APPLICATION OF SHORT TIME FOURIER TRANSFORM (STFT) IN POWER QUALITY MONITORING AND EVENT CLASSIFICATION

BY

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DEDICATION

I would like to dedicate my thesis work to my beloved family and friends. A very special feeling of gratitude to my loving parents, Gopal Kachhepati and Bijayashowree Kachhepati and my sisters and brother, Brinda Kachhepati, Binita Kachhepati and Santosh Kachhepati whose words of constant encouragement and motivation gave me all the strength to complete this work. Also, I would like to dedicate this work to my little nephew and niece, Rounak and Aavha who always brings smile on my face. I would also like to dedicate my work to my friends who supported me throughout my Masters. I will always appreciate all they have done.
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ABSTRACT

APPLICATION OF SHORT TIME FOURIER TRANSFORM (STFT) IN
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Electrical power is the most essential raw material used by the industry and end user/customer. The perfect power supply needs to be always available, and within specified voltage range and frequency tolerances, and should consist of pure and noise-free sinusoidal voltage waveforms. The study of power quality (PQ) addresses these issues in obtaining perfect power supply. PQ is the measure of system reliability, equipment security, and power availability in the electrical power system. PQ has become a major concern recently because of increasing use of sensitive devices along with restructuring of the electric power industry and small scale distributed generation, putting more stringent demand on the quality of the electric power being supplied. Degradation in PQ is normally caused
by power-line disturbances that cause malfunctions, instabilities, short lifetime, failure of electrical equipment, etc. To improve PQ, the sources and causes of PQ disturbances/events must be known prior to taking appropriate mitigating actions. However, to determine the causes and sources of PQ disturbances, it is important to detect, localize, and classify them. This thesis explores a theoretical framework based on the Short Time Fourier Transform (STFT) for two important applications. The first application provides a comprehensive study of the implementation of STFT in PQ monitoring for identification and event classification. The STFT tool is implemented in detecting and localizing seven different types of PQ disturbances in a simulation framework. The feature vector thus extracted from the STFT matrix, when fed to the $k$ Nearest Neighbor ($k$-NN) and Support Vector Machine (SVM) classifiers, is found to be capable of classifying the multi-class PQ disturbances even in the presence of noise. The second application explores two important problems in a renewable rich electric power system - harmonic analysis and fault detection. The theoretical STFT tool, based on a time-frequency transform is shown to be promising in measuring time varying harmonics over a wide range, and distinguishing between two dynamic events, fault and capacitor switching, by analyzing the inverter output current. In particular, a limited set of window lengths provides harmonic analysis accuracy competitive with the more computationally demanding S-transform.
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1 INTRODUCTION

Traditional power system structures have changed in recent years, and the electrical power system can no longer be viewed as a single entity. The conventional way of transporting electric power via transmission networks which is unidirectional from generators to end users or customers, is now not adequate for current deregulated systems [1].

An electrical power system is always expected to provide undistorted sinusoidal rated voltage and current continuously at a rated frequency to every end user connected in the system. However, the proliferation of power electronics-based controllers and devices along with restructuring of the electric power industry and small-scale distributed generation have increasingly put more stringent demand on the quality of electric power supplied [2]-[4].

1.1 Power Quality and Effects of Disturbances to Power Quality

Power Quality (PQ) is a consumer-driven issue and hence can be best defined as “any power problem manifested in the voltage, current and/or frequency deviations that result in the failure or misoperation of customers’ equipment” [5]. The highest PQ 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. The best measure of PQ is the ability of electrical equipment to function in a satisfactory manner without any adverse effects to the normal operation of other equipment connected to the system.

PQ has become a significant issue for both the utility and customers. In
early days, power quality issues were concerned with power system transients due to switching and lightning surges, induction furnaces, and other cyclic loads. The increase of highly sensitive computerized systems, complex interconnection of systems, widespread use of power electronics devices, embedded generation and renewable energy resources, and fast control schemes used in electrical power networks have been driving factors for the interest in PQ and demand for PQ has resulted in many PQ issues and problems [6].

Most often a disturbance in voltage also causes a disturbance in the current and hence the term PQ is used when referring to both voltage quality or current quality. Degradation in the quality of electric power is normally caused by power-line disturbances such as voltage sag, swell, momentary interruption, harmonic distortion, flicker, notch, spike, and transients [7]. These degradations, even when momentary in nature, can cause problems such as malfunctions, instabilities, short lifetime, failure of electrical equipment, and hours of manufacturing downtime for industries.

PQ disturbances cover a wide range of spectra, significantly different variations in magnitude, and also can be stationary or non-stationary [7]. They can range from a very low magnitude and low frequency (0.1% and less than 25 Hz) voltage fluctuations due to, e.g., arc furnaces, to very high magnitude and high frequency transients (0-8 pu, 5 MHz) caused by lighting strikes, switching, and other phenomena [7], [8]. To resolve these PQ events or to take action to mitigate these events/disturbances, firstly the source and cause of a PQ disturbance must be determined and this requires monitoring, identification, and classification of PQ disturbances. In fact, the most important issue is how to detect and classify these PQ events. The identification of PQ events can be judged on the
basis of information regarding typical magnitude, duration, and spectral content for each category of an event and comparison to specifications of the Institute of Electrical and Electronics Engineers (IEEE) and International Electrotechnical Commission (IEC) standards [1], [9], [10]. The detection based on inspection of the disturbance waveform by human operators is laborious, time consuming and inaccurate. Hence, PQ monitoring should be an integral part of overall system performance assessment procedures.

1.2 Importance of Identification and Classification of PQ Disturbances

The increased connection and widespread use of power electronics devices with sensitive and fast control schemes in electrical networks have brought many technical and economic advantages, but they have also caused degradation of PQ. There are various reasons for the deterioration of the power quality. The main reasons for the growing interest in PQ problems are summarized as follows:

- Modern electric appliances are equipped with power electronics devices that are built on microprocessor/microcontroller architectures. These appliances introduce various types of PQ disturbances.

- Complex interconnected systems result in more severe consequences if any of the connected components fail. Moreover, sophisticated power electronics equipment, which is very sensitive to PQ disturbances, are used for improving system stability, operation, and efficiency.

- Industrial equipment 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.
• There has been a significant increase in renewable energy sources, microsources and inverter interfaced distributed energy resources (IIDERs) that result in PQ disturbances such as voltage variations, flicker, and waveform distortions with higher order harmonic and interharmonic components. Moreover, inverter output current is limited to the rated current in a subcycle time frame, which appears similar for faults and other disturbances like capacitor switching, and these disturbances also have high frequency transients at the onset of each event, thus making it hard to detect and distinguish between these disturbances.

To maintain a reasonable level of power quality, the identification and classification of PQ disturbances causing a particular PQ problem are necessary. The ability to locate the sources of that disturbance in the power system is also important so that necessary corrective action can be taken to mitigate the problems promptly. The detection and analysis of interharmonics and supraharmonics associated with IIDERs has been particularly difficult with existing monitoring systems. There is thus much interest in adaptation of existing or development of new techniques capable of analyzing interharmonics and supraharmonics.

1.3 Difficulties in Classification of PQ Disturbances

The complexity of PQ problems and the lack of reliable techniques for analyzing these problems have hindered power utilities’ ability to maintain the required level of power quality without 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 the classification of PQ disturbances.
• Classifier performance is highly dependent on the extracted features of the disturbance signal. Defining effective features for classifying PQ disturbances is a difficult task, especially when a new disturbances such as harmonics, interharmonics, and supraharmomics are introduced. This thesis focuses on application of the Short Time Fourier Transform (STFT) specifically to analyze harmonics, interharmonics, and supraharmomics.

• An important concern is the number of decomposition levels required in wavelet analysis to avoid loss of important information and to have an accurate classifier since PQ disturbances cover a wide range of frequencies. This thesis focuses on application of the STFT with a limited set of window lengths to cover a wide range of PQ monitoring and analysis applications.

• Noise present in the signal caused by control circuits, loads with solid-state rectifiers, switching power supplies, and power electronics devices [1], has been a major issue in accurate feature extraction and classification of PQ events. This thesis studies the effect of noise on PQ event classification.

• Most studies have trained and tested on synthetic data. A comprehensive standard PQ database for testing and comparison of state of the art techniques is also needed. Due to the difficulties in acquiring real-world disturbance measurements and accurate modeling of a real-world power system, this thesis generates synthetic signals from parametric equations for the study of the signal processing methods.
1.4 Problem Definition

The increase in occurrence and variety of PQ disturbances and the impact to end users/customers necessitates the development of signal processing tools to monitor and analyze PQ disturbances. A good monitoring system should incorporate detection capabilities into the monitoring so that events of interest can be recognized and captured automatically. Recently, to detect, localize, and classify PQ disturbances, researchers have focused on signal processing techniques to decompose power signals into a set of features from where decision making becomes easier and more accurate than conventional methods of visual inspection [11]-[14]. The majority of signal processing methods reported in the literature utilize time, frequency, and time-frequency domain representations of the PQ disturbance waveform, on the basis of which many specific features are derived in order to classify different types of PQ disturbances.

With the increasing usage of renewable energy resources (wind and solar) and micro-sources (fuel cells and micro-turbine), IIDERs have become important components in power systems nowadays. Therefore, there is also a need to monitor these renewable-rich power systems. The broadband spectrum of power inverters [15]-[17] and interconnection of IIDERs to the power system generate significant higher order harmonic and interharmonic components. There is a much required need to accurately measure these kind of harmonics and interharmonics.

The most difficult problem faced by today’s PQ disturbance classification method is the large variation in the morphology of PQ disturbance waveforms. 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 PQ disturbance classification that is capable of providing performance with greater accuracy
with simplicity in computation is indeed a difficult problem.

1.5 Thesis layout

The layout of this thesis is as follows.

Chapter 1 has provided an introduction to power quality particularly as it applies to current changes in power system. It has also summarized PQ problems, the importance for identifying and classifying the PQ events/disturbances, the associated difficulties in classifying PQ problems and problems in a renewable rich power system.

Chapter 2 provides a literature review on PQ studies and then briefly reviews the state-of-the-art in PQ identification and classification.

Chapter 3 provides details on types of PQ problems, various PQ disturbances considered in this thesis, associated difficulties in measuring time varying harmonics and problems in identifying disturbances in renewable rich electric power systems.

Chapter 4 elaborates on PQ monitoring and its significance in the electrical power system. The detection process, various signal processing methods implemented for the signal analysis, and some widely used characterization for PQ disturbances are discussed in detail. PQ standards currently used are discussed briefly.

Chapter 5 discusses how time-frequency analysis can be implemented to identify different non-stationary signals. Different types of time-frequency analysis including limitations of the Discrete Fourier Transform (DFT) are discussed. The discrete Short Time Fourier Transform (STFT) is then introduced and its application in PQ monitoring, the time-frequency resolution problem inherited by
the STFT, spectral peak correction, and correction for amplitude and phase are discussed.

Chapter 6 explains the proposed methodology used in the thesis. The first part proposes a combination of an STFT framework and $k$-Nearest Neighbor ($k$-NN) along with Support Vector Machine (SVM) classifiers for the identification and classification of different types of PQ disturbances in PQ monitoring. The second part proposes a real-time monitoring strategy based on the theoretical framework of the STFT focusing mainly on the renewable rich electric power system.

Chapter 7 provides the experimental analysis and results from the research work. The first section of this chapter explains the seven different PQ disturbance signals generated for the analysis and study. Mathematical models are used in simulating these PQ disturbance signals. Details regarding the feature extraction using the STFT and the classification results from the two classifiers are presented. The second section then estimates the amplitudes and phases of time varying harmonic and interharmonic components, including supriharmonic components, for monitoring the renewable rich electric power system. Also, results for distinguishing among two dynamic events are presented.

Chapter 8 summarizes the research work and Chapter 9 provides insight into the future work and improvements that can be done to this work.
2 LITERATURE REVIEW

This chapter provides a literature review on PQ studies. It also briefly reviews the state of the art in PQ identification and classification.

