

SIGNAL PROCESSING-BASED ARTIFICIAL INTELLIGENCE APPROACH FOR POWER QUALITY DISTURBANCE IDENTIFICATION

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CERTIFICATE OF APPROVAL

The project entitled as "**Signal Processing Based Artificial Intelligence Approach for Power Quality Disturbance Identification**" submitted by **Md. Sadman Sakib** bearing Matric ID. **ET 171023** and **S.M.Sazzadul Haque Tanim**, bearing Matric ID. **ET 171024** of session **Spring 2021**, to the Department of Electrical and Electronic Engineering, International Islamic University Chittagong, has been accepted as satisfactory in partial fulfilment of the requirements for the degree of Bachelor of Science in Engineering and approved for the examination held on **16th April, 2022**.

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DECLARATION

It is hereby declared that this work has been done by us and no portion of the work contained in this project has been submitted for the award of any degree or diploma.

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ABSTRACT

Power quality has become a vital concern recently due to the expansion of the consumption of electrical load and the growth in the use of sensitive devices connected to power systems. Nevertheless, complexity in modern life and the increased usage of semiconductors for non-linear load, make a real threat to power quality level. The modern power supply, based on developing renewable sources such as solar, wind and nuclear energy, has increased power quality disturbances to a significant level. In order to maintain good power quality and to ensure its reliability, power quality disturbances must be detected and identified correctly and precisely. Thus, detection algorithms assist decision makers to solve the disturbance, and protect the power network from a high level of financial loss. In this thesis, a new approach of a detection algorithm and classification technique is proposed for power quality disturbances based on the methodology of an Advanced Signal Processing algorithm and Artificial Neural Networks. Firstly, an investigation process covering the most important and common power quality disturbances is analyzed and discussed. Thereafter, most of the powerful signal processing algorithms in addition to Artificial Intelligence techniques are investigated, their results are discussed. Since power quality disturbances are non-stationary signals, a characterization process is built by simulating 7 power quality disturbances in power systems. As a result, a validation methodology is conducted based on discrete Wavelet Transform and the extracted features are recorded. Artificial Intelligence techniques can classify complex data and enhancing the evaluation process. Therefore, these extracted features are fed to Artificial Neural Networks to train the database of the generated power quality disturbances. This method achieved a sufficient detection algorithm which overcame the Fourier and other transform limitation and resulted in an accuracy of near 98%. In this thesis, a comparison analysis for both detection algorithms combined with the Artificial Neural Networks classifier is presented, this shows the robustness and the effectiveness of the proposed methodology.

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LIST OF ABBREVIATIONS

| | |
|------|------------------------------|
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| CWT | Continuous Wavelet Transform |
| DWT | Discrete Fourier Transform |
| EMD | Empirical Mode Decomposition |
| FFNN | Feed Forward Neural Network |
| FFT | Fast Fourier Transform |
| FT | Fourier Transform |
| HHT | Hilbert-Huang Transform |
| PQ | Power Quality |
| PQDs | Power Quality Disturbances |
| RMS | Root Mean Square |
| RNN | Recurrent Neural Network |
| ST | Stockwell Transform |
| STFT | Short Time Fourier Transform |
| SVM | Support Vector Machine |
| WT | Wavelet Transform |
| RMS | Root Mean Square |

CHAPTER 1

INTRODUCTION

1.1 Introduction

Power quality is a topic that today's energy businesses and consumers, as well as electrical components manufacturers, are concerned about. People who work with electricity now have more equipment that is more concerned about Power Quality because the equipment contains things like power electronic parts that are very sensitive to changes in power quality. Any time there is a problem with the voltage, current, or frequency of the power signal, it can also affect the customer. This is called a power quality problem. Therefore some equipment has been upgraded including power electronically switched loads, solid-state switching devices, power electronic converters, nonlinear loads, computer and data processing equipment, industrial plant rectifiers and inverters, and relaying protective devices. As a result, electrical power quality is now more significant since electrical supply distortion is one of the major issues that industries are facing. The disturbance like voltage sag, swell, harmonics, harmonics with sag and swell, voltage interruption, harmonic distortion, notch, flicker, impulses, momentary interruptions, wave faults spike and transients related problems like a short lifetime, malfunction instability, and so on are now a matter of concern [1]. To increase the quality and raise the standard, the disturbance in the power system must be identified. Otherwise, it will cause the protective electrical and electronic equipment to fail or malfunction and as well as harm to the computer file and memory feature of sympathetic loads automated control action. In a practical distribution network, to improve power quality, these disturbances must be found first before the right steps can be taken to fix them.

