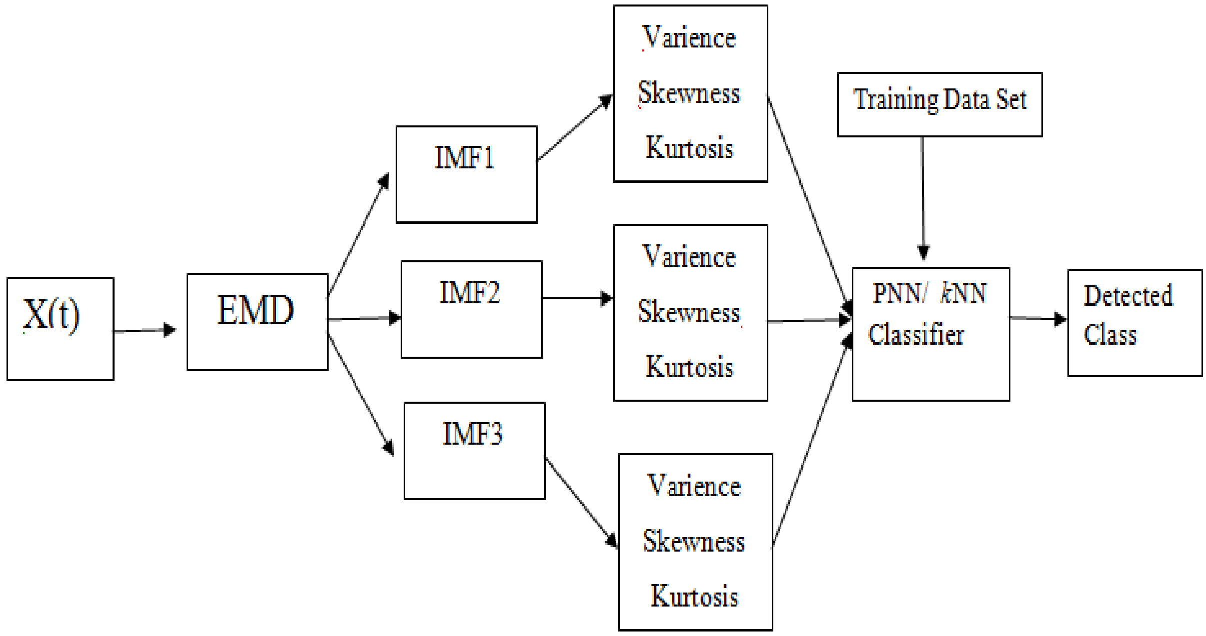



Figure 3.1: Block diagram of the proposed method

to develop the means by which appropriate features can be selected to improve the efficiency of classification. Higher order statistics (HOS) of the extracted intrinsic mode functions (IMF), such as variance, skewness and kurtosis are utilized to form the feature vector. The feature set thus obtained is then fed to the Probabilistic Neural Network (PNN) and $k$-Nearest Neighbor ($k$NN) classifiers for classifying the multi class PQ disturbance signals [84]. The block diagram of the proposed method described in this Chapter is shown in Fig. 3.1.

## 3.1 Proposed Method

Let us consider a pure power system signal represented by

$$x(t) = E \sin \omega_c t \tag{3.1}$$

here, $E$ represents the amplitude and

$$\omega_c = 2\pi f \tag{3.2}$$

$f$ symbolizes fundamental frequency of 50 Hz. Different types of power quality signals sag, swell, fluctuation, interruption, transient, harmonics, sag with harmonics, swell with harmonics, spike and notch are considered in this thesis. The mathematical models that are used to characterize different types of PQ disturbances to the power signal $x(t)$ are presented in Table 3.1. Hereafter, the PQ disturbance signal is also symbolized as $x(t)$.

The proposed method consists of two major steps, namely, feature extraction and classification.

## 3.2 Feature Extraction

### 3.2.1 Empirical Mode Decomposition

A function is considered to be an IMF if it satisfies two conditions; first, in the whole data set, the number of local extrema and that of zero crossings must be equal to each other or different by at most one and second, at any point, the mean value of the envelope defined by the local maxima and that defined by the local minima should be zero. The systematic way to decompose the data into IMFs, known as the as sifting process, is described as follows:

**i.** All the local maxima of the data are determined and joined by cubic spline line thus constructing an upper envelope.

**ii.** All the local minima of the data are found and connected by cubic spline line to obtain the lower envelope.

**iii.** The mean m1 of both the envelopes are calculated and the difference between the PQ disturbed signal $x[t]$ and $m_1$ is computed as $h_1[t]$.

$$h_1[t] = x[t] - m_1 \tag{3.3}$$

If $h_1[t]$ satisfies the conditions of IMF, then it is the first frequency and amplitude modulated oscillatory mode (IMF) of $x[t]$.

**iv** If $h_1[t]$ dissatisfies the conditions to be an IMF, it is treated as the data in the second sifting process, where steps i, ii and iii are repeated on $h_1[t]$ to derive the second component $h_2[t]$ as:

$$h_2[t] = h_1[t] - m_2 \tag{3.4}$$

in which $m_2$ is the mean of upper and lower envelopes of $h_1[t]$.

Table 3.1: Models of Power Quality Disturbance Signals

| Disturbance | Equations | Parameters |
|---|---|---|
| Normal | $x(t) = E\sin\omega_c t$ | u(t) is the unit function |
| Sag | $x(t) = E[1-\beta\{u(t-t_1)-u(t-t_2)\}]\sin\omega_c t$ | $0.1 \le \beta \le 0.9$, $T \le (t_2-t_1) \le 9T$ |
| Swell | $x(t) = E[1+\beta\{u(t-t_1)-u(t-t_2)\}]\sin\omega_c t$ | $0.1 \le \beta \le 0.9$, $T \le (t_2-t_1) \le 9T$ |
| Flicker | $x(t) = E[1+\beta\sin(2\pi\alpha t)]\sin\omega_c t$ | $0.1 \le \beta \le 0.2$, $5Hz \le \alpha \le 20Hz$ |
| Interruption | $x(t) = E[1-\beta\{u(t-t_1)-u(t-t_2)\}]\sin\omega_c t$ | $0.9 \le \beta \le 1$, $T \le (t_2-t_1) \le 9T$ |
| Transient | $x(t) = E[\sin\omega_c t + \beta e^(t - t_1/\tau)\sin\{2\pi f_n(t - t_1)\}\{u(t_2)-u(t_1)\}]$ | $0.1 \le \beta \le 0.9$, $0.5T \le (t_2-t_1) \le 3T$, $300Hz \le f_n \le 900Hz$, $8ms \le \tau \le 40ms$ |
| Harmonics | $x(t) = E[\sin\omega_c t + \beta_3\sin 3\omega_c t + \beta_5\sin 5\omega_c t]$ | $0.1 \le \beta \le 0.9$, $T \le (t_2-t_1) \le 9T$, $0.05 \le \beta_3, \beta_5 \le 0.15$ |
| Sag with Harmonics | $x(t) = E[1-\beta\{u(t-t_1)-u(t-t_2)\}] * [\sin\omega_c t + \beta_3\sin 3\omega_c t + \beta_5\sin 5\omega_c t]$ | $0.1 \le \beta \le 0.9$, $T \le (t_2-t_1) \le 9T$, $0.05 \le \beta_3, \beta_5 \le 0.15$ |
| Swell with Harmonics | $x(t) = E[1+\beta\{u(t-t_1)-u(t-t_2)\}] * [\sin\omega_c t + \beta_3\sin 3\omega_c t + \beta_5\sin 5\omega_c t]$ | $0.1 \le \beta \le 0.9$, $T \le (t_2-t_1) \le 9T$, $0.05 \le \beta_3, \beta_5 \le 0.15$ |
| Spike | $x(t) = E[\sin\omega_c t - sign(\sin\omega_c t)\times\{\sum_{n=0}^{9}\kappa\times\{u(t-(t_1+0.02n)) - u(t-(t_2+0.02n))\}\}]$ | $0.1 \le \kappa \le 0.4$, $0 \le (t_2, t_1) \le 0.5T$, $0.01T \le (t_2-t_1) \le 0.05T$ |
| Notch | $x(t) = E[\sin\omega_c t + sign(\sin\omega_c t)\times\{\sum_{n=0}^{9}\kappa\times\{u(t-(t_1+0.02n)) - u(t-(t_2+0.02n))\}\}]$ | $0.1 \le \kappa \le 0.4$, $0 \le (t_2, t_1) \le 0.5T$, $0.01T \le (t_2-t_1) \le 0.05T$ |