2.1 PQ Studies

The degradation in quality of electric power due to various disturbances has become a major concern nowadays. References [18]-[20] provide various guidelines regarding monitoring PQ disturbances. A basic introduction to various PQ disturbances possible in a power distribution scenario is provided in [19]. [18] provides a survey of various distribution sites and concluded various interesting observations about the various disturbance occurrence statistics which includes statistics 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.

2.2 Detection Methods

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 to extract features from a PQ disturbance signal based on the time-frequency domain and then use different classifiers for classification.

One of the most widely used tools in signal processing is Fourier analysis [21]. The Fourier transform is very useful in the analysis of harmonics. However, there
are some disadvantages, such as losses of temporal information, so that it can only be used in the steady state.

Time frequency information related to voltage disturbance waveforms can be obtained using the Short Time Fourier Transform (STFT) [22]. The STFT as a time-frequency analysis technique depends critically on the choice of the window. In [11], the discrete STFT is used for the time-frequency domain whereas a dyadic and binary-tree wavelet filter is used for time-scale domain for analysis of voltage disturbances, particularly voltage sags. Dyadic wavelet filters are not suitable for harmonic analysis of disturbance data as the filter center frequencies and bandwidths are inflexible [11]. The band-pass filter outputs from the discrete STFT are more suitable for time-frequency domain analysis of harmonic related voltage disturbances. The STFT method is also compared to wavelet transform (WT) in [11]. The choice of these methods depends heavily on the particular applications [11]. By selecting a small window length, discrete STFT is able to detect and analyze transient change at voltage sag-initiation and at voltage recovery. Overall it appears more favorable to use discrete STFT than dyadic wavelet and binary-tree wavelet filters for voltage disturbance analysis [11].

Wavelet transforms (WTs) are widely used for disturbance detection in PQ recently [23]- [24]. Wavelets have been very useful in electrical transient analysis. Papers [25]- [29] present the properties of WT and their use in scenarios similar to power quality disturbance classification. Paper [25] applies wavelet models to model several short term events like a capacitor switching transient, an autoreclosure, and a voltage dip. Paper [26] uses continuous wavelet transform to detect and analyze voltage sags and transients. Paper [27] present unique features to characterize three common power quality events at the distribution level and
methodologies to extract them using Fourier and wavelet transforms, the Fourier transform characterizes the steady state phenomena, and the wavelet transform is applied to the transient phenomena. An event identification module is then built by utilizing these characteristics [27]. Paper [28] implements WT and detects various transient events and it then integrates the WT with the probabilistic network (PNN) model and classify those events. The classified accuracy rate was 90% with more training examples in consideration [28]. Paper [29] uses a WT for on-line voltage disturbance detection where the WT was faster and more precise in discriminating transient events than the conventional detection approach based on voltage transformation to a synchronously rotating frame.

The S-transform introduced in [30] is used to analyze PQ disturbances in [13], [31]-[34]. An S-Transform based intelligent system in [32] is proposed for classification of power quality disturbance signals, where the classification accuracy was found very high (94% from the feedforward network and 92.67% from the PNN) and was practically invariant to noise, showing S-transform’s robustness. In [34], a comparison between the WT and S-transform for PQ disturbance recognition is provided, where the S-transform showed good computational scalability and very low sensitivity to noise levels during the classifications.

2.3 Classification Methods

Approaches for classification of PQ disturbance signals are based on $k$-nearest neighbor ($k$-NN) classifiers, artificial neural networks (ANN), support vector machines (SVMs), fuzzy expert systems and evolving algorithms (EA) and have all been successfully applied to automated detection and diagnosis of the conditions of different kinds of disturbances.
Reference [36] presents a novel approach of using a fuzzy-expert system for automated detection and classification of PQ disturbances. The use of a Fourier linear combiner and a fuzzy expert system for the classification of signals is proposed in [31]. Applications using SVMs have been reported in [37]-[40]. An SVM based algorithm has been proposed for classification of common types of voltage sag disturbances [37]. The performance of a proposed SVM classifier is investigated in [39] when the voltage disturbance data are used for training and testing originated from different sources. Data from both real disturbances recorded in two different power networks and from synthetic data are used. A high accuracy of 95.9% is achieved when the SVM classifier was trained on data from a real power network and test data originated from synthetic data [39]. A lower accuracy of 82.6% resulted when the SVM classifier was trained on synthetic data and test data originated from the power network [39]. Two classification methods: a deterministic method (expert system as an example) and a statistical method (SVM as an example) are used for classifying PQ disturbance signals in [40]. The expert system in [40] makes more optimal use of power-system knowledge and has been applied to a large number of measured disturbances with good classification results. SVM classifier trained on data from one power network gives good classification accuracy of 96.1% for data from another power network [40]. The training using synthetic data gives a lower accuracy of 78.12% for measured data, due to a less realistic model used in generating the synthetic data as compared with the real data [40]. ANN have been proposed in [38], [41] for automatic disturbance recognition. An automatic classification of different PQ disturbances using the wavelet packet transform and fuzzy $k$-NN-based classifier is proposed in [42] where the $k$-NN classifier was used as an efficient tool to recognize the distur-
bances at particular point of time, and the classifier provided a good classification accuracy of 93.7% with the optimal feature vector used. In [43], a multi-label classification predicted the classes of multiple disturbances for a power quality (PQ) event, classified them effectively with good accuracy of 96.27%.
3 POWER QUALITY DISTURBANCES

This chapter introduces the various power quality disturbances that are being considered in this thesis. This chapter also details the time varying harmonics which are non-trivial to measure and the problems in identifying disturbances in renewable rich electric power systems.

3.1 Types of PQ Problems

PQ problems fall into two basic categories [1].

- Events or Disturbances: Events or disturbances are measured by triggering on an abnormality in the voltage or the current. Transient voltages may be detected when the peak magnitude exceeds a specified threshold. RMS (Root Mean Square) voltage variations (e.g., sags or interruptions) may be detected when voltage exceeds a specified level.

- Steady-State Variations: Steady state variation is a measure of the magnitude by which the voltage or current may vary from the nominal value, plus distortion and the degree of unbalance between the three phases. These include normal RMS voltage variations and harmonic distortion.

According to the nature of the waveform distortion, PQ events can be further categorized. Table 1 shows information regarding typical spectral content, duration and magnitude for each category of common electromagnetic disturbances. The phenomena given in the Table 1 can be described further by various appropriate attributes. For steady-state disturbances, the amplitude, frequency, spectrum,
modulation, source impedance, notch depth, and notch area attributes can be utilized whereas attributes like rate of rise, rate of occurrence, and energy potential are useful for non-steady state disturbances [44].

3.2 Various Power Quality Disturbances

PQ disturbances are usually characterized in terms of the effect to the system voltage and supply frequency. They can be broadly classified according to voltage magnitude variations, frequency variations and transients. The definitions according to IEEE standard 1159-2009 [1] and summarized in Table 1 are given in the following sections. Some usual causes of these disturbances and their negative effects to the power system [1] are also discussed.

The example waveforms shown in the following sections are generated from parametric equation-based simulation of various PQ events; further details about the simulation and PQ disturbance signals are provided in Chapter 6.

3.2.1 Sags (Dips)

A voltage sag or dip is a decrease in RMS voltage to between 0.1 pu and 0.9 pu for durations at the power frequency of 0.5 cycles to 1 min. Figure 1 shows an instantaneous voltage sag, simulated using the mathematical model in Table 1. The main causes of voltage sags 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, transfer of a load from one power source to another, animal contact, or tree interference [1]. Some major effects of voltage sag include voltage instability and malfunctions in electrical low-voltage devices, converters, uninterruptible power supplies (UPS), and measuring and control equipment [1].
<table>
<thead>
<tr>
<th>Categories</th>
<th>Duration</th>
<th>Voltage Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Short Duration Variation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sag</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instantaneous</td>
<td>0.5 - 30 cycles.</td>
<td>0.1 - 0.9 pu.</td>
</tr>
<tr>
<td>Momentary</td>
<td>30 cycles - 3 sec.</td>
<td>0.1 - 0.9 pu.</td>
</tr>
<tr>
<td>Temporary</td>
<td>3 sec. - 1 min.</td>
<td>0.1 - 0.9 pu.</td>
</tr>
<tr>
<td>Swell</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instantaneous</td>
<td>0.5 - 30 cycles.</td>
<td>1.1 - 1.8 pu.</td>
</tr>
<tr>
<td>Momentary</td>
<td>30 cycles - 3 sec.</td>
<td>1.1 - 1.4 pu.</td>
</tr>
<tr>
<td>Temporary</td>
<td>3 sec. - 1 min.</td>
<td>1.1 - 1.2 pu.</td>
</tr>
<tr>
<td>Interruption</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Momentary</td>
<td>0.5 cycles - 3 sec.</td>
<td>&lt;0.1 pu.</td>
</tr>
<tr>
<td>Temporary</td>
<td>3 sec. - 1 min.</td>
<td>&lt;0.1 pu.</td>
</tr>
<tr>
<td><strong>Long Duration Variation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interruption</td>
<td>&gt; 1 min.</td>
<td>0.0 pu.</td>
</tr>
<tr>
<td>Under-voltage</td>
<td>&gt; 1 min.</td>
<td>0.8 - 0.9 pu.</td>
</tr>
<tr>
<td>Overvoltage</td>
<td>&gt; 1 min.</td>
<td>1.1 - 1.2 pu.</td>
</tr>
<tr>
<td><strong>Transients</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impulsive</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nanosecond</td>
<td>&lt;50 nsec.</td>
<td>0 - 4 pu.</td>
</tr>
<tr>
<td>Microsecond</td>
<td>50 - 1 msec.</td>
<td>0 - 8 pu.</td>
</tr>
<tr>
<td>Milisecond</td>
<td>&gt;1 msec.</td>
<td>0 - 4 pu.</td>
</tr>
<tr>
<td><strong>Oscillatory</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Frequency</td>
<td>0.3 - 50 msec.</td>
<td>N/A</td>
</tr>
<tr>
<td>Medium Frequency</td>
<td>20 µsec.</td>
<td>N/A</td>
</tr>
<tr>
<td>High Frequency</td>
<td>5 µsec.</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Voltage Imbalance</strong></td>
<td>Steady State</td>
<td>0.5 - 2%</td>
</tr>
<tr>
<td><strong>Waveform Distortion</strong></td>
<td>Steady State</td>
<td></td>
</tr>
<tr>
<td>DC offset</td>
<td>Steady State</td>
<td>0 -0.1%</td>
</tr>
<tr>
<td>Harmonics</td>
<td>Steady State</td>
<td>0 -20%</td>
</tr>
<tr>
<td>Inter-harmonics</td>
<td>Steady State</td>
<td>0 -2%</td>
</tr>
<tr>
<td>Notching</td>
<td>Steady State</td>
<td>N/A</td>
</tr>
<tr>
<td>Noise</td>
<td>Steady State</td>
<td>0.1%</td>
</tr>
</tbody>
</table>

Table 1: Classification of PQ events according to IEEE standard 1159-2009 [1]
Also, problems in interfacing with communication signals can arise. Lights may dim briefly. More sensitive equipment could be more noticeably affected.

3.2.2 Swell

A voltage swell is an increase above 1.1 pu in RMS voltage for power frequency duration from 0.5 cycles to 1 min. Typical voltage swell magnitudes are between 1.1 pu and 1.2 pu. Swells are characterized by their magnitude (RMS value) and duration [1]. Figure 2 shows a voltage swell of an instantaneous voltage variation, simulated using the mathematical model in Table 1. The main causes of voltage swells include energizing of capacitor banks, shutdown of large loads, unbalanced faults, transients, and power frequency surges [1]. Voltage swell can cause insulation breakdown in equipment and tripping of protective circuitry in some power electronics systems [1].