1.2 Background

Detecting power quality problems is crucial to enhancing power quality level in electric power systems. There are several ways to identify and classify power disturbances such as engineers capturing waveforms in the field. Unfortunately, manual capturing is almost impossible due to the data required to be sampled in modern power systems. Moreover, power quality is one of the main factors in meeting the demands of power utilities and customers. The growth in transformation to renewable energy and the increased usage of nonlinear applications, including microelectronic processors, caused more equipment failure in power systems and damage to its sensitive

controllers. Consequently, the cost of repairing these problems is severe in financial terms, and also leads to losses in load and time. Therefore, it is essential to investigate and study the waveforms of power quality disturbances, so they can be precisely detected and classified.

Signal processing algorithms such as Fourier Transform, Stockwell Transform and Wavelet Transform have provided powerful mathematical algorithms for detecting power quality problems in electrical power systems, where they show significant successes in this field. Classification techniques support the detecting algorithm by testing, validating and training large amounts of power signals to ensure the effectiveness and efficiency of the chosen algorithm.

1.3 Objectives

The primary objective of this work is to develop a novel technique for detecting and classifying power quality (PQ) disturbances.

- ❖ Generation of various PQ disturbance
- ❖ Feature Extraction by Wavelet Transform & Stockwell Transform
- ❖ Detection of PQ events using ANN
- ❖ Classification of the events by analyzing ANN
- ❖ Comparison of classification accuracy for both cases (Wavelet Transform & S-Transform).

1.4 Chapter Outline

This thesis consists of five chapters overall. The thesis outline are given below:

Chapter 1 describes the background of the project. There is few line of introduction about power quality studies for the beginning. Then, continued with introduction, literature survey, objective of the work.

Chapter 2 describes about the detail of different kinds of detection algorithms and classification techniques.

Chapter 3 introduced the whole idea about characterization of PQ disturbances.

Chapter 4 introduced our detection algorithms and classification techniques.

Chapter 5 has discussed the conclusion, future scope of the work, and generalization of work implemented in this project.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In general, power quality generation is non-stationary and disturbances occur for a short period of time. Time and frequency information are required to identify the signals. Because the normal Fourier Transform only provides spectral information and not time localization, it is impossible to analyze a signal using the normal Fourier Transform. And it's crucial to know where the disturbance occurred at the time and for how long it lasted. [2]. Time frequency analysis is better suited to analyzing non-stationary signals because it provides both temporal and spectral data on the signal. Many researchers have frequently used Discrete Wavelet Transform (DWT) and Short Time Fourier Transform (SFT) for feature extraction are the FFT method [3], fractal-based method [4], S-transform method [5], time-frequency ambiguity plane method [6], Wavelet transform [7], Hilbert transform [8], and Chirp-Z transform [9]. The commonly accepted methodologies for non-stationary signal analysis are Wavelet transform, Gabor transform, filter bank, S-transform, short-time Fourier transform, Cohen class, and parametric methods. Traditional methods of analysis have a major problem in that they do not provide enough information in the time domain. [1]. Moreover, the Fourier transform (FT) is the most well-known frequency-domain analytic method. *However, it is limited to the unlimited time case of a stationary signal and incapable of resolving any brief information in connection with fluctuations [10]. On the other hand, it is used to analyze the PQ events after extracting the voltage spectrum at specific frequencies [11]. Fast Fourier transform is a derivative of the Fourier transform that is commonly used in the PQ analysis. It is called a time-domain version of the Fourier transform, although it is not suited for obtaining frequency and amplitude due to leakage [12]. Short-Time Fourier transform (STFT) is another FT variant that breaks power signals into small components, each of which can be assumed to be a stationary signal [10]. However, as explained previously, non-stationary waveforms are difficult to analyze using STFT [13]. Power signal analysis is one of several methods. As a result, (SFT) does not adequately analyze real power quality events because it uses a fixed window width to shift in time. DWT, on the other hand, employs a fixed window width for time-frequency variation detection. [3].

2.2 Detection Algorithms

The advantages and disadvantages of each signal processing algorithm in power quality studies must be understood in order to discuss signal processing algorithms effectively. The extraction of features from a signal's waveform is the heart of a detection algorithm, which will be discussed in detail in this thesis. To meet the event characterization and efficiently report the disturbance signal, the root mean square measurements (RMS values) as well as the detection algorithm must be available [14]. In the feature extraction process, the obtained mathematical coefficients that represent the original signals are used to find unique features.