**v** Let after $w$ cycles of operation, if $h_w[t]$, given by

$$h_2[t] = h_1[t] - m_2 \tag{3.5}$$

becomes an IMF, it is designated as $c_1[t] = h_w[t]$, the first IMF component of the original signal.

**vi.** Subtracting $c_1[t]$ from $x[t]$, $r_1[t]$ is calculated as

$$r_1[t] = x[t] - c_1[t] \tag{3.6}$$

which is treated as the original data for the next cycle for calculating the next IMF.

**vii.** Repeating the above process for $L$ times, $L$ no. of IMFs is obtained along with the final residue $r_L[t]$. A popular stopping criteria for the sifting process is to have the value of standard difference (SD) within a threshold as:

$$SD = \sum_{n=1}^{N} \frac{|h_{w-1}[t] - h_w[t]|^2}{h_w[t]^2} \tag{3.7}$$

here, $w$ and $w1$ are index terms indicating two consecutive sifting processes. Thus the decomposition process is stopped since $r_L[t]$ becomes a monotonic function from which no more IMF can be extracted. To this end, for L level of decomposition, the PQ disturbance signal $x[t]$ can be reconstructed by the following formula,

$$x[t] = \sum_{k=1}^{L} c_k[t] + r_L[t] \tag{3.8}$$

### 3.2.2 IMF Selection

The PQ disturbance signals, namely sag and swell, each results in six IMFs through EMD analysis, whereas EMD decomposition of the other PQ disturbance signals, such as harmonics and fluctuation, each provides only one or two IMFs. Figs. 3.2 and 3.3 show sag and swell signals and their empirically decomposed IMFs, respectedly. From these two figures, it is seen that as the level of an IMF increases, the corresponding data becomes smoother. Since, most of the frequency content of almost all the PQ disturbance signal $x(t)$is found to lie in the first three IMFs, in this work, we are motivated to exploit the first three IMFs for feature extraction. For

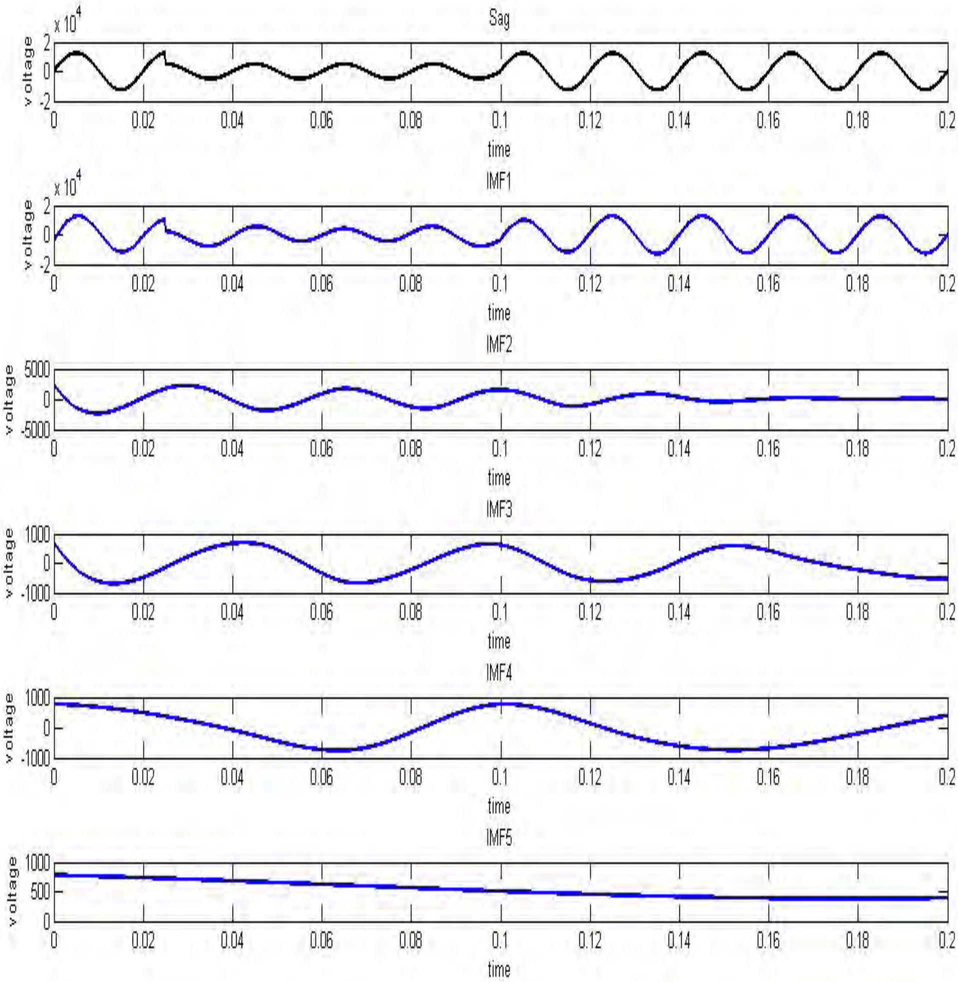



Figure 3.2: Voltage Sag and It's Intrinsic Mode Functions

the PQ disturbance signals that can be decomposed into one or two IMFs, we will consider the remaining IMFs as zero

### 3.2.3 Higher Order Statistics

The use of Higher Order statistics (HOS) is motivated by the fact that distribution of the samples of a data set is often characterized by its level of dispersion, asymmetry and concentration around the mean [85], [86]. For an $N$-point data, $X = x_1, x_2, ..., x_N$, the corresponding variance ($\sigma^2$), skewness ($\beta_1$) and kurtosis ($\beta_2$)