3.2.3 Harmonics

Harmonics in power systems are the voltages and currents which have frequencies other than the fundamental frequency. The most common harmonics in power
systems are those which are an integer multiple of the fundamental frequency. Combined with the fundamental voltage or current, harmonics produce waveform distortion. An example of a power system signal with harmonic components can be seen in Figure 3, simulated using the mathematical model in Table 1. Harmonic distortion exists due to nonlinear characteristics of devices and loads on the power system. Harmonics 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 magnetizing nonlinearities of transformers [1]. The general effects of harmonics include increased thermal stress and losses in capacitors and transformers, as well as poor damping, increased losses or degraded performance of rotating motors. Furthermore, transmission systems under harmonic distortion are subject to higher copper losses, corona, skin effect, dielectric stress, and 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].
3.2.4 Interharmonics

Interharmonics are the voltages or currents with frequency components that are not integer multiples of the fundamental frequency. They may appear as discrete frequencies or as a wideband spectrum. An example of a power system signal with interharmonic components can be seen in Figure 4. Interharmonics are rapidly becoming a problem in power systems due to the increase in interharmonic inducing loads. The main sources of interharmonic waveform distortion are static frequency converters, sub-synchronous converter cascades, cycloconverters, induction motors, arc furnaces, High Voltage Direct Current (HVDC) schemes, and large DC link drives to synchronous or induction motors [1]. Power line carrier signals can also be considered as interharmonics. Interharmonics affect power line carrier signaling and can induce visual flicker in display devices [1].
3.2.5 Flicker

Voltage fluctuations are a series of random voltage changes. Flicker is an undesirable result of voltage fluctuation. Flicker is defined by its RMS magnitude expressed as a percent of the fundamental frequency magnitude. Flicker magnitude generally is in the range of 0.9 to 1.1 pu. The instantaneous flicker level may vary with time depending on the length of the measure interval. Figure 5 shows a voltage flicker signal, simulated using the mathematical model in Table 1. Arc furnaces are one of the common causes of voltage flickers. Rolling mills, large industrial motors with variable loads are other causes. Flicker at certain amplitudes can cause discomfort for people exposed to the effects [1]. However, flicker does not cause any malfunctions in the power system [1].

3.2.6 Interruption

Voltage interruption can occur when the supply voltage or load current decreases to less than 0.1 pu for a period of time not exceeding 1 min. They also can be the result of power system faults, equipment failures, and control malfunctions. Inter-
ruptions are measured by their duration since the voltage magnitude is always less than 10% of nominal. This event could be very momentary or sometimes could be repetitive for a short duration. Figure 6 shows a momentary voltage interruption, simulated using the mathematical model in Table 1. 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 [1]. Interruptions result in loss of computer/controller memory, equipment shutdown/failure, hardware damage, and product loss [1].
3.2.7 Notch

Notching disturbances are non-sinusoidal, periodic waveform distortions which 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. Figure 7 represents a voltage notch signal having only 5 cycles to represent the distinct notches in the fundamental sine wave component, simulated using the mathematical model in Table 1. Three-phase converters that produce continuous DC output are the most important cause of voltage notching [1]. Notching disturbances cause negative operational effects, such as signal interference introduced into logic and communication circuits. Also, at sufficient power, the voltage notching effect may overload electromagnetic interference filters, and other similar high-frequency sensitive capacitive circuits [1].

3.2.8 Transients

Transients are short-duration 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.
Figure 8: Oscillatory voltage transient in a voltage signal.

Figure 8 shows a low-frequency oscillatory voltage transient signal, simulated using the mathematical model in Table 1. Capacitor bank energization typically results in an oscillatory voltage transient with a primary frequency between 300 Hz and 900 Hz. Main causes for transients are switching on secondary systems, lightning-induced ringing, and local ferroresonance [1]. 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].

3.3 Harmonics and Problems in Identifying Disturbances in Renewable Rich Electric Power Systems

Renewable rich electric power systems have a range of time varying harmonics that are non-trivial to measure. On the other hand, more IIDERS using renewable energy (wind and solar) or micro-sources (fuel cells and micro-turbine) are used
nowadays and also several other nonlinear loads connected to power systems have impacts on the stability of the system.

Common sources of harmonics include nonlinear loads, saturable devices and power electronics devices [45]. As the power systems grid continually changes, new phenomena related to traditional power systems harmonics are being introduced. As intermodulation between the fundamental and the harmonic components of a system occur, a component with a frequency of a non-integer multiple can occur [46]. Interharmonics are rapidly becoming a problem in power systems because of a drastic increase in loads inducing interharmonics. The broadband spectrum of power inverters used in power systems comprising renewable energy sources generate significant higher order harmonic and interharmonic components. Supra-harmonics, the harmonics in the 2-150 kHz range, are presently of high interest for two reasons; 1) there is a lack of standards (emission, immunity and compatibility) [48]- [50] and 2) frequencies within this range are used for automated meter reading (9 to 95 kHz) [47]. There is a much required need to develop a signal processing technique to accurately measure these kind of harmonics [47]. Narrow band components in the supraharmonics are not stationary and change amplitude over time. The emission can also have other features like time-frequency variations which are not common in the harmonic range [48], [49] and thus need joint time-frequency analysis rather than traditional Fourier analysis [51].

Inverter response to disturbances has been a major operational issue. IIDERs’ output current is limited to the rated current in a sub cycle time frame which creates a difficult scenario for fault detection for any protective device installed at point of interconnection (POI) of such DERs. The sudden switching of large loads or a capacitor in distribution feeders will also result in similar rise in currents.
This limitation of currents from the IIDERs create difficulties in distinguishing between the power disturbances as both of these disturbances have high frequency transients at the onset of each event that looks similar, making it hard to identify by traditional detection methods.

A major problem for power resources is that their response to faults is such that they are typically “fault-blinded” because they are not able to detect a fault. Additionally, they are not able to distinguish a typical fault from other dynamic events taking place on the system. Also, nonlinear loads and power sources inject time-varying harmonics into the system. To account for these diverse issues, a generalized framework based on signal processing is required.
4 POWER QUALITY MONITORING

PQ monitoring in an electric power system is necessary to characterize different PQ disturbances at a particular location in the system. PQ monitoring forms an integral part of the overall system performance assessment procedures. Under the deregulation of utilities, the necessity for monitoring has increased due to the difficulty in diagnosing incompatibilities between the electric power supply and the load equipment. The need to study distortion levels at particular locations becomes very important in order to refine modeling techniques or to develop a PQ baseline. Monitoring the PQ can be used to predict future performance of load equipment or PQ mitigating techniques [1]. However, preventing economic damage occurring due to PQ disturbances in a critical load environment is the most important reason for monitoring electric PQ. The frequency of PQ disturbances and their duration affect PQ costs.

PQ monitoring is the process of collecting, analyzing, and interpreting raw data into useful information. The process of collecting data is usually carried out by continuous measurement of voltage and current over some extended time period. The process of analysis and interpretation has traditionally been performed manually. However, recent advances in signal processing techniques and artificial intelligence have made it possible to design and implement intelligent automated systems to automatically analyze and interpret raw data, with minimal human intervention [5].
4.1 Detection Process

The detection process is the first step in PQ monitoring which deals with PQ problems. The techniques used in the detection process are time-dependent which require sample data to be compared with a threshold to determine start and end points of a disturbance. The simplest detection method is to identify any deviation of time-dependent RMS voltage/current magnitudes from the nominal waveform. This method has been used for detecting voltage dips, swells, and interruptions [52]-[54]. Another technique in detecting fast step changes (in voltage or current), is to use high pass or band pass filters. A disturbance in a power system often results in a fast step change, and also results in high-frequency oscillations. A high pass filter can thus be used to detect such step changes or oscillations. Wavelet filters are known to be effective in detecting multi-scale singular points and these filters can detect the start and end points of a disturbance usually relating to the significant sudden changes or singularities in the signal waveform [54].

4.2 Signal Analysis

Signal analysis is the second step in PQ monitoring which involves signal processing techniques to analyze the voltage and current measurements from the detected sampled disturbance waveform. Signal processing techniques are needed for the characterization (feature extraction) of variation and events, for the triggering mechanism needed to detect events, and to extract additional information from the measurements [7]. Several signal processing techniques have been used to analyze PQ disturbance signals. Some common techniques are reported below.
Discrete Fourier Transform (DFT)

The traditional method used to obtain the fundamental and harmonic components of a signal is the application of the DFT to the samples of the signal taken in a time window.

Short Time Fourier Transform (STFT)

The STFT provides a time-frequency signal decomposition, which is equivalent to applying a set of equal-bandwidth sub-band filters. The STFT is a Fourier-based transform used to determine the sinusoidal frequency and phase content of local sections of a signal as they changes over time.

S-Transform

The S-transform is a time-localized Fourier spectrum and has a window whose height and width vary unlike the STFT [30]. It can be considered an extension of the WT [30], [34]. The S-transform has an advantage over the WT in that it it provides multi-resolution analysis while retaining the absolute phase of each frequency [30]- [34]. However, selecting a suitable window to match the specific frequency content of the signal results a poor energy concentration in the time-frequency domain: poor time resolution at lower frequencies and poor frequency resolution at higher frequencies [30], [33], [34]. Additionally, the S-transform is more computationally complex to implement and more complicated to interpret than standard Fourier-based methods.

Wavelet Transform

The wavelet transform (WT) is a significant tool for monitoring PQ problems
The multi-resolution capabilities of the WT distinguishes it from the Fourier-based methods technique. A wavelet transform using a multi-resolution signal decomposition technique is efficient in analyzing transient events [27]. A multi-resolution signal decomposition has the ability to detect and localize transient events and furthermore classify different power quality disturbances using unique features extracted from WT for different power quality disturbances.

**Kalman Filters**

Kalman filters have been used as an alternative method to the Root Mean Square (RMS) method to detect and analyze voltage events in power systems [53], [55]. Unlike the RMS method [52], [54], the Kalman filtering method gives information both on the magnitude and phase angle of the voltage supply during an event and the time when the voltage event begins. Kalman filters are used to estimate the time dependent signal components, magnitudes, and frequency components using selected harmonic frequencies.

4.3 Disturbance Characterization

Disturbance characterization is the process of categorizing PQ disturbance signals into different types according to their extracted features. It is important to define and extract good-quality features in the analysis step for any successful disturbance characterization. Artificial Neural Networks (ANN), Support Vector Machine (SVM), k-Nearest Neighbour (k-NN), Expert Systems and so on are highlighted in this section.

**Artificial Neural Networks:** ANNs have been an important tool for the statistical-based categorization of power system disturbances [38], [41]. Neural
networks are nonlinear statistical data modeling tools. Categorization using neural networks is a good alternative only when enough data is available.

Support Vector Machines: A Support Vector Machine (SVM) performs classification by constructing an N-dimensional hyper-plane that optimally separates the data into two categories. SVMs are able to find non-linear boundaries if classes are not linearly separable. SVM models use a kernel function to project the features into a higher dimensional space where the data may be better separated by a hyperplane.

$k$-Nearest Neighbour: The $k$-nearest neighbor ($k$-NN) classifier is a method for classification based on the closest training examples in the feature space. The classifier compares a new sample (testing data) with the baseline data (training data) and finds the $k$-neighborhood in the training data and assigns the class which appears more frequently in the $k$-neighborhood. 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.

Expert System: An expert system is a deterministic approach for categorization. A set of rules, where the “real intelligence” from human experts in power systems is translated into the “artificial intelligence” in computers, forms the core of an expert system [36]. The performance of categorization is directly dependent on the set of IF-THEN rules, and the inference that performs the reasoning of rules. The main disadvantage of an expert system is the need for predetermined thresholds to make binary decisions, and choosing undesirable thresholds leads to less accuracy in categorization.

The PQ monitoring process depends on power quality standards that define
acceptable limits for the monitoring process. The different threshold limits and the standard classification of PQ disturbance signals in PQ monitoring is useless if it is not compared to the power quality baselines or standards. Power quality standards define acceptable and measurable limits of voltage, current, and deviations from normal frequency. The main benefits of PQ standards are to make clear to utilities and customers about acceptable and unacceptable levels of service and to protect the utility’s and end user’s equipment from failing or operating improperly when PQ disturbances occur.