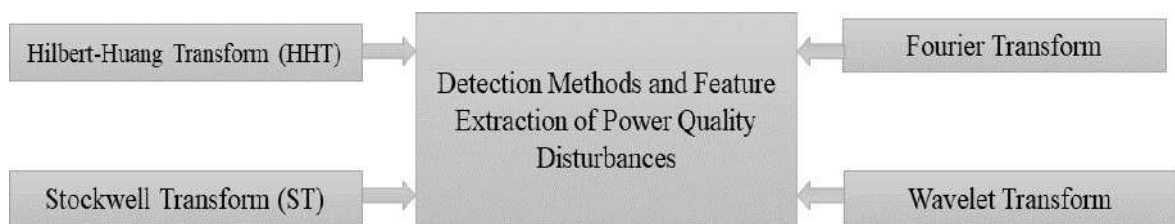


Fig. 2.1 Detection algorithms discussed in this thesis

In **Fig. 2.1**, a set of effective signal processing algorithms is shown including Fourier Transform, Wavelet Transform, Stockwell Transform and Hilbert-Huang Transform, as shown. For the greatest degree of precision, the PQD features that have been extracted are fed into a classification technique system that uses them [15].

2.2.1 *Fourier Transform*

The Fourier Transform (FT) is widely used in many fields, including engineering and physics, to analyze signals in the frequency domain. [16]. IEEE standard 1459-2010 [14] defines power quantities using FT as the foundational analysis method. It is based on decomposing the signal into a series of sine functions at specific frequencies. Short Time Fourier Transform (STFT) and Fast Fourier Transform are all Fourier Transform derivatives used in the field of power quality (FFT). For stationary signals, FT is used a lot. It breaks the signal into a sum of frequencies. However, FT has a hard time getting time information when the signal changes [17]. So, changes were made to FT, which led to the derivatives of FT that were mentioned earlier. One of these derivatives is the Discrete Fourier Transform (DFT), which is used to look for problems in power systems [18]. DFT can't deal with changes in power quality disturbances; it's only good for steady PQDs.

Another version of the Fourier Transform, called the Short Time Fourier Transform (STFT), is used to look for PQDs. It can break up the disturbed signal into small parts, and each of these parts is treated as a separate signal, like in the example above [19]. The authors established a relationship between signal frequency and time [20], but it is still difficult to detect non-stationary signals using STFT, as proved in [21]. Fast Fourier Transform (FFT) is sufficient for analyzing harmonics, as it is one of the steady state events [22], where it has the same results that can be achieved by DFT, but in less time. Windowed FFT was used in a new version to only look at harmonics in the power quality. [23]. FFT leakage, on the other hand, prevented exact measurement of the signal factors (amplitudes, frequencies and phases) [24].

2.2.2 Wavelet Transform

An algorithm called the Wavelet Transform (WT) is used to look at how well electricity is getting to people's homes. When WT can detect and show power signals in both the time and frequency domains, it has a lot of power. WT can also break down the signal in the frequency domain and figure out the wave coefficients, which is the key to figuring out what's going on in the signal [25].

Even though WT was at first interesting to researchers in the medical field, it became interesting to researchers in the field of power quality [26]. WT provides a robust feature extraction process for contorted power signals that has been demonstrated in harmonic applications, such as [27]. In detail, signals are preceded by a decomposition procedure that breaks the signal down into many sums of short-term waveforms referred to as the mother wavelet. The primary distinction between WT and FT is that WT provides signal information in the time–frequency domain, giving it an advantage when analyzing power quality disturbances. Additionally, WT has a mathematical coefficient that is capable of retaining the characteristics of the signal across multiple frequency bands. Additionally, these coefficients contain additional information about signals, such as their amplitude, energy level, and standard deviation [28]. WT is capable of detecting non-stationary disturbances in power quality in short time intervals, as in [29]. Initially, WT was divided into two broad categories: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) [30]. The multiresolution method was used by the authors to develop WT as a power quality disturbance detection algorithm [31]. CWT is introduced to measure power quality disturbances, as in [32]. DWT is an extremely powerful algorithm for detecting PQ disturbances, as demonstrated in the proposed method for determining