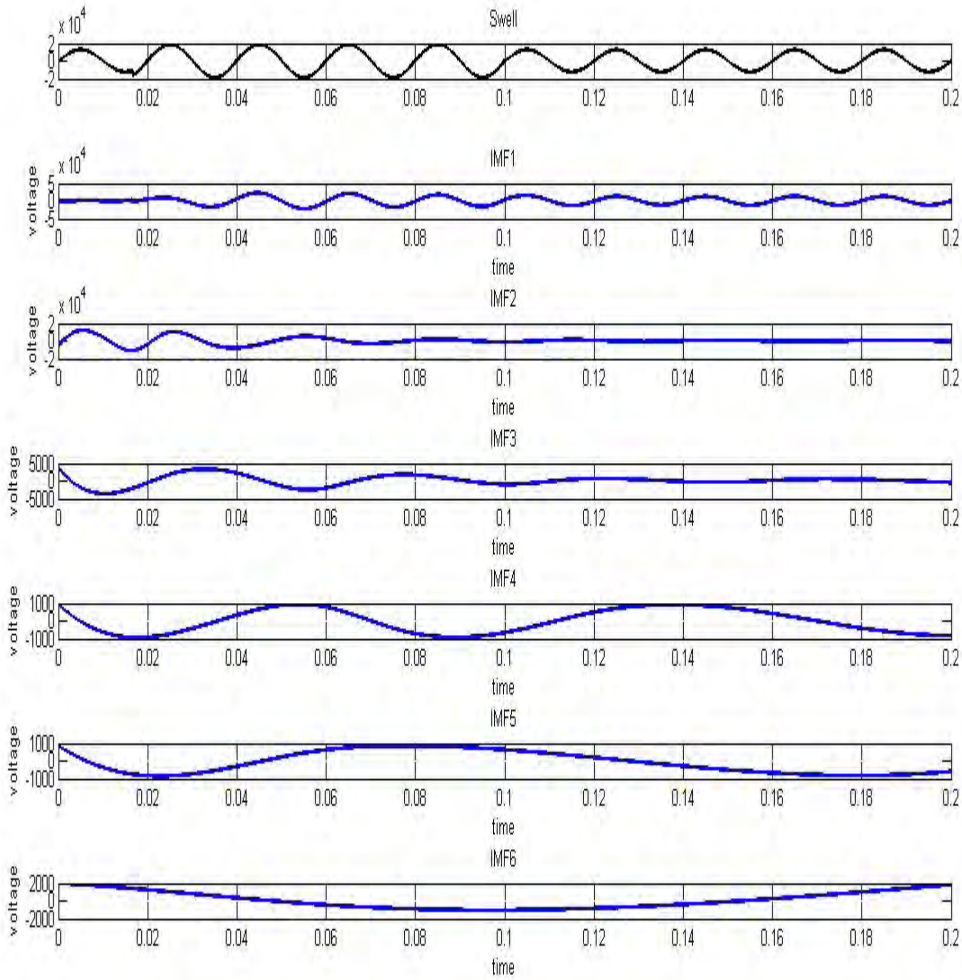



Figure 3.3: Voltage Swell and It's Intrinsic Mode Functions

are calculated as

$$\sigma^2 = \frac{1}{N}\sum_{n=1}^{N}(x_i - \mu)^2; \mu = \frac{1}{N}\sum_{n=1}^{N}(x_i) \tag{3.9}$$

$$\beta_1 = \frac{1}{N}\sum_{n=1}^{N}(\frac{x_i - \mu}{\sigma})^3 \tag{3.10}$$

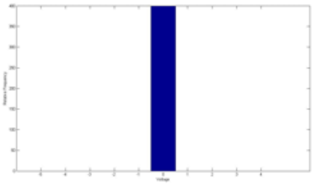
$$\beta_2 = \frac{1}{N}\sum_{n=1}^{N}(\frac{x_i - \mu}{\sigma})^4 \tag{3.11}$$

where, $\mu$ denotes the sample mean of the data. If skewness is negative, the data is spread out more to the left of the mean than to the right, while a positive skewness indicates spreading more to the right. For a perfectly symmetric distribution about mean, the skewness is zero. The kurtosis of a data with a histogram having a sharper peak and longer, fatter tails is greater than that for a distribution having a more rounded peak and shorter thinner tails. Notice that the variance itself is the 2nd order moment of the data, whereas the skewness and kurtosis are computed from the 2nd, 3rd and 4th order moments.

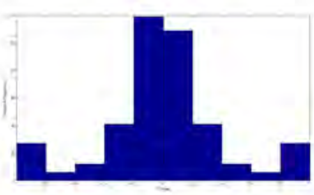
### 3.2.4 Statistical Analysis

The histograms of pure signals and that of third IMF (IMF3) of PQ disturbance signals are plotted in Figs. 3.4 and 3.5, respectively. Note that the shapes of the PQ disturbance signals are different from each other. It is expected since the values of the corresponding variance, skewness and kurtosis are different from each other and these quantities are representative of the dispersion, asymmetry and peakedness of a data. The discriminatory attributes of these quantities are more prominent in the EMD domain as seen from the shape of the corresponding histograms and the values of the corresponding variance, skewness and kurtosis. Thus, one may expect that these statistical measures would be more effective if computed in the EMD domain rather than in spatial domain for classifying the PQ disturbance signals.

For the purpose of analysis, each PQ disturbance signals are decomposed into IMFs using the algorithm described in Section 3.2.1 and HOS are computed for the first three IMFs. For the sake of comparison, HOS values are also calculated for the PQ disturbance signals. Table 3.2 shows the HOS values obtained for the different PQ disturbance signals. The HOS values for IMF1, IMF2 and IM3, respectively,