4.4 Power Quality Standards

There are various organizations that develop PQ standards. The Institute of Electrical and Electronics Engineers (IEEE), American National Standards Institute (ANSI), and Electric Power Research Institute (EPRI) are very famous in North America, whereas the International Electrotechnical Commission (IEC) is a widely known organization in Europe. Utilities and end-users/customers need standards that set limits on electrical disturbances that their equipment can withstand and also allow a normal and effective operation of their equipment. Table 2 shows the IEC standards as well as IEEE standards that are referred for various PQ studies.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Harmonics</td>
<td>IEC 61000-2-1: 1990; IEEE 1159: 2009</td>
</tr>
<tr>
<td>Voltage flicker</td>
<td>IEC 61000-4-15: 1997</td>
</tr>
</tbody>
</table>

Table 2: Power quality standards
5 TIME FREQUENCY REPRESENTATION

Due to increased awareness of PQ, the need for PQ monitoring is important. PQ monitoring forms an integral part of overall system performance assessment procedures. Signal processing techniques form an important part of PQ monitoring and analysis of voltage and current measurements from the sampled waveform. Signal processing techniques are needed for the characterization (feature extraction) of variation and events, for the triggering mechanism needed to detect events, and to extract additional information from the measurements [7]. The increase in occurrence and variety of PQ disturbances and impact to end users/customers has necessitated the development of signal processing tools to monitor and analyze PQ disturbances.

Moreover, inverter response to disturbances creates a major operational issue where the limitation imposed on the currents from the IIDERs create difficulties in identifying and discriminating between faults or sudden switching of large loads or a capacitor in distribution feeders, making it hard to be detected by traditional detection methods. Also, nonlinear loads and power sources inject time varying harmonics into the system. To account for these diverse issues, a generalized framework based on signal processing is required.

5.1 Time Frequency Analysis

Time Frequency Analysis (TFA) is a signal processing tool which has wide field applications particularly in extracting valuable information from non-stationary signals [56], [57]. It combines time domain analysis and frequency domain analysis
to yield a potentially more revealing picture of temporal localization of a signal’s spectral components [58], [59]. Since time-frequency representations (TFR) indicate variations of the spectral characteristics of the signal as a function of time, they are ideally suited for non-stationary signals.

Non-stationary signals are signals in which frequency components are not present at all the times in the signal. To analyze any non-stationary signal such as a voltage or current, we need to use a multi-resolution technique which provides the TFR. TFA techniques decompose any non-stationary signal in terms of a joint time-frequency domain representation, which captures the time evolving contribution of the frequency components present in the signal. In other words, TFA techniques can extract instantaneous estimates of amplitude and phase change of frequency components. Therefore, every unique type of non-stationary signal is expected to have a unique signature in the time-frequency (TF) plane. This property enables the TFA approach to be used as a potential tool to distinguish among different types of non-stationary signals; voltages and currents are the non-stationary signals in this study.

Techniques of TFA for non-stationary signals can generally be divided into two categories: (1) linear transforms, which primarily include the Short-Time Fourier Transform (STFT) and Wavelet Transform (WT), and (2) Quadratic (Bilinear) Transforms, which mainly include the Wigner Distribution (WD) and Ambiguity Function (AF) [60]. Linear TF transforms are preferred because of their low computation and ease of parameter estimation in general [44]. The discrete STFT, which is a linear TF transform, overcomes the lack of time resolution of the DFT by using the moving windowing technique performing Fourier analysis of data sliced by the moving window. Although the STFT has a fixed frequency
resolution for all frequencies once the size of the window is chosen, it enables an easier interpretation compared to the WT in terms of harmonics and maintains the absolute phase of each localized frequency component.

5.2 Discrete Fourier Transform

The Fourier transform is one of the most common spectral analysis techniques. It transforms a time domain signal to a frequency domain signal, which is an alternate representation of a signal. In most cases the frequency domain shows certain features of the signal that were not visible in the time domain.

The Fourier transform \( X(j\Omega) \) of a time domain signal \( x(t) \) is given by

\[
X(j\Omega) = \int_{-\infty}^{\infty} x(t)e^{-j\Omega t} dt
\]  

(1)

The Discrete Time Fourier Transform (DTFT) of a discrete time signal \( x[n] \) is a periodic function of a frequency variable \( \omega \) and is given by

\[
X(e^{j\omega}) = \sum_{n=-\infty}^{\infty} x[n]e^{-j\omega n}
\]  

(2)

where \( x[n]=x(nF_s) \) and \( \omega=2\pi F/F_s \), where \( F \) is the frequency in consideration and \( F_s \) is the sampling frequency. The Discrete Fourier Transform (DFT) is obtained by sampling the DTFT at \( N \) discrete frequencies \( w_k = 2\pi(k/N), k = 0, 1, 2, \ldots, N - 1 \) which yields the transform:
The DFT has some disadvantages. The DFT computes spectral content for all integer values $k$, but the spectral content in between integer values must be otherwise estimated. For non-stationary signals, the spectral content changes with time and hence the time averaged amplitude spectrum computed using the DFT may be inadequate to track changes. A solution to most of the above mentioned difficulties of the DFT is a TFA.

### 5.3 Discrete Short Time Fourier Transform

The STFT is used for TFA of non-stationary signals, where the Fourier Transform alone becomes inadequate. The STFT decomposes a time-varying signal into time-frequency domain components, hence it provides an insight into the time-evolution of each signal component. Given a signal $x[n]$, the mathematical definition of the STFT for frequency $\omega$ at time $m$ is defined as,

$$X_m(j\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n - mR]e^{-j\omega n} \quad (4)$$

where $x[n]$ is the input signal at time $n$, $w[n]$ is the length $M$ window function (e.g., Hamming), $X_m(j\omega)$ is the Discrete-Time Fourier Transform (DTFT) of windowed data centered about time $mR$ and $R$ is the hop size in samples between successive DTFTs [61].

The STFT in (4) can be rewritten by shifting $x[n]$ instead of $w[n]$, as

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j2\pi kn/N} \quad (3)$$
\[ X_m(j\omega) = \sum_{n=-\infty}^{\infty} x[n + mR]w[n]e^{-j\omega(n+mR)} \]

\[ X_m(j\omega) = e^{-j\omega mR} \sum_{n=-\infty}^{\infty} x[n + mR]w[n]e^{-j\omega n} \]

\[ X_m(j\omega) = e^{-j\omega mR} DTFT_{\omega}(SHIFT_{-mR}(x) \cdot w) \quad (5) \]

The data centered about time \( mR \) are translated to time 0, multiplied by the window \( w \), and then the DTFT is performed.

The discrete STFT, using the DFT rather than the DTFT can be interpreted as a sampling of the STFT in frequency. Sampling the frequency axis is information-preserving when the signal is properly time limited. Let \( M \) denote the window length (typically an odd number) and \( N \geq M \) be the DFT length (typically a power of 2). Then sampling from (5) at \( \omega_k = \frac{2\pi k}{N}, k = 0, 1, 2, 3, \ldots, N - 1 \), and using the fact that the window \( w[n] \) is time-limited to \( N \) samples centered about time zero, yields

\[
X_m[\omega_k] = e^{-j\omega_k mR} \sum_{n=-\frac{N}{2}}^{\frac{N}{2}} x[n + mR]w[n]e^{-j\omega_k n}
\]

\[
X_m[\omega_k] = e^{-j\omega_k mR} DFT_{N,\omega_k}(SHIFT_{-mR}(x) \cdot w) \quad (6)
\]

The discrete STFT is computed as a succession of DFTs of windowed data frames, where the window slides or hops forward through time. The discrete STFT \( X_m[\omega_k] \) is a function of both time (frame number \( m \)) and frequency \( \omega_k = \frac{2\pi k}{N} \).
The time-frequency resolution of the spectrogram obtained from the STFT is dependent upon the chosen window size.

The window size is chosen in such a way to make sure that the windowed signal segment can be assumed to be stationary. The windowing results in a localization in time and hence the spectrum thus obtained is called a local spectrum. This localizing window is moved in time along the entire length of the signal and localized spectra are calculated. The 2D visualization of the magnitude of this spectrum is called a spectrogram.

Figures 9 (a) and (b) show the sound of a sea lion barking [62], which is sampled at 11,025 Hz and its spectrogram. A Blackman window of length 512 length was used. The spectrogram has three distinct barks that provides the spectrum of the signal with maximum frequency of 5012.5 Hz. Also every bark has a fundamental frequency (the lowest with significant amplitude) and a number of harmonics at integer multiples of the fundamental.
5.3.1 Time Frequency Resolution Trade-off

Time resolution is defined as how well a transform can resolve rapid variations in the time domain and frequency resolution refers to how well the changes in frequencies of a signal can be tracked. The time and frequency resolution are dependent directly on the width of the window used in time frequency analysis. Frequency resolution is proportional to the bandwidth of the windowing function while time resolution is proportional to the length of the windowing function. Thus a short window is needed for good time resolution and a wider window offers good frequency resolution.

The limitation of the time frequency resolution is due to the Heisenberg-Gabor inequality [63] that states

\[ \Delta t \cdot \Delta f \geq K \]  

where \( \Delta t = NT_s \) is the time resolution, \( \Delta f = mF_s/N \) is the frequency resolution, \( m \) is the coefficient depending on the window type used, \( F_s \) is the sampling frequency, \( T_s = 1/F_s \) is the sampling interval, \( N \) is the window length and \( K \) is a constant that depends on the type of window used. Therefore to attain good time resolution as well as frequency resolution, one may have to use a pair of STFTs, one with a narrow window (which gives good time resolution) and another with a wider window (good frequency resolution).

Figure 10 is from [64] which is a chirp signal having four repetition pulses where each pulse starts at a lower frequency of 100 Hz and ends at a higher frequency of 4000 Hz. The spectrograms for a long window and a short window length shown in Figure 10 show the limitation of the time frequency resolution inherited due to the chosen window length. Figure 10 (a) is the spectrogram of
the signal with a long Blackman window of length 256 which shows the loss in time resolution, but an improvement in frequency resolution. The loss in time resolution can be seen prominently in the thick vertical bars when the chirp signal changes from high to low frequency; the improvement in frequency resolution can be seen by the smoother variation across frequency. The spectrogram in Figure 10 (b) considers a short Hamming window of length of 64 which shows the loss in frequency resolution, but an improvement in time resolution. The loss in frequency resolution is seen in the blocky variation across frequency whereas the thin vertical lines show the improvement in the time resolution.

Figure 10: Spectrograms at different window lengths; (a) Spectrogram with a longer window length (b) Spectrogram with a shorter window length.

5.3.2 Spectral Peak Correction in Discrete STFT

One of the pitfalls of the DFT is known as the picket fence effect. Thus, the STFT is affected from the limitations imposed by the DFT, such as picket fence effect. The picket fence effect arises due to the finite number of frequency bins or a fixed frequency resolution. For any frequency component that is a non-integer multiple of the frequency spacing or frequency resolution, the desired peak lies in between two frequency bins, which makes the exact peak to be completely
indistinguishable. In addition, spectral leakage due to window sidelobes affect the discrete STFT. Both fixed frequency resolution and window effects result in inaccurate measurement of harmonic and interharmonic components. To enhance the resolution of the DFT and to identify the accurate peak of a frequency component, a correction method based on three consecutive DFT samples was proposed in [65]. Based on this approach, a frequency correction to the TFR obtained by the STFT was proposed. For the $n^{th}$ time and $k^{th}$ frequency sample, a frequency correction of $\delta(n,k)$ is applied to estimate the exact spectral-temporal peak in the time-frequency grid at the point $(n, k + \delta(n, k))$. The value of $\delta(n, k)$ is calculated from consecutive TFR matrix elements $S_d(n, k - 1)$, $S_d(n, k)$, and $S_d(n, k + 1)$ by:

$$\delta(n, k) = \frac{\tan\left(\frac{\pi}{N}\right)}{\pi} \text{Real} \left( \frac{S_d(n, k - 1) - S_d(n, k + 1)}{2S_d(n, k) - S_d(n, k - 1) - S_d(n, k + 1)} \right)$$  \hspace{1cm} (8)$$

Figure 11: Magnitude plot of TFR showing actual peak and observed sampled TFR values. (Figure taken from [66] with permission)

A more precise value of the peak at the point $(n, k + \delta(n, k))$ can be found by calculating the STFT at that point by interpolating the TFR over the three
consecutive TFR values $S_d(n, k-1)$, $S_d(n, k)$, and $S_d(n, k+1)$ with a cubic spline interpolation. Figure 11 illustrates the accurate peak detection.