the magnitude of a single event, voltage sag in [33]. Furthermore, authors applied a hybrid approach based on DWT with FFT to detect PQ disturbances [34], where DWT is responsible for detecting distorted signals and gaining the benefit of the process of features extraction. DWT demonstrates its ability to decompose ten cases of stationary and non-stationary power quality disturbances into eight different levels of resolution in the time domain using the feature extraction process. Other derivatives of WT have effects in the field of power quality as well. Authors in [35] introduced a combined algorithm to analyze power disturbance information using DWT and wavelet packet transform (WPT). Authors' proposal in [36] is produced based on WPT for power quality indices for balanced and unbalanced systems under operating conditions. The authors in [37] proposed a perspective for the IEEE standard 1459-2000 definitions using the stationary wavelet transform (SWT) to define power components.

2.2.3 Stockwell Transform

Stockwell introduced the Stockwell Transform (ST) as a time–frequency signal processing algorithm [38], which is a hybrid of WT and STFT, providing both time and frequency representation. ST precisely tracks the signal dynamics, combining the real and imaginary spectra.

Once implemented to detect power waveforms, ST becomes a component of power quality detection algorithms, as proposed in [39]. Complex Fourier sinusoidal signals are localized by a window in the same way that STFT does, but the width and height of the window change with frequency, just like with waves. In [44], they show how to use multiresolution S-transforms to look for power quality disturbances in seven cases, and they say that this method has an accuracy close to 98 percent.

2.2.4 Hilbert-Huang Transform

In signal processing, the Hilbert-Huang Transform (HHT) is a relatively new and highly advanced algorithm for analyzing non-stationary signals when time is critical. Dr. Huang first proposed HHT in 1998 [45]. The Hilbert Spectral Analysis (HSA) and the empirical mode decomposition (EMD) are the two main processes of HHT (HSA). For any non-stationary power signal, the EMD procedure is able to decompose it into an array of sub-signals. Afterwards, EMD separates the sub-signals into more specific categories known as intrinsic mode functions based on their frequency (IMFs). The first IMF is from the maximum frequency component of the signal that was extracted. The minimum frequency component is the one that comes from the lower one [46]. After that, Hilbert

Spectral Analysis (HSA) uses a time curve to figure out the instantaneous magnitude and frequency of the waves. The HHT is the result of combining EMD with HSA as a signal processing algorithm [47]. If you want to study PQ, you should use HHT instead of FT or WT, because the EMD process is based on the signal itself, so it is acting in line with nature.

The first time HHT is used, it's only for voltage sags. This makes the bath in power quality studies [48]. After that, the authors used HHT a lot with eight power quality disturbances, and they found that the method worked 97.22% of the time, as reported in[49]. Wavelet and Hilbert Transforms were used in another hybrid analysis of power quality, as described in [50]. For seven power quality events, authors present two classification attempts based on the HHT algorithm, with 94.57 percent success rate using support vector machine (SVM) [51].

Since HHT is a new algorithm that has only been used in a few publications for power quality, it lacks categorization or derivatives. An EMD improvement is assumed to be a category of HHT in this literature. Authors have proposed a new HHT derivative called ensemble empirical mode decomposition (EEMD), where the accuracy in the study is not clearly provided, where most studies are based on the EMD approach. For data analysis, a new variant of HHT known as CEEMD (complementary ensemble empirical mode decomposition) has been proposed [52].

2.3 Classification Techniques Based on Artificial Intelligence

The automation of human thinking and actions, such as learning, problem solving, estimation, and decision making, can be defined as artificial intelligence (AI). With such a strong mathematical foundation, artificial intelligence techniques became effective tools for accurately diagnosing problems with power quality.

Each of these distorted signals must be handled in a short period of time due to their similarity in shape. In order to properly classify power quality disturbances, artificial

intelligence is required. Data gathered by detection algorithms can be used to identify power signal disturbances, and AI has shown that it is capable of doing so [53].



Fig. 2.2 Classification techniques using artificial intelligence (AI)

Fig. 2.2 shows AIs discussed in this study where the proposed classification method is Artificial Neural Network.

2.3.1 Artificial Neural Networks

In power systems and PQD classification, artificial neural networks (ANNs) are one of the most widely used, robust AI techniques, [54]. The neural network approach to identifying distorted power waveforms was first proposed by authors in [55]. A neural network-based approach is proposed for identifying the harmonics source [56]. There are seven possible cases of transmission line disturbances that can be detected using an Artificial Neural Network (ANN) [57]. Data extracted from smart grid power quality events can be classified using an ANN classifier based on the DWT algorithm, according to the authors [58]. Authors in [59] made a detector based on WT and used neural networks to classify real-time PQ disturbances that were set up by an Electric Power Generator.