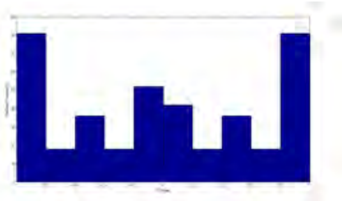


(a) Normal Signal

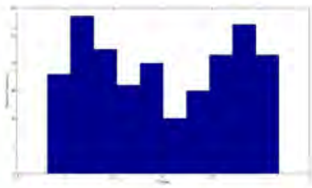


(b) Sag

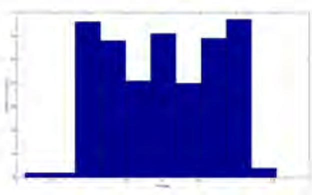
(c) Swell



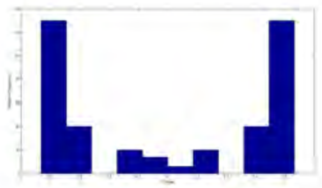
(d) Interruption



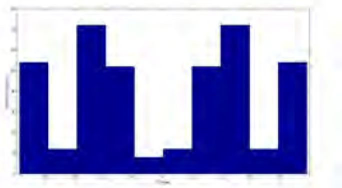
(e) Flicker



(f) Transient



(g) Harmonics



(h) Sag with Harmonics

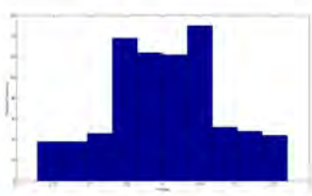
(i) Swell with Harmonics

(j) Spike

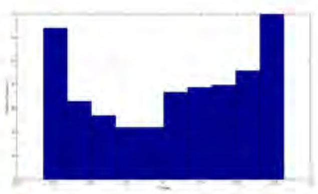
(k) Notch

Figure 3.4: Histograms of Pure of PQ disturbance signals

(a) Normal Signal

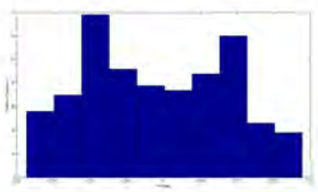


(b) Sag

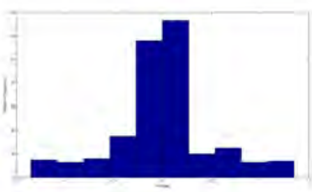


(c) Swell

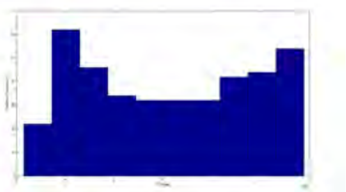
(d) Interruption



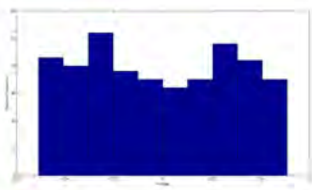
(e) Flicker



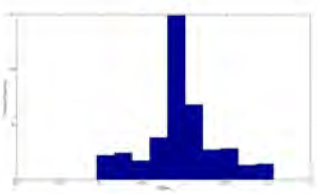
(f) Transient



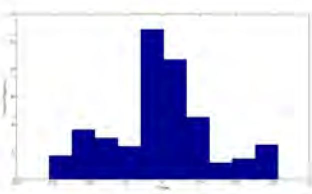
(g) Harmonics



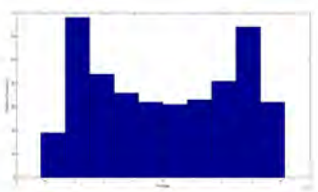
(h) Sag with Harmonics



(i) Swell with Harmonics



(j) Spike



(k) Notch

Figure 3.5: Histograms of Third IMF of PQ disturbance signals

Table 3.2: HOS Values of PQ disturbance Signals

| **Classes** | **Varience** | **Skewness** | **Kurtosis** |
|---|---|---|---|
| Normal Signal | 0.5 | -2.77E-16 | 0.375 |
| Sag | 0.167 | 1.11E-18 | 0.304 |
| Swell | 0.6594 | 8.19E-18 | -0.6358 |
| Flicker | 0.5147 | 9.36E-04 | -0.7302 |
| Interruption | 0.45 | -1.78E-17 | -0.27 |
| Transient | 0.5287 | -0.152 | -0.3586 |
| Harmonics | 0.5 | -2.66E-16 | 0.4453 |
| Sag with Harmonics | 0.3734 | -7.78E-18 | -0.189 |
| Swell with Harmonics | 0.6186 | -1.61E-16 | -0.6304 |
| Spike | 0.5114 | -0.0027 | -0.3997 |
| Notch | 0.4781 | -0.0059 | -0.3391 |

are summarized in Tables 3.3, 3.4 and 3.5 for all PQ disturbance signals. It is seen that the values are clearly distinguishable for the different sets of PQ signals. Also, note that the difference becomes larger in the EMD domain as compared to that of the pure signal. It is seen that kurtosis gives significant statistical difference among eleven groups for PQ signals as well as for the first three IMFs. Varience and skewness do the same work.

Therefore, in this work, from the three extracted IMFs, nine features based on HOS, such as variance, skewness and kurtosis are derived to form the feature vector for classifying PQ disturbance signals.

### 3.2.5 Classification

In this thesis, we employ two different classifiers to determine the efficacy of the feature vector in classifying different PQ disturbance signals.

**Probabilistic Neural Network Classifier**

Probabilistic neural networks (PNNs) are a kind of radial basis network suitable for classification problems. The PNN model belongs to the family of supervised learning networks, but it is distinct from others in the following manner.

1. It is implemented using the probabilistic model with a Gaussian mapping function.

Table 3.3: HOS Values of IMF1 of PQ Disturbance Signals

| **Classes** | **Varience** | **Skewness** | **Kurtosis** |
|---|---|---|---|
| Normal Signal | 0 | 0 | 0.5 |
| Sag | 0.0018 | 3.60E-03 | 0.148 |
| Swell | -0.0025 | 0.0022 | 0.66 |
| Flicker | -0.0095 | -9.93E-04 | 0.523 |
| Interruption | -0.0043 | 0.011 | 0.417 |
| Transient | -7.26E-04 | 0.0053 | 0.8284 |
| Harmonics | -4.74E-04 | 2.25E-04 | 0.0184 |
| Sag with Harmonics | -1.20E-03 | -0.0012 | 7.40E-03 |
| Swell with Harmonics | -1.8E-03 | -0.0034 | 0.0187 |
| Spike | 3.7E-03 | -8.74E-04 | 0.0174 |
| Notch | -3.403E-03 | 3.23E-05 | 0.149 |

Table 3.4: HOS Values of IMF2 of PQ Disturbance Signals

| **Classes** | **Varience** | **Skewness** | **Kurtosis** |
|---|---|---|---|
| Normal Signal | 0 | -2.78E-16 | 0 |
| Sag | 0.0057 | 7.80E-03 | 3.44E-05 |
| Swell | 4.58E-04 | 3.29E-04 | 1.49E-06 |
| Flicker | 9.44E-05 | 3E-03 | 1.03E-04 |
| Interruption | 0.0176 | -8.90E-03 | -2.72E-05 |
| Transient | 0.2426 | 0.0369 | -0.0011 |
| Harmonics | 1.17E-05 | 2.01E-05 | 4.20E-04 |
| Sag with Harmonics | 8.96E-04 | -2.56E-06 | 2.47E-04 |
| Swell with Harmonics | -1.8E-03 | -1.82E-05 | 3.30E-05 |
| Spike | 1.92E-04 | 1.66E-04 | -4.04E-04 |
| Notch | 5.803E-06 | 2.92E-04 | 6.77E-04 |

Table 3.5: HOS Values of IMF3 of PQ Disturbance Signals

| **Classes** | **Varience** | **Skewness** | **Kurtosis** |
|---|---|---|---|
| Normal Signal | -0.375 | 0 | 0 |
| Sag | 0.0188 | -6.54E-05 | -1.99E-05 |
| Swell | -0.64 | -3.97E-07 | -2.89E-07 |
| Flicker | -0.4085 | -1.98E-04 | -9.83e-09 |
| Interruption | -0.2277 | -1.93E-03 | -4.61E-04 |
| Transient | 0.0767 | -0.0013 | 0.0741 |
| Harmonics | -3.89E-04 | -0.4124 | -1.86E-10 |
| Sag with Harmonics | -7.21E-05 | -0.1851 | -1.06E-06 |
| Swell with Harmonics | -4.01E-04 | -0.6012 | 1.28E-06 |
| Spike | -4.00E-04 | -0.3125 | -3.29E-10 |
| Notch | -3.38E-04 | -0.1807 | -4.74E-11 |

2. No requirement of setting initial weights of the network. Only the spread of the Gaussian function needs to be specified.