5.3.3 Amplitude and Phase Correction in STFT

The time-frequency matrix $S(n, k)$ can be computed with the STFT framework for a window beginning at the $n^{th}$ time sample and for the $k^{th}$ frequency bin. The estimation of amplitudes and phases for each row of the $S$ matrix representing the harmonic and interharmonic frequency components requires correction in amplitude as well as phase.

The frequency bin at $k$ corresponding to the desired harmonic component in the amplitude matrix of the complex $S$ matrix is found for amplitude correction. The amplitude correction for each element of the desired harmonic in the matrix is multiplied by the corresponding amplification factor of the window used in the STFT. The correction factor $\beta$ is derived as

$$\beta(n, k) = \left| \frac{1 - e^{j2\pi f_s N}}{1 - e^{j2\pi (f - \frac{k}{N})}} \right|$$

where $k$ represents the frequency bin of interest, $f_s$ is the sampling frequency, $N$ is the window length, and $f$ is the frequency of the harmonic.

A signal waveform of the desired frequency component, whose phase is to be estimated is used as a reference signal. The reference phases obtained from the STFT matrix are used for phase correction. The reference phases are then subtracted from the phases that are to be corrected. The phase difference is compared to a threshold (360 degrees or $2\pi$ radians), adjusted accordingly by either subtracting or adding, and unwrapped.
6 METHODOLOGY

This chapter explains the methodology proposed in this thesis. The first part of this chapter describes a combination of an STFT framework and k-Nearest Neighbor (k-NN) along with Support Vector Machine (SVM) classifiers for the identification and classification of different types of PQ disturbances in PQ monitoring of particular interest here is a study of appropriate window lengths for an STFT-based analysis of PQ events. The second part describes a real-time monitoring strategy based on the theoretical framework of the STFT focusing mainly on the renewable rich electric power system, where the amplitudes and phases of time varying harmonics and interharmonics, including the supraharmonics are estimated. The second part then uses the same STFT based monitoring approach in discriminating among different dynamic events. Two dynamic events, namely fault and capacitor switching are considered for the discrimination.

6.1 Proposed Method for PQ Monitoring in Identification and Event Classification Using STFT Framework

The proposed method for the PQ events identification and classification has three key parts: pre-processing, feature extraction, and classification.

6.1.1 Pre-processing

In pre-processing of the proposed method, a normalization step is carried out. In the normalization step, the event voltage waveform is converted to relative scale, per unit (pu.) by dividing the input signal, by the nominal Root Mean Square
6.1.2 Feature Extraction

The time-frequency matrix $S(n, k)$ can be computed with the STFT framework for a window beginning at the $n^{th}$ time sample and for the $k^{th}$ frequency bin. The column vector represents the signal's amplitude-frequency characteristic at a particular moment whereas the row vector represents the time domain distribution of signal in a certain frequency component.

By means of feature extraction, distinctive features of the disturbances are obtained and the dimensionality of the feature space is lessened. Feature extraction in this thesis is done by applying standard statistical techniques to each of the $S$ matrices obtained by applying the STFT to each PQ disturbance signal.

Features such as amplitude, slope (or gradient) of amplitude, time of occurrence, mean, standard deviation and energy of the transformed signal can be used for the classification [33]. Features based on standard deviation (SD), energy, mean amplitude, and mean frequency of the transformed signals are extracted.

6.1.3 Classification

For the purpose of classifying different PQ disturbances, a training database formed by the extracted features is needed for PQ signals of different events or classes. Features extracted from the signals are used as the input of a classification system instead of the signal waveform itself. Selecting a proper set of features is thus an important step toward successful classification. The classification accuracy depends upon the quality of the extracted features.

In this thesis, we employ two different classifiers to determine the efficacy of
the extracted feature vector using the STFT framework in classifying different PQ disturbance signals. We note that the study of the STFT for standard PQ disturbances has been done before [11], [22], [31]. We include this analysis to complement our study of the STFT specifically for analysis of harmonics and interharmonics including supraharmoinics to demonstrate the versatility of the STFT for PQ analysis. In particular, we demonstrate that STFT analysis with only a few window lengths yield good results across a wide range of PQ disturbances, including the difficult interharmonics and supraharmoinics.

**k-Nearest Neighbor Classifier** (k-NN) is a simple, linear classifier. 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 assigns the class which appear more frequently in the neighborhood of $k$. 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 neighbor. In a $k$-NN classifier, different types of mathematical distances can be 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 distance setting is Euclidean.

**Support vector machine (SVM)** belongs to the family of generalized linear classifiers [14]. A SVM separates two different groups of data by searching for the hyperplane with maximum margin [39]. SVMs are able to find non-linear boundaries if classes are linearly non-separable. Each instance in the training set contains one “target value” (class labels) and several “attributes” (features) [35].
Figure 12: Block diagram of the proposed method for PQ monitoring and events classification

The goal of the SVM is to produce a model which predicts the target value of data instances in the testing set when given only the attributes.

Figure 12 represents the overall proposed system for PQ monitoring and event classification where power disturbance signals are mapped to the time-frequency representation based on the STFT and features of different events are extracted from the $S$ matrix. The extracted features are classified using $k$-NN and SVM classifiers.


The proposed monitoring approach for monitoring renewable rich electric power system is given as in a block diagram in Figure 13. Voltages and currents are the input non-stationary signals to the system.

IEC 61000-4-7 standard appendix B [67] recommends measuring a 2-9 kHz
range of frequencies with a frequency resolution of 5 Hz. We choose a sampling frequency of 50 kHz, which is well above the Nyquist rate to measure the components in the range 2-9 kHz and a frequency resolution of 5 Hz is used for the proposed monitoring approach. As per IEEE standard 519-2014 [68], the measurement window was kept 12 cycles, i.e., approximately 200 milliseconds for a 60 Hz power system, for estimating harmonics. This ensures that the spectral resolution, i.e., the spacing between any two consecutive frequency bins or samples is 5 Hz. The sampling frequency used in the paper is not synchronized with the fundamental frequency of the signal, but the spectral peak correction employed in the STFT calculation compensates for this lack of synchronization.

Figure 13: Proposed system for PQ monitoring and events classification

The time varying amplitudes and phases of harmonic, interharmonic and supraharmonic components are then extracted from the time-frequency matrix based on the STFT theoretical framework. In addition to harmonic assessment, the proposed monitoring approach is also applied to inverter output waveforms for faults and capacitor switching to evaluate its potential to discriminate between these two dynamic events. The dominant frequency component for these two events are extracted from the time-frequency matrix and are used to distinguish between them by looking at their distinct characteristics or signatures.
This chapter details the experimental results obtained from the two proposed systems based on the theoretical framework of the STFT. The first section documents the result obtained during PQ monitoring in the identification and analysis based on the STFT for different PQ disturbance signals. This section then evaluates the performance of the two classifiers used in classifying different PQ events, where the overall accuracy obtained from each classifier are documented. The second section documents the estimated amplitude and phase results for time varying harmonics. For interharmonics including supraharmoinics, only estimated amplitudes are presented. The second section concludes with the results obtained in distinguishing between two dynamic events (fault and capacitor switching) using the STFT based theoretical framework.

7.1 Data Generation for PQ Analysis

It is difficult to capture real-time PQ disturbance signals. Usually PQ disturbance signals are produced by simulation for further analysis. Seven different PQ disturbances have been generated using the mathematical models shown in Table 3, at a sampling frequency of 50 kHz. Each PQ disturbance waveform consists of 12 cycles or approximately 200 ms for a 60 Hz power system (10000 data points). The choice of a 50 kHz sampling frequency is to be consistent with the analysis of the harmonics, interharmonics and supraharmoinics presented later.
<table>
<thead>
<tr>
<th>Disturbances</th>
<th>Equation</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sag</td>
<td>$x(t) = A (1 - \alpha(u(t - t_1) - u(t - t_2)))sin(\omega t)$</td>
<td>$0.1 \leq \alpha \leq 0.9$; $T \leq t_2 - t_1 \leq 9 ; T$</td>
</tr>
<tr>
<td>Swell</td>
<td>$x(t) = A (1 + \alpha(u(t - t_1) - u(t - t_2)))sin(\omega t)$</td>
<td>$0.1 \leq \alpha \leq 0.9$; $T \leq t_2 - t_1 \leq 9 ; T$</td>
</tr>
<tr>
<td>Harmonics</td>
<td>$x(t) = \alpha_1 sin(\omega t) + \alpha_3 sin(\omega t)$ + $\alpha_5 sin(\omega t) + \alpha_7 sin(\omega t)$</td>
<td>$0.05 \leq \alpha_3 \leq 0.15$; $0.05 \leq \alpha_5 \leq 0.15$; $0.05 \leq \alpha_7 \leq 0.15$; $\sum \alpha_i^2$</td>
</tr>
<tr>
<td>Flicker</td>
<td>$x(t) = A [1 + \alpha sin(2 \pi f_t)]sin(\omega t)$</td>
<td>$0.1 \leq \alpha \leq 0.2$; $5 ; Hz \leq f_t \leq 20 ; Hz$;</td>
</tr>
<tr>
<td>Interruption</td>
<td>$x(t) = A (1 - \alpha(u(t - t_1) - u(t - t_2)))sin(\omega t)$</td>
<td>$0.9 \leq \alpha \leq 1$; $T \leq t_2 - t_1 \leq 9 ; T$</td>
</tr>
<tr>
<td>Notch</td>
<td>$x(t) = A [sin(\omega t) - sgn(sin(\omega t)) \times \sum_k \alpha {u(t-(t_1+0.02n))-{u(t-(t_2+0.02n))}]$</td>
<td>$1 \leq k \leq 8$; $0.1 \leq \alpha \leq 0.4$; $0.01 \leq t_2 - t_1 \leq 0.05 ; T$;</td>
</tr>
<tr>
<td>Oscillatory Transients</td>
<td>$x(t) = A [sin(\omega t) + \alpha e^{-(t-t_1)} \times sin(2\pi f_n (t-t_1))((u(t_2) - u(t_1)))]$</td>
<td>$0.1 \leq \alpha \leq 0.8$; $0.5 \leq t_2 - t_1 \leq 3 ; T$; $0.1 \leq ms \tau \leq 0.2 ms$; $300 \leq f_n \leq 900 Hz$;</td>
</tr>
</tbody>
</table>

Table 3: Mathematical Model of PQ Disturbances [1].
7.2 PQ Analysis Using STFT

In this thesis, seven different types of PQ disturbances, namely voltage sag, swell, interruption, flicker, oscillatory transient, harmonic, and notch events are analyzed and studied. The starting and ending time of PQ disturbances are varied but with a predetermined range based on the parameters in Table 3. A Hamming window length of 834 samples is used for computing the STFT matrix for the PQ analysis for the disturbance signals in study.

For the \( n^{th} \) time and \( k^{th} \) frequency sample, the time-frequency matrix \( S(n, k) \) can be computed with the STFT. The columns of the complex \( S \) matrix correspond to the sampling time points whereas the rows correspond to the frequency components (0 Hz to 25 kHz for a sampling frequency of 50 kHz). The first row \((k=0)\) of the \( S \) matrix corresponds to the DC component and the frequency difference between adjacent rows is:

\[
\Delta f = f_s/N
\]

where \( N \) is the number of samples and \( f_s \) is the sampling frequency.