2.3.2 Support Vector Machine

The principle of a support vector machine (SVM) was introduced by Vapnik [60]. An SVM is a supervised learning machine that can be used for pattern recognition in many different fields of science and classification system techniques. SVM was used as a classifier in the study of power quality to identify voltage disturbances [61].

Pattern recognition is a statistical learning theory-based approach that is used to solve problems and forecast and estimate future outcomes. S-transform and SVM were used to identify and classify five different power quality disturbances, as shown in the paper. [62]. The WT-based detection algorithm presented in [63] was used to identify distorted events with an SVM classifier. In [64], DWT detected five single power quality disturbances and classified them using SVM.

2.3.3 Fuzzy Expert System

A classic AI technique, the fuzzy expert system (FES) is based on two possible outcomes in uncertain situations. Models with no fixed boundaries can be applied because of the calculation made by human intellectuals [65]. The membership function of a fuzzy system is used to plan objects in a given domain according to their membership values [66].

A fuzzy logic-based approach to evaluating and quantifying power quality has been proposed in power quality studies. [67]. As a replacement for Boolean sets, the authors presented a fuzzy expert system that uses a group of fuzzy set and rule rules [68]. A fuzzy classifier based on WT's decomposition process at four levels is implemented, as shown in [69].

The Neuro-Fuzzy system, introduced by authors in, is another approach to classifying power disturbances based on a combination of FES and ANN. [70]. The study has looked at how people learn to recognize these disturbances, with an overall accuracy rate of 96%. Moreover, a classification system is proposed for PQ disturbances using 3-D space referential representation, and Principal Component Analysis (PCA) is based on the neuro-fuzzy approach [71].

2.3.4 Genetic Algorithm

In evolutionary terms, the Genetic Algorithm (GA) is a way to look for things. It is based on the idea of natural range. A lot of people talk about GA a lot when they talk about finding problems, optimization, machine learning and solutions; it is also talked about very much [72]. The GA is used to figure out how well the power is in a single case in the simulation environment. This method is shown in the article [73]. Wavelet transform and Genetic Algorithm (GA) are used to come up with a new way to look at power quality events. [74].

2.4 Summary

A lot of research is being done to improve power quality. If you look at the detection algorithms used in this field, you can say that FT, WT, ST, and HHT are the most likely ones to be used.

Since FT is used as the foundation of the detection algorithms in this power quality analysis, but it has been shown to that FT suffers from representing PQDs in time, particularly when the disturbance fluctuates, where the fixed window width of the FT does not provide information needed [75]. STFT is still a good way to look at stationary

PQDs, but it's hard to find and look at non-stationary signals, which are the main ones that cause problems for power utilities [76].

WT is a useful algorithm that is capable of describing PQDs in both time and frequency. The time-frequency resolution and analysis are adequate. WT has been proven to be superior to STFT in terms of performance [76]. It's still essential, however, to pick a wavelet branch with a high computational cost per additional pixel. In spite of this, WT is frequently used when a precise frequency is not required, but low-frequency features in the distorted power signal, as in [77].

As a result of its ability to analyze power quality disturbances and its magnificent feature extraction via the empirical mode decomposition process (EMD), HHT is a potent algorithm for determining the exact magnitude and frequency information, as well as for determining the precise signal detection. A well-proved analysis of the HHT algorithm in comparison to other powerful algorithms in the same environment and conditions is necessary, as it is a relatively new PQ algorithm in the field. It's possible to answer questions about power quality detection and measurement algorithms using appropriate indicators and robust comparison analysis.

This literature has many studies about how to find and classify power quality problems. It is clear that many of these studies only looked at one or two disturbances, like sagging or swelling. A few others looked at five cases and looked at the results. Also, it can be seen that most of these studies were done for one person, not for a group of people. The average of detecting accuracies using AI classifiers was in the range of 90.0% to 96%. Even though not enough research has been done on comparison analysis of on-line disturbances in power lines caused by faults in power systems, there is still a lack of research.

According to the literature reviewed in this thesis, WT and HHT are two promising yet debatable algorithms for precisely detecting power quality disturbances. A suitable approach for this thesis would be to examine both of these algorithms under identical conditions and for specific power disturbance formulas. In order to get a better idea, an ANN is also used to classify PQDs. Both approaches are shown and analyzed.