3. No relationship between learning processes and recalling processes.

4. The difference between the inference vector and the target vector are not used to modify the weights of the network.

High learning speed of PNN model makes it suitable for diagnosing PQ events. Fig. 3.6 shows architecture of PNN model composed of radial basis layer and the competitive layer. For a classification application, the training data is classified according to their distribution values of probabilistic density function (PDF). A simple PDF is shown as

$$f_k(x) = \frac{1}{N_k}\sum_{j=1}^{N_k} exp(\frac{-\|X - X_{kj}\|}{2\sigma^2}) \tag{3.12}$$

Modifying and applying Eqn. 3.12 to the output vector H of the hidden layer in the PNN is as

$$H_h = exp(\frac{-\sum_i (X_j - W_{ih}^{xh})^2}{2\sigma^2}) \tag{3.13}$$

$$net_j = \frac{1}{N_k}\sum_h W_{hj}^{hy} H_h \tag{3.14}$$

$$net_j = max_k(net_k) \tag{3.15}$$

then $y_j = 1$ or $y_k = 0$, where $i$ = number of input layers;
$h_j$ = number of hidden layers;
$j$ = number of output layers;
$k$ = number of training examples;
$N$ = number of classifications (clusters);
$\sigma$ = smoothing parameter (standard deviation);
$X$ = input vector;
$\|X - X_{kj}\|$ = Euclidean distance between the vectors $X$ and $X_{kj}$ ;
i. e. $\|X - X_{kj}\|=\sum_i (X - X_{kj})^2$
$W_{ih}^{xh}$= connection weight between the input layer $X$ and and the hidden layer $H$
$W_{hj}^{hy}$= connection weight between the hidden layer $H$ and the output layer $Y$

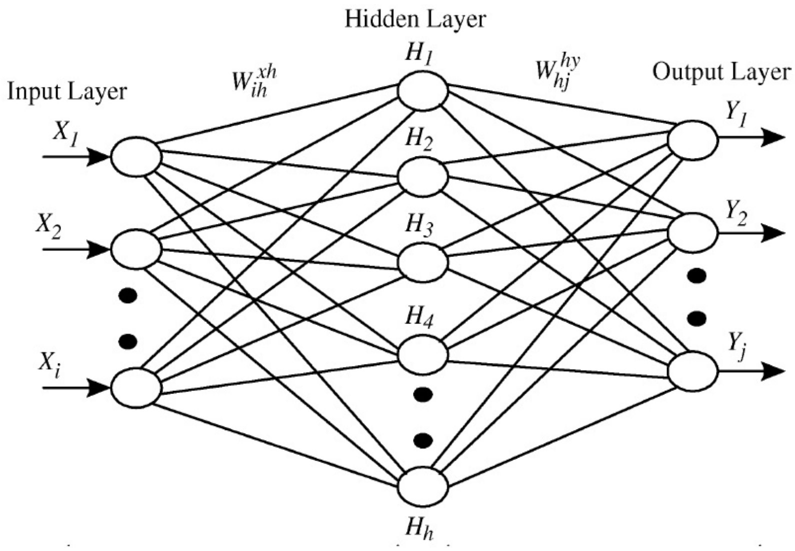



Figure 3.6: Architecture of PNN

### $k$-nearest Neighbor Classifier

$k$-nearest neighbor ($k$-NN) is the simplest, linear and robust classifier. Usually the classifier works by comparing a new sample (testing data) with the baseline data (training data). The classifier finds the $k$- neighborhood in the training data and assign class which appear more frequently in the neighborhood of $k$. The value of $k$ needs to be varied in order to find the match class between training and testing data. Therefore, an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its $k$ nearest neighbors, where $k$ is a typically small positive integer. The default value of $k$ is 1. If $k = 1$, then the object is simply assigned to the class of its nearest neighbour. In a $k$-NN classifier, different types of mathematical distances is used to rate all neighbors. Among them, $k$-NN classifier with Euclidian distance is attractive in the sense of reducing the processing time.The default neighborhood setting is Euclidean and nearest. The Euclidean distance is used to find the object similarity in the $k$-neighborhood.

In this thesis, the value of $k$ is varied from 1 to 10. The $k$-NN classifier is also evaluated by changing the default setting of distance from Euclidean to cityblock, cosine and correlation. Meanwhile, the $k$-NN classifier rule is changed from the default setting of nearest to random and consensus.

## 3.3 Conclusion

PQ disturbance signals are the most important signal which is analyzed for the diagnosis of any abnormal situation. Since conventional analysis is found inadequate to describe the characteristics of a non-stationary signal, in this chapter, we propose to transform the PQ disturbance signals by EMD. The IMFs thus obtained from the EMD transformed data are exploited to formulate a feature vector consisting of varience, skewness and kurtosis which can better model detail characteristics of the PQ disturbance data. The feature vector is fed to Probabilistic Neural Network and $k$ Nearest Neighbor classifier in order to classify PQ disturbance of ten different types along with normal pure PQ signal. A number of simulations are carried out using model equations of each events. It is shown that the proposed method based on HOS in the EMD domain is capable of producing greater efficiency in comparison to that obtained by using some state-of-the-art methods of PQ disturbance classification using the same classifiers and the data set.

# Chapter 4

# SIMULATION RESULTS AND PERFORMANCE EVALUATION

Performance evaluation of the proposed method for classifying eleven types of PQ disturbances is an important task. For this purpose the evaluation criteria taken into account in this Chapter are clustering analysis, confusion matrix, overall efficiency calculation, overall efficiency with increased training and testing data set and required CPU time. State-of- the-art S-transform and Hilbert-Huang transform (HHT) based methods are used for performance comparison with the proposed method.

## 4.1 Data set and Simulation Conditions

In the proposed method, PQ disturbance signals are generated using MATLAB based on the equations in Table 3.1 with a sampling frequency of 2 kHz. Eleven types of PQ disturbance signals are termed as:

1. C1- Normal,
2. C2- Sag,
3. C3 - Swell,
4. C4- Flicker,
5. C5 - Interruption,
6. C6- Transient,
7. C7- Harmonics,

8. C8- Sag with harmonics,
9. C9- Swell with harmonics,
10. C10- Spike,
11. C11- Notch.

For each of the above classes, 135 signals are considered, 35 signals are selected for training and the rest of the signals are left for testing and validation.

## 4.2 Comparison Methods

For the purpose of comparison, we use state-of-the-art S Transform and HHT based methods [42], [52]. We have implemented the S transform and HHT based methods independently using the parameters specified therein.

Extracted features based on S-transform according to [42] are-

- Standard deviation of magnitude contour.
- Energy of the magnitude contour.
- Standard deviation of the frequency contour.
- Energy of the of the frequency contour.
- Standard deviation of phase contour.

In [42], the PNN classifier is employed for classification of the various PQ disturbance signals.

Combining EMD and HT, HHT is suggested in [52]. The HT is applied to first three IMF extracted from the EMD to assess instantaneous amplitude and phase which are then employed for feature vector formulation. The feature vector set is formed by considering -

- Energy of the elements corresponding to magnitude of the Hilbert array at each sample .
- Standard deviation of the amplitude contour.
- Standard deviation of phase contour.

PNN classifier is also used for the classification purpose for this method.

## 4.3 Performance Evaluation Criteria

For the performance evaluation of the proposed and comparison methods, criteria considered in our simulation study are:

- clustering analysis
- efficiency derived from confusion matrix
- increased training and testing data set
- required CPU time

**Clustering Analysis**

Clustering Analysis is performed to determine the goodness of the proposed feature. The effectiveness of the proposed feature sets in classifying different types of PQ disturbances in terms of clusters is justified by the inter-class separability and intra class compactness of the feature. Intra class compactness gives us the idea about how closely the feature sets of a particular event are related. Interclass separability is a measure that exhibits how clearly signals of the different classes remain separated from each other.

**Confusion Matrix**

Confusion matrix is a form of representing the result from a classification exercise. The rows in the matrix stand for the actual classes to be tested and columns provide the class classified by a method. In particular, any [row, column] entry in the confusion matrix indicates the number of cases from the test database that belongs to the class corresponding to the row but classified as the class corresponding to the column. In Fig. 4.1, a general confusion matrix for a two class problem (C1 and C2) is shown, where $TP$, $FP$, $FN$ and $TN$ are represented for class C1.