The magnitude and phase of each element in the time-frequency matrix \( S \) matrix can be calculated by:

\[
\rho_S(n, k) = \sqrt{x(n, k)^2 + y(n, k)^2}
\]

\[
\theta_S((n, k)) = \arctan(y(n, k)/x(n, k))
\]

where \( S(n, k) = x(n, k) + jx(n, k) \) is the complex TF matrix, with \( j \) as the imaginary unit. \( \rho(\cdot) \) represents the calculation of magnitude and \( \theta(\cdot) \) is the calculation
of the phase. Each column of the matrix $\rho_S$ can be ranked in order of size and the frequency component with maximum amplitude is called the feature frequency component, whose magnitude and phase are $\rho_{S,max}$ and $\theta_{S,max}$, respectively.

Figures 14-20 (a) show seven different types of PQ disturbance signals and the time-frequency representation generated from the $S$ matrix are shown in Figures 14-20 (b). The time-maximum amplitude plot of Figures 14-20 (c) represent the maximum amplitude versus time obtained by searching columns of the $S$ matrix amplitude at every frequency. This defines the amplitude of the fundamental frequency as it is has the largest amplitude. Figures 14-20 (d) represent the frequency-maximum amplitude plot, presents maximum amplitudes versus normalized frequency values, and the values in these plots are obtained by searching the maximum value of the rows of the $S$ matrix at every frequency.

In Figures 14-17 (d), there is only one peak at the fundamental frequency, while in Figures 18-20 (d), there is more than one peak. This suggests that the disturbances of voltage sag, swell, flicker, and interruption have only the fundamental frequency component, whereas the harmonics, oscillatory transient, and notch have other frequency components.

The harmonic and oscillatory transient signals have more than one frequency component, as shown in Figure 18 (d) and Figure 19 (d). Figures 18 (e) and 19 (e) are the frequency-mean amplitude plots which present mean amplitudes versus normalized frequency values, and the values in these plots are obtained by calculating the mean value of each row of the $S$ matrix. The magnitude at the high frequency in Figure 19 (e) is much lower than that in Figure 19 (d). This illustrates that the transient disturbance is time varying whereas harmonic signal is stable.
In Figures 14 (c) and 17 (c), the time-maximum amplitude curve shows a large decrease in magnitude for the disturbance of voltage sag and interruption, while for voltage swell, shown in Figure 15(c), the curve has an obvious increase.

Figure 14: Voltage Sag and its feature waveforms.
(a) Simulated Swell Signal.

(b) Spectrogram.

(c) Maximum amplitude versus time.

(d) Maximum magnitude versus frequency.

Figure 15: Voltage Swell and its feature waveforms.
(a) Simulated Flicker Signal.

(b) Spectrogram.

(c) Maximum amplitude versus time.

(d) Maximum magnitude versus frequency.

Figure 16: Voltage Flicker and its feature waveforms.
Figure 17: Voltage Interruption and its feature waveforms.
(a) Simulated Harmonic Signal.

(b) Spectrogram.

(c) Maximum amplitude versus time.

(d) Maximum magnitude versus frequency.

(e) Mean amplitude versus frequency.

Figure 18: Harmonics and its feature waveforms.
(a) Simulated Oscillatory Transient Signal.

(b) Spectrogram.

(c) Maximum amplitude versus time.

(d) Maximum magnitude versus frequency.

(e) Mean amplitude versus frequency.

Figure 19: Oscillatory transient and its feature waveforms.
Figure 20: Voltage Notch and its feature waveforms.
The difference between voltage sag and interruption is the fall degree (slope of the falling edge). The time-maximum amplitude plot of the interruption indicates a bigger fall than that from a sag, shown in Figures 14 (c) and 17 (c), respectively.

The sag depth for voltage sag is 0.35 units with a sag duration of 0.1487 seconds as shown in Figure 21 (a). The interruption depth is 0.91125 units with interruption duration of 0.1518 seconds as shown in Figure 21 (b). It can be clearly seen that interruption has a larger fall and depth than a sag.

Figure 21: (a) Sag depth and duration (b) Interruption depth and duration
7.3 Feature Extraction Using STFT

The $S$ matrix of a signal can characterize changes across different frequencies clearly and intuitively, so we propose to use the STFT for feature extraction. Feature extraction in this thesis is done by applying standard statistical techniques to each of the $S$ matrices obtained from applying the STFT to each PQ disturbance signal. 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 classification [33]. These features from the $S$ matrix have been found to be useful for detection, classification or quantification of relevant parameters of the PQ disturbance signals [33], [34]. In this thesis, features based on standard deviation (SD), energy, mean and maximum (amplitude and frequency) of the transformed signals are extracted as follows:

Feature 1: Mean value of the data set values corresponding to maximum value of each column of the $S$ matrix.

Feature 2: Maximum value of frequency (frequency corresponding to maximum amplitude) in the $S$ matrix.

Feature 3: Standard deviation of the data set comprising the phase elements corresponding to the maximum magnitude of each column of the $S$ matrix.

Feature 4: Standard deviation (SD) of the data set comprising the elements corresponding to the maximum magnitude of each row of the $S$ matrix.

Feature 5: Standard deviation (SD) of the data set comprising the elements corresponding to the maximum magnitude of each column of the $S$ matrix.

Feature 6: Energy of the data set comprising the elements corresponding to the maximum magnitude of each column of the $S$ matrix. Energy is calculated
by:

$$E_n = \sum_{k=M_1}^{M_2} |S(n,k)|^2$$  \hspace{1cm} (13)

where the sampling point in the $S$ matrix of $n^{th}$ row and $k^{th}$ column is $S(n,k)$ and $M_1$ and $M_2$ are the starting column and the ending column of the required sub-matrix ($8193 \times 2292$ matrix) for the calculation of relevant energy features respectively.

To relate the extracted features defined above, 100 signals of each type of seven PQ events are sampled at a sampling frequency of 50 kHz. The random distributions used for the parameters for each PQ disturbance signal are based on the mathematical model in Table 3. The starting and ending time for each PQ event is varied but in a predetermined range based on Table 3. Sag, swell and interruption are modeled as in Table 3, where $u$ is the unit step function, $\alpha$ is the magnitude and $t_1$ and $t_2$ are the starting and ending time of the disturbance respectively. Flicker has a subharmonic frequency ($f_t$) of less than 20 Hz and less than 20\% in magnitude ($\alpha$) as in Table 3. Harmonics modeled as in Table 3 have three odd harmonic components at respective odd integer multiples of the fundamental frequency. Low frequency oscillatory transient in the 300-900 Hz frequency range, is modeled as shown in Table 3, where $(t - t_1)$ as the transient starting time, $\alpha$ as the transient magnitude, $f_n$ as the frequency of the transient element and $1/\tau$ responsible for the transient settling time are varied as in Table 3. Notch modeled as in Table 3 has $k$ as the magnitude, $sgn$ as the signum function and $n$ as the number of total cycles. Additionally, random white noise with SNR (Signal to noise Ratio) of 50 or 35 dB and zero mean is added to these simulated PQ events. To illustrate the nature of the feature sets for all the seven classes,
Figures 22, 23, 24, and 25 based on the extracted features are presented here for no noise.

In Figure 22, the seven different PQ events are shown in the scatter plot of Feature 5 (SD of columns) versus Feature 1 (Mean value). It is well visualized that some of the events or classes have distinct features and can be easily discriminated from others while some of the events or classes are overlapped with each other.

Figure 23 is a Feature 2 (Maximum frequency) versus Feature 5 (SD of columns) scatter plot. The feature used is able to similarly differentiate PQ events effectively. From this figure, voltage sag, swell, flicker and interruption can be clearly separated from the remaining three PQ disturbance signals.

Figure 24 is a Feature 4 (SD of rows) versus Feature 5 (SD of columns) scatter plot. The overlapping set (harmonic, oscillatory transient and notch) can be visually distinguished from the remaining four PQ disturbance signals.

To visualize the suitability of these features for classification, a three dimensional scatter plot of Feature 1, Feature 2, and Feature 5 is shown in Figure 25. It
is clearly visible that events sag, swell, interruption, and flicker occupy different locations in the 3D feature space. From these feature scatter plots, we qualitatively see the potential for discrimination between different PQ events.
7.4 Classification Results

We will quantitatively study the classification of the PQ events in this section. In order to evaluate the performance of the classifiers, accuracy of the classification is documented.

Based on the feature extraction by the STFT method, six-dimensional feature sets for training and testing are constructed. The dimensions here represent the six different features derived from the $S$ matrix. These data sets of features for various PQ events or classes are applied to $k$-NN and SVM for automatic classification of the PQ events.

A total of 700 signals with 100 signals for each event, are generated and are used as the training and testing data. Each classifier is trained with 90% of the 700 simulated events and tested with 10% of the 700 simulated events. The classifiers are then tested with signals without noise and with noisy signals, consisting of SNR 35 and 50 dB for each set. The seven types of PQ disturbance signals are
mapped as seven different input classes as shown in Table 4.

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>Sag</td>
</tr>
<tr>
<td>C2</td>
<td>Swell</td>
</tr>
<tr>
<td>C3</td>
<td>Flicker</td>
</tr>
<tr>
<td>C4</td>
<td>Interruption</td>
</tr>
<tr>
<td>C5</td>
<td>Harmonics</td>
</tr>
<tr>
<td>C6</td>
<td>Oscillatory transient</td>
</tr>
<tr>
<td>C7</td>
<td>Notch</td>
</tr>
</tbody>
</table>

Table 4: Mapping PQ signals to input classes for interpretation of the confusion matrices

7.4.1 Performance Comparison using Confusion Matrix Analysis

The 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. The confusion matrix has diagonal elements representing the correct classification and off-diagonal elements as misclassification. The overall accuracy of correct classification is the ratio of correctly classified events to that the total number of events considered.

$k$-NN Classifier

The classification results using only 3 features (mean value, maximum frequency, and SD of rows) of the $k$-NN classifier are shown in the confusion matrix of Table 5 and 6 for two different values of $k$.

The overall accuracy obtained from the $k$-NN classifier for $k = 3$ is 99.0% as shown in the confusion matrix in Table 5. The highest accuracy of 100% is obtained for the default value of $k = 1$. Accuracy decreases with increasing values of $k$ because the number of nearest neighbors taken by the classifier is increasing,
resulting in more chances for misclassification. An overall accuracy of 89.4% is obtained for \( k = 9 \) from the confusion matrix in Table 6.

It can be seen from the diagonal entries of the confusion matrices in Table 5 and 6 that \( k \)-NN classifier with \( k=3 \) and \( k=9 \) find it more difficult to distinguish among some PQ disturbance signals. The confusion matrix in Table 5 shows that sag (C1) is occasionally misclassified as interruption (C4), whereas oscillatory transient (C6) is occasionally misclassified as notch (C7). Likewise, notch (C7) is sometimes misclassified as harmonic (C5). From the confusion matrix shown in Table 6, sag (C1) is again misclassified as interruption (C4) and also swell (C2), whereas swell (C2) is misclassified as sag (C1) and interruption (C4). Interruption (C4) is misclassified as sag (C1) and swell (C2), whereas harmonic (C5) is misclassified as notch (C7) and flicker (C3). Likewise, oscillatory transient (C6) is misclassified as notch (C7), whereas notch (C7) is misclassified as harmonic (C5).