In general, $TP_{C1}$, true positive for any class C1, denotes the number of testing cases, which are correctly classified as class C1.

$FP_{C1}$, false positive for any class C1, measures the number of testing cases, which are incorrectly classified as class C1.

$FN_{C1}$, false negative for any class C1, measures the number of testing cases, which are incorrectly classified as other than class C1.

| | | Class classified by the classifier | |
|---|---|---|---|
| | | C1 | C2 |
| Actual Class | C1 | $TP_{C1}$ | $FN_{C1}$ |
| | C2 | $FP_{C1}$ | $TN_{C1}$ |

Figure 4.1: Confusion Matrix for two class with respect to C1

$TN_{C1}$, true negative for any class C1, denotes the number of testing cases, which are correctly classified as other than class C1.

So,the efficiency for C1 is calculated using the formula given as

$$Efficiency_{C1} = \frac{TP_{C1}}{TP_{C1} + FP_{C1}} \tag{4.1}$$

Considering efficiency of all classes, overall efficiency for a method is calculated as

$$OverallEfficiency = \frac{Numberofeventsclassifiedcorrectly}{Totalnumberofevents} \tag{4.2}$$

**Increased training and testing dataset**

The performance of a classification method in classifying different PQ disturbance signals can be evaluated in terms overall efficiency with the random selection of increased training and testing dataset.

**Required CPU time**

CPU time is an important factor that should be considered for the evaluation of performance of a method. Method which is faster than the other method, can be considered as an efficient one.

## 4.4 Performance Evaluation

This section presents the results of the proposed method and its performance is compared with the comparison methods on the basis of the following performance evaluation criteria as described before.

### 4.4.1 Clustering Analysis

The proposed feature sets for Sag and Swell events are shown in Figs. 4.2 and 4.3. In these figures, the feature sets of 10 data of each class are plotted. It is seen from Figs. 4.2 and 4.3 that among different data of a class, most of the feature elements show better resembles in terms of their values . It is found from Figs. 4.2 and 4.3 that the feature elements of the proposed feature set provide stronger compactness as a feature while comparing different data of the same class. In Fig. 4.4, plots of feature sets consisting of different classes are shown. This figure attests that the proposed feature set is capable of providing the high separability among different classes.

### 4.4.2 Performance Comparison using Confusion Matrix Analysis

The confusion matrix derived for the S Transform based method using PNN classifier is represented in Table 4.1. In this table, the diagonal entries stand for the number of cases when a particular class of PQ disturbance signal is correctly classified. It can be seen from the diagonal entries of the confusion matrix in Table 4.1 that S Transform based method is unable to distinguish among PQ disturbance signals and misclassification occurs in case of swell (C3),flicker (C4), transient (C6), harmonics (C7), swell with harmonics (C9), spike (C10) and notch (C11).

Table 4.2 represents the confusion matrix derived for the HHT based method using PNN classifier. It is vivid from Table 4.2 that HHT based method misclassifies some interruption (C5) and sag with harmonics (C8) signals. It also misclassifies a small number of sag(C2),harmonics (C7), spike (C10) and notch (C11) data.

Table 4.3 shows the confusion matrix derived for the proposed method using $k$NN Classifier. It is demonstrated from Table 4.3 that HOS based EMD domain features of the proposed method are able to classify all of the PQ disturbance signals almost perfectly.

Classification performance in terms of overall efficiency (%) resulting from the proposed method and other comparison methods using PNN and $k$-NN classifiers are calculated over all classes and are presented in Table 4.4. Compared to the other methods, the proposed method shows higher overall efficiency (%) while using PNN

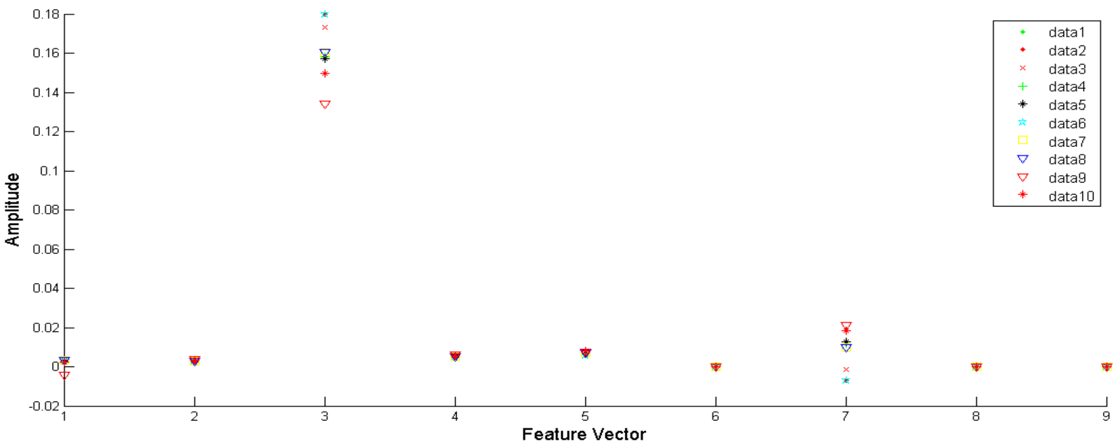



Figure 4.2: Feature sets of different data of the same class (sag)

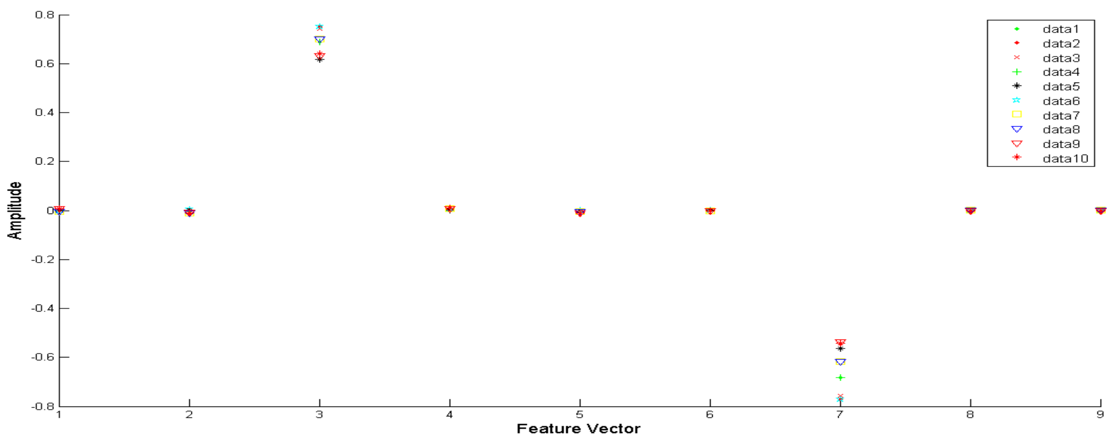



Figure 4.3: Feature sets of different data of the same class (swell)