<table>
<thead>
<tr>
<th>Input classes</th>
<th>Classified Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C1</td>
</tr>
<tr>
<td>C1</td>
<td>98</td>
</tr>
<tr>
<td>C2</td>
<td>0</td>
</tr>
<tr>
<td>C3</td>
<td>0</td>
</tr>
<tr>
<td>C4</td>
<td>0</td>
</tr>
<tr>
<td>C5</td>
<td>0</td>
</tr>
<tr>
<td>C6</td>
<td>0</td>
</tr>
<tr>
<td>C7</td>
<td>0</td>
</tr>
<tr>
<td>Classification Accuracy(%)</td>
<td>98.0</td>
</tr>
<tr>
<td>Classification Error(%)</td>
<td>2.0</td>
</tr>
<tr>
<td>Overall Accuracy(%)</td>
<td>99.0</td>
</tr>
</tbody>
</table>

Table 5: Classification result of \( k \)-NN for \( k=3 \)

as notch (C7) and flicker (C3). Likewise, oscillatory transient (C6) is misclassified as notch (C7), whereas notch (C7) is misclassified as harmonic (C5).
The comparative results with 2 features (mean value and maximum frequency), 3 features (mean value, maximum frequency and SD of rows), 4 features (mean value, maximum frequency, SD of rows and energy) and all 6 features for $k = 3$ are shown in Table 7. The 3 features has the highest overall accuracy among other relevant number of features in consideration.

An overall accuracy of 96.9% and 98.1% are obtained for SNR of 35 and 50 dB respectively using only 3 features from the $k$-NN classifier. Likewise, an overall accuracy of 98.3% is calculated for signals without noise, for a value of $k=3$, using 2 features. An overall accuracy of 96.1% and 97.7% are calculated for SNR of 35 and 50 dB respectively using only 2 features obtained using the $k$-NN classifier. The accuracy decreases with decreasing SNR as expected.

<table>
<thead>
<tr>
<th>Input classes</th>
<th>Classified Classes</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
<th>C7</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td></td>
<td>89</td>
<td>2</td>
<td>0</td>
<td>9</td>
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</tr>
<tr>
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<td>0</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C3</td>
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<td>C5</td>
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<td>0</td>
<td>0</td>
<td>1</td>
<td>98</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>C6</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>79</td>
<td>21</td>
<td></td>
</tr>
<tr>
<td>C7</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>92</td>
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<tr>
<td>Classification Accuracy(%)</td>
<td>89</td>
<td>85.0</td>
<td>100</td>
<td>83.0</td>
<td>98.0</td>
<td>79.0</td>
<td>92.0</td>
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</tr>
<tr>
<td>Classification Error(%)</td>
<td>11.0</td>
<td>15.0</td>
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<td>17.0</td>
<td>2.0</td>
<td>21.0</td>
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<tr>
<td>Overall Accuracy(%)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Classification result of $k$-NN for $k=9$
An overall accuracy of 97.0% is calculated for signals with no noise, for \( k=3 \), using 4 features. The overall accuracy of 95.1% and 96.3% for SNR of 35 dB and SNR of 50 dB are calculated respectively for the same value of \( k=3 \).

Likewise, an overall accuracy of 95.6% is calculated for signals without noise, for \( k=3 \), using all 6 features. The overall accuracy of 93.1% and 94.7% for SNR of 35 dB and SNR of 50 dB are calculated respectively for the same value of \( k=3 \).

The results from the overall accuracy with the total number of features taken in consideration shows that the 3 and 2 features respectively have higher overall accuracy compared to the 6 feature or even 4 feature overall accuracy. As the 3 features has the highest overall accuracy among other relevant number of features in consideration, we can take 3 features in evaluating the performance of the \( k\)-NN classifier.

The \( k\)-NN classifier accuracy obtained using the STFT is comparable with that obtained using the WT in [42] and the S-transform in [43].
SVM Classifier

The classification results using 3 features (mean value, maximum frequency and SD of rows) of the SVM classifier are shown in the confusion matrix in Table 8 where the overall accuracy obtained from SVM classifier for signals without noise is 86.1%.

The SVM classifier finds it difficult to distinguish among some PQ disturbance signals. From the confusion matrix of Table 8, Sag (C1) is misclassified as swell (C2) and interruption (C4), whereas swell (C2) is misclassified as interruption (C4) and sag (C1). Likewise, interruption (C4) is misclassified as sag (C1) and swell (C2), whereas harmonic (C5) is misclassified as flicker (C3). Oscillatory transient (C6) on the other hand is misclassified as notch (C7), whereas notch (C7) is misclassified as harmonic (C5).

<table>
<thead>
<tr>
<th>Input classes</th>
<th>Classified Classes</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
<th>C7</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>90</td>
<td>2</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C2</td>
<td>7</td>
<td>80</td>
<td>13</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C3</td>
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<td>0</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C4</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C5</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C6</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>61</td>
<td>39</td>
<td>0</td>
</tr>
<tr>
<td>C7</td>
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<td>0</td>
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<td>0</td>
<td>5</td>
<td>0</td>
<td>95</td>
<td>0</td>
</tr>
<tr>
<td>Classification Accuracy(%)</td>
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<td>99.0</td>
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<tr>
<td>Classification Error(%)</td>
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<td>20.0</td>
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<td>22.0</td>
<td>1.0</td>
<td>39.0</td>
<td>5.0</td>
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<tr>
<td>Overall Accuracy (%)</td>
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<td></td>
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</tr>
</tbody>
</table>

Table 8: Classification result of SVM with 3 features
The confusion matrix shown in Table 9 has an overall accuracy of 85.0% obtained from the SVM classifier for signals without noise, using only 2 features. As seen from the confusion matrix, the SVM classifier has some difficulty distinguishing among some PQ disturbance signals.

The comparative results with 2 (mean value and maximum frequency), 3 (mean value, maximum frequency and SD of rows), 4 features (mean value, maximum frequency, SD of rows and energy) and all 6 features are shown in Table 10 for the SVM classifier. The 3 features has the highest overall accuracy among other relevant number of features in consideration.

An overall accuracy of 83.7% and 85.3% are calculated for SNR of 35 and 50 dB respectively using only 3 features obtained using SVM classifier, whereas overall accuracy of 82.6% and 84.1% are calculated for SNR of 35 and 50 dB respectively using only 2 features.
<table>
<thead>
<tr>
<th>Event</th>
<th>Correct Classification</th>
<th>With 2 features</th>
<th>With 3 features</th>
<th>With 4 features</th>
<th>With 6 features</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td></td>
<td>90</td>
<td>90</td>
<td>87</td>
<td>85</td>
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<td>98</td>
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<tr>
<td>C6</td>
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<td>58</td>
<td>61</td>
<td>53</td>
<td>48</td>
</tr>
<tr>
<td>C7</td>
<td></td>
<td>95</td>
<td>95</td>
<td>93</td>
<td>93</td>
</tr>
<tr>
<td>Overall Accuracy (%)</td>
<td>85.0</td>
<td>86.1</td>
<td>82.9</td>
<td>81.6</td>
<td></td>
</tr>
</tbody>
</table>

Table 10: Comparison of SVM accuracy with 2, 3, 4 and 6 features

An overall accuracy obtained from the SVM classifier using 4 features is 82.9%, for signals with no noise. The overall accuracy with 4 features decreased to 80.3% and 81.7% for SNR of 35 and 50 dB respectively.

Likewise, the overall accuracy obtained from the SVM classifier using all 6 features is 81.6%, for signals with no noise. And, the overall accuracy decreased to 79.4% and 80.7% for SNR of 35 dB and 50 dB respectively.

Since the 3 features has the highest overall accuracy among other relevant number of features in consideration, we can take 3 features in evaluating the performance of the SVM classifier.

The SVM classifier accuracy obtained using the STFT is comparable with that obtained using the S-transform in [39], [40] where the classifier was trained on the synthetic data.
7.5 Monitoring Harmonics and Interharmonics

We simulated the same test cases used in [66] with known parameters to evaluate the performance of the proposed approach to measure time-varying harmonics, including interharmonics and supraharmnics.

The test signal model is defined as:

$$x(n) = \sum_{k=1}^{K} A_k \sin\left(2\pi f_k \frac{n}{F_s} + \phi_k\right) + \zeta(n),$$

where $K$ denotes the maximum number of frequency components, $f_k$ is the frequency of the $k^{th}$ spectral component, $A_k$ and $\phi_k$ are, respectively, the instantaneous amplitude and phase of the $k^{th}$ spectral component, and $\zeta(n)$ is an additive white Gaussian noise sequence with an SNR of 35 dB. A sampling frequency of 50 kHz is used in the simulation for the test signals in consideration in the study.

The selection of an appropriate window size is vital for the STFT [69]. However, the optimum window length will depend on the application. If the application is such that we need time domain information to be more accurate, a window of smaller size is preferred. If the application demands frequency domain information to be more specific, a window of bigger size is preferred.

The best selection for the window length for our STFT computation is determined by analyzing the respective Root Mean Square (RMS) estimation error of amplitude and phase estimates for a range of window lengths. For estimation
accuracy, RMS estimation error was calculated according to

\[
e(n) = \sqrt{\frac{1}{L} \sum_{n=1}^{L} (x_d(n) - x_e(n))^2}
\]  

(15)

where \(x_d(n)\) and \(x_e(n)\) are the desired and estimated signal components, respectively, and \(L\) is the length of the dataset taken.

Figures 26 and 27 show the plots of RMS estimation error versus window length for time-varying harmonics and inter-harmonics including supra-harmonics. The smaller the RMS estimation error, the better the window length.

To determine the best window size possible, simulations are executed for both harmonics and interharmonics including supra-harmonics cases. For a signal with time-varying harmonic components, the Hamming window size is varied between 400 samples and 1600 samples (8 ms - 32 ms, or 0.480 - 1.92 cycles of the fundamental). Figures have been zoomed to give a clear illustration showing the calculated RMSE at the y-coordinate and window size at the x-coordinate in both figures. A window size of 834 samples (16.68 ms, 1.0008 cycles) gives the least RMS estimation error for harmonic components as shown in Figure 26 and this window size is selected for estimating time-varying amplitude and phase of signals with harmonics.

Likewise, for signals with inter-harmonics including supra-harmonic components, the Hamming window size is varied between 700 samples and 1700 samples (14 ms - 34 ms, or 0.84 - 2.04 cycles of the fundamental). For estimating the amplitude and phase of signals of time-varying inter-harmonics and supra harmonics, a window size of 1600 samples (32 ms, 1.92 cycles of the fundamental) is selected.
as shown in Figure 27. The window size of 1600 samples selected does not give the least RMS estimation error for all of the interharmonic and supraharmonic components as shown in Figure 27. However, this length 1600 window provides a good compromise to RMS estimation error compared to other window lengths and the amplitude estimates are much closer to the desired values compared to other. This compromise in the selection of the window size gives a fair estimation of the amplitude for each of the interharmonic including supraharmonic components in the signal. The ability to find just 2 window lengths, one for the harmonic analysis and one for the interharmonic and supraharmonic analysis will provide computational savings over the S-transform which defines a different window for each frequency.

As we can see there are periodic variations in these Figures 26 and 27. These periodic variations are due to Gibb’s ringing effect, introduced due to sharp transitions of window edges. At higher frequencies, the translation of the narrower window, i.e., sliding of the window across the entire duration of the signal is reflected as the periodic variation.

Once the best window size is selected, the amplitude and phase of time-varying harmonic and interharmonic components associated with two test signals (described below) are then estimated. The third case (described below) shows that the proposed method based on STFT is also capable of discriminating between two different dynamic events of the power disturbances- fault and capacitor switching in an IIDER system.
Figure 26: Estimation of the best window length possible for signals with (a) Fundamental (b) 3\textsuperscript{rd} harmonic, (c) 5\textsuperscript{th} harmonic, (d) 11\textsuperscript{th} harmonic and (e) 21\textsuperscript{st} harmonic components.
Figure 27: Estimation of the best window length possible for signals with (a) Fundamental component, (b) Inter-harmonic component at 130 Hz, (c) Inter-harmonic component at 370 Hz, (d) Supraharmonic component at 2500 Hz and (e) Supraharmonic component at 4000 Hz.
7.5.1 Case 1: Test Signal with Time Varying Harmonic Components

In this test, the amplitude and phase of the harmonic components are varied, keeping the system frequency constant. The parametric variations of a test signal model with respect to time are indicated in Table 11. The resulting signal with fundamental and harmonic components is shown in Figure 28 (a). The frequency spectrum of the signal is also plotted in Figure 28 (b). The plot of the magnitude of the $S$ matrix computed using a length 834 Hamming window is shown in Figure 28 (c) which also provides an accurate frequency localization along with the change in intensity of the harmonic components.

![Signal with harmonic components](image1)

![Frequency Spectrum of Original Signal](image2)

![Magnitude Spectrogram Analysis](image3)

Figure 28: (a) Signal with harmonic components; (b) Frequency spectrum of the signal determined by simple DFT (c) Frequency distribution determined by STFT.
The amplitude and phase tracking of the fundamental as well as the harmonic components as extracted out of the $S$ matrix are shown respectively in Figures 29 and 30. The DFT estimates were calculated based on IEEE 519-2014 [68] and are used for comparison.

The performance of amplitude and phase estimation of fundamental and harmonic components as RMS estimation error for each spectral component is tabulated in Table 12. The RMS estimation error for the S-transform from [66] are included for comparison. In the case of phase estimation, the result from DFT analysis is not reported due to high distortion in the phase spectrum. The proposed method has comparable results to the S-transform. The results for the estimated amplitudes for the time varying harmonics are better compared to results from the S-transform based on the RMS estimation error. The phase results are also comparable to that of the S-transform, although the S-transform has

<table>
<thead>
<tr>
<th>k</th>
<th>$f_k$ (Hz)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-100 ms</td>
<td>$A_k$ (pu.)</td>
<td>1</td>
<td>0.05</td>
<td>0.1</td>
<td>0.07</td>
<td>0.055</td>
</tr>
<tr>
<td></td>
<td>$\phi_k$ (Degree)</td>
<td>60</td>
<td>33</td>
<td>43</td>
<td>75</td>
<td>20</td>
</tr>
<tr>
<td>101-200 ms</td>
<td>$A_k$ (pu.)</td>
<td>0.9</td>
<td>0.08</td>
<td>0.2</td>
<td>0.09</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>$\phi_k$ (Degree)</td>
<td>60</td>
<td>39</td>
<td>48</td>
<td>95</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 11: Parameter variations of the test signal with harmonics

<table>
<thead>
<tr>
<th>k</th>
<th>$f_k$ (Hz)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>DFT</td>
<td>$A_k$ (pu.)</td>
<td>0.0216</td>
<td>0.2462</td>
<td>0.3557</td>
<td>0.2716</td>
<td>0.2127</td>
</tr>
<tr>
<td>S Transform</td>
<td>$A_k$ (pu.)</td>
<td>0.0147</td>
<td>0.0031</td>
<td>0.0070</td>
<td>0.0023</td>
<td>0.0023</td>
</tr>
<tr>
<td></td>
<td>$\phi_k$ (Degree)</td>
<td>0.1142</td>
<td>3.8376</td>
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<td>1.3526</td>
<td>1.0443</td>
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<tr>
<td>Proposed</td>
<td>$A_k$ (pu.)</td>
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<td>0.0026</td>
<td>0.0068</td>
<td>0.0018</td>
<td>0.0015</td>
</tr>
<tr>
<td></td>
<td>$\phi_k$ (Degree)</td>
<td>0.5139</td>
<td>5.9496</td>
<td>0.5913</td>
<td>1.5988</td>
<td>1.1947</td>
</tr>
</tbody>
</table>

Table 12: RMS estimation error for Harmonics
Figure 29: Estimated amplitude of: (a) Fundamental, (b) $3^{rd}$ harmonic, (c) $5^{th}$ harmonic, (d) $11^{th}$ harmonic, (e) $21^{st}$ harmonic components with the proposed method.
Figure 30: Estimated phase of: (a) Fundamental, (b) $3^{rd}$ harmonic, (c) $5^{th}$ harmonic, (d) $11^{th}$ harmonic (e) $21^{st}$ harmonic components from the proposed method.
slightly smaller RMS estimation error. The STFT is simple to implement because of its low complexity in design and a comparable computational time make it perform better than S-transform which supports STFT to be promising in measuring time varying harmonics over a wide range.

The phase of the 3\textsuperscript{rd} harmonic component, i.e., 180 Hz, in Figure 30(b) has an abnormally large peak during the transition instant having a maximum phase of 70 degrees at 0.1 seconds, shifting by more than 30 degrees from the desired phase at that time instant. This can be accounted to the fact that phases get adversely affected due to the harmonic distortion and the noise content in such a way that its reconstruction will not be able to correctly determine the original phase of the signal. However, the amplitudes on the other hand can be reconstructed to an extent close enough to the original. This change in phase of the harmonic component depends on the simulated signals in consideration and the addition of noise sequence since this particular abnormal sudden rise in phase at the transaction can occur at different harmonic components depending on the simulation. Both the proposed STFT method and the S-transform method have similar issues in tracking the 3\textsuperscript{rd} harmonic component in this case.

7.5.2 Case 2: Test Signal with Time Varying Interharmonic and Supra-harmonic Components

A time varying test signal comprising fundamental, two interharmonics, and two supraharmonics is shown in Figure 31 (a). The two interharmonic components have frequencies of 130 Hz and 370 Hz and the two supraharmonic components have frequencies of 2500 Hz and 4000 Hz. The frequency spectrum of the test signal is shown in Figure 31 (b). The plot of the magnitude of the $S$ matrix, using
a length-1600 Hamming window is shown in Figure 31 (c) which also provides an accurate frequency localization by observing the plot. The change in intensity of the interharmonic components can also be observed from the figure. The amplitude variations of these spectral components with respect to time are shown in Table 13.

<table>
<thead>
<tr>
<th></th>
<th>k</th>
<th>( f_k ) (Hz)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-100 ms</td>
<td>( A_k ) (pu.)</td>
<td>1</td>
<td>0.06</td>
<td>0.02</td>
<td>0.012</td>
<td>0.010</td>
<td></td>
</tr>
<tr>
<td>101-200 ms</td>
<td>( A_k ) (pu.)</td>
<td>1</td>
<td>0.09</td>
<td>0.04</td>
<td>0.01</td>
<td>0.015</td>
<td></td>
</tr>
</tbody>
</table>

Table 13: Parameter variations of the test signal with Interharmonic and Supra-harmonic components

Figure 31: (a) Signal with interharmonic components (b) Frequency spectrum of the signal determined by simple DFT, and (c) Frequency distribution determined by STFT.
The amplitude tracking of the fundamental as well as the inter-harmonic and the two supra harmonic components as extracted out of the TF matrix are shown in Figure 32. There is high distortion in the phase spectrum because of the fact that phases get adversely affected due to the interharmonic and supraharmomic components and the noise content present in the signal. The result of the phase estimations are thus not reported.

The calculated RMS estimation error are summarized in Table 14, which shows the proposed approach has promising performance in measuring the interharmonic and supra-harmomic components up to 4000 Hz. However, the compromise made in the selection of window length can be directly associated with RMS estimation error results for the fundamental and interharmonic components at 130 and 370 Hz. The estimated amplitudes for the supraharmomic components are comparable with that from the S-transform from [66]. The fundamental component has the worst estimation and it can be accounted to the distinct offset seen in Figure 32 (a) which is the result of a sub-optimal window length for analysis of the fundamental (1600 versus 834 samples).

<table>
<thead>
<tr>
<th></th>
<th>k</th>
<th>( f_k ) (Hz)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>DFT</td>
<td>( A_k ) (pu.)</td>
<td>0.00014</td>
<td>0.2632</td>
<td>0.1705</td>
<td>0.1049</td>
<td>0.1111</td>
<td></td>
</tr>
<tr>
<td>S Transform</td>
<td>( A_k ) (pu.)</td>
<td>0.00017</td>
<td>0.0037</td>
<td>0.0012</td>
<td>0.0002</td>
<td>0.00035</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>( A_k ) (pu.)</td>
<td>0.00992</td>
<td>0.0063</td>
<td>0.0032</td>
<td>0.0002</td>
<td>0.00053</td>
<td></td>
</tr>
</tbody>
</table>

Table 14: RMS estimation error for Inter-harmonics and Supra-harmonics
Figure 32: Estimated amplitude of: (a) Fundamental, (b) Interharmonic at 130 Hz, (c) Interharmonic at 370 Hz (d) Supraharmonic at 2500 Hz, and (e) Supraharmonic at 4000 Hz components with DFT based method prescribed in IEEE 519-2014 [68], and the proposed method.
7.5.3 Case 3: Discriminating Disturbances in an IIDER System

The test signals comprising two dynamic events are the output current reading of the inverter and are from [66]. The current signals are analyzed and the calculated $S$ matrix, using a length-834 Hamming window from the proposed method is shown in Figure 33. The visually distinct dominant frequency component during the disturbances - fault and capacitor switching, in a disturbed state are shown in Figure 33. Both of these dynamic events show distinct visual characteristics or signatures that differ from each other, using the same window length as for the harmonic analysis.

These two dynamic events - fault and capacitor switching are analyzed simply by observing the inverter currents. The previous comprehensive classification case study were on voltage signals only.

The extracted dominant frequency component, which is the time-maximum amplitude, during the disturbances is achieved by seeking columns of the STFT matrix amplitude at every frequency. The fault as observed has a continual positive deviation with reference to the base value, whereas capacitor switching has several oscillations per cycle. The results show that detection and distinction between these disturbances is possible and can be done within a one-cycle time, using the same window length as for the harmonic analysis.
Figure 33: The inverter output current waveform, calculated TFR from $S$ matrix of the STFT and extracted dominant frequency component. From top to bottom on left: during a fault and on right: during a capacitor switching occurring at peak of the current waveform.
8 CONCLUSION

In this thesis, a theoretical tool based on an STFT framework has been proposed and implemented in two important applications of an electrical power system.

A monitoring approach comprising a combination of STFT and $k$- Nearest Neighbor ($k$-NN) along with Support Vector Machine (SVM) classifiers is proposed and implemented for identification and classification of multi-class PQ disturbance signals. The proposed method performs feature extraction based on time-frequency statistical features of the STFT and the feature set thus obtained is then fed to the two classifiers for classification. The performance evaluation of both classifiers are carried out using confusion matrix analysis. Comparative results with 2, 3, 4 and 6 features as the feature set in consideration are presented for both of the classifiers, which shows the feasibility of study under noisy signals with ease in computation. The proposed system is simple in design, has a low computational time, and is able to discriminate the main characteristics of signal without losing its distinguishing characteristics. The analysis and the results presented in the thesis clearly reveal the promising capability of the proposed system in PQ identification and classification.

A new theoretical framework for monitoring of renewable-rich power systems based on the STFT is proposed and implemented. Both steady-state harmonic analysis and disturbance classification are addressed by a common time-frequency analysis method, based on the STFT, using only 2 window lengths. The method is shown to perform well for real time-estimation of a large spectrum of time-varying harmonics - low order harmonic, interharmonic and supra-harmonic components. For time varying harmonics it outperforms the DFT based technique. The esti-
mated amplitudes for the time varying harmonics from the proposed method are found better compared to the S-transform results. The estimated phases are also comparable. Also, the proposed approach has promising performance in measuring supraharmonic components up to 4000 Hz. Verification over representative simulated waveforms show the potential capability of the proposed method in uniquely identifying two dynamic events for which inverter currents appear similar - faults and capacitor switchings, in less than a cycle, by simply analyzing the inverter currents.
9 FUTURE WORK

The future work will be focused on extensively analyzing the capability of the proposed TFA tool for a comprehensive PQ monitoring solution with online classification capabilities for an electrical power system.

The effectiveness of the classification method can be improved through clustering analysis using the inter-class separability and intra-class compactness, and increasing the training and testing data set used in the classification.

The distinct peak at 180 Hz of the phase estimate for harmonics from the proposed method and S-transform can be studied. Also, a median filtering can be implemented for the estimation of amplitude and phase for better performance.

Implementing a sliding-window estimation of signal parameters via rotational invariance techniques (ESPRIT) in PQ monitoring may solve the long existing problem of quantifying interharmonic components when there is no preknowledge of their frequencies [70].

Particular attention will be on the assessment with field data, automated disturbance detection and diagnosis, and computational issues.
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