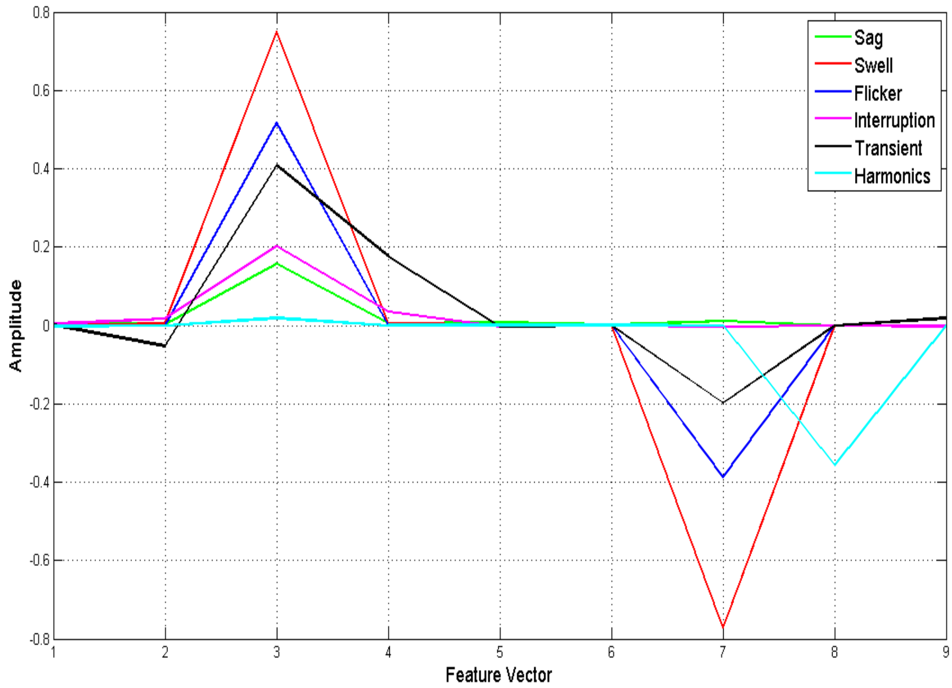



Figure 4.4: Feature sets of different classes (6 classes)

classifier. For each method, overall efficiency (%) increases while using the $k$-NN classifier instead of the PNN classifier. However, the proposed method is found provide the highest overall efficiency (%) using the $k$-NN classifier.

### 4.4.3 Performance Comparison with Increased Training and Testing dataset

Classification accuracy can be further enhanced by using higher number of events in the training and testing dataset. Table 4.5 shows the testing results in terms of overall efficiency (%) for the proposed method using $k$-NN classifier when training and testing dataset are made double (70 events of each class for training and 200 events of each class for testing). By increasing the training and testing dataset, classification performance in terms of overall efficiency (%) resulting from the proposed method and other comparison methods using PNN and $k$-NN classifiers are calculated over all classes and are presented in Table 4.6. As expected, it is found from comparing Tables 4.4 and 4.6 that the overall efficiency (%) of each method increases with the increased training and testing dataset using both PNN and $k$-NN classifiers. It is noticeable from Table 4.5 and Table 4.6 that the overall efficiency

Table 4.1: Confusion Matrix for the S-Transform based Method using PNN Classifier

| **Input Classes** | **Classified Classes** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **C7** | **C8** | **C9** | **C10** | **C11** |
| **C1** | **100** | | | 15 | | 26 | | 2 | 5 | | |
| **C2** | | **97** | | | | | | | | | |
| **C3** | | | **58** | | | | | | 44 | | |
| **C4** | | | | **54** | | 1 | | | | 28 | |
| **C5** | | 3 | | | **100** | | | | | | |
| **C6** | | | | 5 | | **62** | | | | | |
| **C7** | | | | | | | **71** | | | | 47 |
| **C8** | | | | | | | 3 | **97** | | | 1 |
| **C9** | | | 42 | | | | | | **51** | | |
| **C10** | | | | 26 | | 11 | | | | **72** | |
| **C11** | | | | | | | 29 | 1 | | | **52** |
| Classification Efficiency(%) | 100 | 97 | 58 | 54 | 100 | 62 | 71 | 97 | 51 | 72 | 52 |
| Classification Error(%) | 0 | 3 | 42 | 46 | 0 | 38 | 29 | 3 | 49 | 28 | 48 |
| Overall Efficiency(%) | | | | | | 74.0 | | | | | |

Table 4.2: Confusion Matrix for the HHT based Method using PNN Classifier

| **Input Classes** | **Classified Classes** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **C7** | **C8** | **C9** | **C10** | **C11** |
| **C1** | **100** | | | | 10 | | | 2 | | | |
| **C2** | | **95** | | 2 | | | | | | | |
| **C3** | | | **100** | | | | | | | | |
| **C4** | | 5 | | **98** | 4 | | | 1 | | | |
| **C5** | | | | | **86** | | | 1 | | | |
| **C6** | | | | | | **100** | | | | | |
| **C7** | | | | | | | **97** | | | 2 | |
| **C8** | | | | | | | | **82** | | | |
| **C9** | | | | | 2 | | | | **100** | | |
| **C10** | | | | | | | 3 | | | **98** | 4 |
| **C11** | | | | | 1 | | | 16 | | | **96** |
| Classification Efficiency(%) | 100 | 95 | 100 | 98 | 86 | 100 | 97 | 82 | 100 | 98 | 96 |
| Classification Error(%) | 0 | 5 | 0 | 2 | 14 | 0 | 3 | 18 | 0 | 2 | 4 |
| Overall Efficiency(%) | | | | | | 95.6 | | | | | |

Table 4.3: Confusion Matrix derived for the Proposed Method using $k$NN Classifier

| **Input Classes** | **Classified Classes** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **C7** | **C8** | **C9** | **C10** | **C11** |
| **C1** | **100** | | | | 2 | | | | | | |
| **C2** | | **97** | | | | | | | | | |
| **C3** | | | **100** | | | | | | | | |
| **C4** | | | | **100** | | | | | | | |
| **C5** | | 3 | | | **98** | 1 | | | | | |
| **C6** | | | | | | **99** | | | | | |
| **C7** | | | | | | | **97** | 2 | | | |
| **C8** | | | | | | | 3 | **98** | | | |
| **C9** | | | | | | | | | **100** | | |
| **C10** | | | | | | | | | | **100** | |
| **C11** | | | | | | | | | | | **100** |
| Classification Efficiency(%) | 100 | 97 | 100 | 100 | 98 | 99 | 97 | 98 | 100 | 100 | 100 |
| Classification Error(%) | 0 | 3 | 0 | 0 | 0 | 2 | 1 | 3 | 2 | 0 | 0 |
| Overall Efficiency(%) | 99 | | | | | | | | | | |

Table 4.4: Performance Comparison of the Proposed and Other Methods using PNN and $k$-NN Classifiers

| **Method** | **Overall efficiency (%)** | |
|---|---|---|
| | **PNN Classifier** | **kNN Classifier** |
| **S-transform based Method** | **74.5** | **81.2** |
| **HHT based Method** | **95.6** | **96** |
| **Proposed Method** | **98.8** | **99** |

(%) enhances to 99.6% for our proposed method using $k$-NN classifier in such a condition of training and testing dataset..

### 4.4.4 Required CPU time

The required CPU time for the proposed and other comparison methods using PNN and $k$NN classifiers are summarized in Table 4.7. Although the S-transform based method shows less CPU time for both the classifiers, this feature is not found attractive considering its least overall efficiency. However, compared to the HHT based method, it can be seen that proposed method requires much less time to classify a particular input data during testing using both PNN and $k$NN classifiers. Moreover, it is clearly observable that the proposed feature set resulting from the HOS in the

Table 4.5: Confusion Matrix derived for the Proposed Method using $k$NN Classifier with Increased Training and Testing Dataset

| **Input Classes** | **Classified Classes** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **C7** | **C8** | **C9** | **C10** | **C11** |
| **C1** | **200** | | | | | | | | | | |
| **C2** | | **200** | | | | | | | | | |
| **C3** | | | **200** | | | | | | | | |
| **C4** | | | | **200** | | | | | | | |
| **C5** | | | | | **200** | | | | | | |
| **C6** | | | | | | **200** | | | | | |
| **C7** | | | | | | | **193** | 2 | | | |
| **C8** | | | | | | | 7 | **198** | | | |
| **C9** | | | | | | | | | **200** | | |
| **C10** | | | | | | | | | | **200** | |
| **C11** | | | | | | | | | | | **200** |
| Classification Efficiency(%) | 100 | 100 | 100 | 100 | 100 | 100 | 96.5 | 99 | 100 | 100 | 100 |
| Classification Error(%) | 0 | 0 | 0 | 0 | 0 | 0 | 3.5 | 1 | 0 | 0 | 0 |
| Overall Efficiency(%) | 99.6 | | | | | | | | | | |

Table 4.6: Performance Comparison of the Proposed and Other Methods using PNN and $k$-NN Classifiers with Increased Training and Testing Dataset

| **Method** | **Overall efficiency (%)** | |
|---|---|---|
| | **PNN Classifier** | **kNN Classifier** |
| **S-transform based Method** | **78.6** | **84.4** |
| **HHT based Method** | **97.2** | **98.3** |
| **Proposed Method** | **98.5** | **99.6** |

EMD domain when fed to $k$NN classifier can effectively classify eleven kinds of PQ disturbances not only with the highest overall efficiency but also with the least CPU time.

Table 4.7: Comparative Analysis of Required CPU time

| **Method** | **Required CPU time in second** | |
|---|---|---|
| | **PNN Classifier** | **kNN Classifier** |
| **S-transform based Method** | **0.0114** | **0.0027** |
| **HHT based Method** | **0.12** | **0.0013** |
| **Proposed Method** | **0.113** | **0.00128** |

## 4.5 Performance Comparison under Noisy Conditions

In an electrical power distribution network, the practical data consists of noise; therefore, the proposed approach has to be analyzed under noisy condition. Gaussian noise is widely considered in the research of power quality issues.

The white noise is added with pure PQ disturbance signals and noisy signal is employed for the feature extraction using the proposed and other comparison methods. In particular, in the proposed method, the HOS based features extracted from the noisy signal are used with 20, 30 and 40 dB noise levels for training and subsequently testing for the purpose classification via $k$NN classifier. The resulting confusion matrix in such noisy conditions is shown in Table 4.8. Table 4.9 shows the comparative analysis of overall efficiency of classification of the HHT based method and our proposed method in noisy condition suing both PNN and $k$NN classifiers. It is clear from Table 4.8 and Table 4.9 that the performance of the HHT based is drastically reduced, whereas the classification results of the proposed method, particularly using the $k$NN classifier remain quite satisfactory even if different noise levels are included during training and testing.

## 4.6 Conclusion

In this chapter, the performance of the proposed method is evaluated by considering various criteria. The proposed method is also compared with two other existing methods, namely S transform and HHT based methods using PNN and $k$NN classifiers. It is found that the proposed method is superior in performance in classifying different PQ disturbance signals in terms of good clustering analysis, higher overall efficiency in percentage, enhanced overall efficiency with increased number of data set and lesser required CPU time. For noisy condition, we have find out that though the overall efficiency of proposed method degrades, it continues to show better performance compared to the HHT based method.

Table 4.8: Classification Results of the Proposed Method using $k$-NN Classifier in Noisy Conditions

| **Input Classes** | **Classified Classes** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **C7** | **C8** | **C9** | **C10** | **C11** |
| **C1** | **87** | | | | | | | | | | |
| **C2** | | **88** | | | | | | | | | |
| **C3** | | | **100** | | | | | | | | |
| **C4** | | | | **97** | | | | | | | |
| **C5** | | 3 | | | **88** | | | | | | |
| **C6** | | | | | | **98** | | | | | |
| **C7** | | | | | | | **87** | | | | |
| **C8** | | | | | | | | **83** | | | |
| **C9** | | | | | | | | | **88** | | |
| **C10** | | | | | | | | | | **95** | |
| **C11** | | | | | | | | | | | **78** |
| Classification Efficiency(%) | 86 | 88 | 97 | 88 | 98 | 88 | 87 | 83 | 88 | 95 | 78 |
| Classification Error(%) | 14 | 12 | 3 | 12 | 2 | 12 | 13 | 17 | 12 | 5 | 22 |
| Overall Efficiency(%) | 90 | | | | | | | | | | |

Table 4.9: Performance Comparison using PNN and $k$-NN Classifiers in Noisy conditions

| **Method** | **Overall Efficiency(%)** | |
|---|---|---|
| | **PNN Classifier** | **kNN Classifier** |
| **HHT based Method** | **52.1** | **54.2** |
| **Proposed Method** | **85.5** | **90** |

# Chapter 5

# CONCLUSION

## 5.1 Concluding Remarks

In this thesis, an EMD based approach using the higher order statisics has been presented to solve the classification problem of different PQ disturbances. In this thesis, IMFs of the PQ disturbance signals are obtained by using EMD operation. As most frequency content of the PQ disturbance signals lies in the first three IMFs, they are selected for further analysis. HOS of the extracted IMFs, such as variance, skewness and kurtosis are utilized to form the feature vector. The feature set thus obtained is then fed to the Probabilistic Neural Network (PNN) and $k$ Nearest Neighbor ($k$ NN) classifiers for classifying the multi class PQ disturbance signals. For the characterization of PQ disturbance signals, mathematical models of eleven classes of disturbances are used. In comparison to the other methods using $k$ NN and PNN classifiers, the more effectiveness of the proposed method in classifying multi-class PQ disturbance signals has been shown through simulation results with increased trainibg and testing dataset and even in the presence of noise. Detail simulation results reveal the effectiveness of the proposed method. It is shown that the proposed method outperforms some of the state-of-the-art methods with superior efficacy.

## 5.2 Contributions of this Thesis

The major contribution of the thesis are,

- Introducing EMD that decomposes the signals of PQ disturbances into IMFs. This decomposed IMFs can be handled more easily for extracting features.

- Appropriateness of HOS in the EMD domain are shown for feature extraction in case of multiclass PQ disturbances classification problem.

- Among two types of classifier, we confirmed that the $k$NN classifier is the most suitable for PQ disturbance classification using the proposed feature set due to its faster processing time and the highest overall efficiency.

- Detail simulations have been carried out in order to investigate the performance of the proposed feature set for the classification of different types of PQ disturbance signals. The performance of our proposed method is compared with state-of-the-art S-tranform and HHT based methods. Simulation results show that the proposed method is able to classify different types of PQ disturbance signals with greater overall efficiency even in case of noisy conditions. Moreover, the performance is enhanced with increased training and testing dataset as expected.

## 5.3 Scopes for Future Work

The prime goal and contribution of the research of this thesis have been focused above. However, there are still some scopes for future research as mentioned below:

- In this research, we used Table I which gives us the mathematical models of eleven class PQ disturbance signals. Our proposed method is needed to be tested for handling data from various practical situations.

- In future, online PQ classification can be performed using different databases.

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