CHAPTER 3

CHARACTERIZATION OF PQ DISTURBANCES

3.1 Introduction

One of the most commonly used buzzwords in the energy industry is "power quality." [78]. Authors in [79] have studied power quality issues according to their causes, and how signal processing algorithms can handle and represent them. Another context is presenting an investigation of electrical power quality disturbances which describe signals variation [2], and the impact of these problems in electrical machines in power systems [80]. International standards and concepts related to power quality will be covered in this chapter. In addition, a lot of power quality problems will be talked about in great detail. There are also definitions of disturbances, waveform phenomena, and mathematical equations. However, the causes and possible effects on power systems when disturbances happen, as well as remedies and solutions for each case, are explained.

3.2 Power Quality

Due to the critical nature of power quality, several definitions were introduced. Early in the eighties, power quality had two main factors to be identified: quality of voltage and continuity of supply [81]. Nowadays, the term 'power quality' has come to refer to voltage fluctuations in electrical power systems. Researchers in the technical field prefer to use the term 'voltage quality' where most of the power quality disturbances are actually based on voltage, representing the majority of such events in the field [82], [83].

Current quality is considered to be complementary to voltage quality, as it is responsible for containing current deviation in power systems. Although it was introduced recently, it is rarely used term as in [84] and [85], it is still related to what can be provided to customers by utilities. So, power quality is thought to show voltage and current quality, even if voltage events still show the meaning of the phenomena. This is because it is widely accepted and is a good way to show the signal phenomenon. The definition of PQ produced by the IEEE (Institute of Electrical and Electronic Engineers) is: "the concept of powering and grounding sensitive equipment in a manner that is suitable to the operation of that equipment and compatible with the premise wiring system and other connected equipment" [86].

When high power quality is reached, power systems' equipment will work well and the power system conditions will be to your liking. Alternatively, with poor quality, the power devices could be destroyed, or their efficiency could be cut down a lot. The power

system will be able to work in the conditions that are being talked about. The cost of fixing and protecting it will be very high [87].

3.3 International Standards of Power Quality

Standards organizations, whether they are national, such as the American National Standards Institute (ANSI), British Standards Institute (BSI), Saudi Standards, Metrology and Quality Org. (SASO), or international, such as the International Organization for Standardization (ISO), are the authorized bodies who are responsible for delivering or adopting standards to a country or region. A lot of rules are in place to give a full description of power quality issues and how they affect electromagnetic waves. Furthermore, these standards have a set voltage and voltage range that can be tolerated in the power networks. These standards also show how to choose the right monitoring instruments and how they work, as well as how to measure results and how to talk about them.

The goal of making power quality standards is to make sure that power utilities, providers, and customers don't have problems when there is a voltage change. [88]. Power quality standards set limits, measurements, and settings for voltage, current, and frequency values when they don't match what's supposed to happen [89]. For both providers and customers, such standards draw lines and provide guidance on what constitutes acceptable and unacceptable levels of service. Providing customers with an acceptable level of disruption events and variations becomes crucial when obtaining a healthy supply becomes impossible [90].

One of the essential standards in the power quality field is the IEEE 1159 standard which was introduced by the Institute of Electrical and Electronics Engineers (IEEE). According to this standard [91], power quality disturbances have specific categories: transient (oscillatory and impulsive), short duration variations (sag, swell and interruption), long duration variations (under voltages and over voltages), steady state variations (harmonics, notch and flickers) and frequency variations. There is a time frame for each event in these groups. It used to be that many studies on PQ were based on IEEE Std. 1459-2010, which is a standard for measuring electric power quantities under sinusoidal, non-sinoidal, balanced, and unbalanced conditions [92]. In addition, the European standard EN 50160 says that root mean square (RMS) measurements should be made at voltages where there are problems [93]. One of the most important standards is from the International Electro Technical Commission, IEC 61000-4-30. This standard

tells power experts and engineers what to do and how to do it when they test and measure techniques for power quality [94].

3.4 The Importance of Power Quality

The quality of electric power has become a big deal for both electric utilities and people who use electricity. Because of the PQ problem, which is also called a power disturbance, the load of the people who use electricity can have a big negative effect on them. These disturbances have hurt the productivity and effectiveness of consumers' loads, especially those that use electricity [28]. PQ is a broad subject that encompasses the majority of areas of power engineering, from generation to end-users [29]. In order to mitigate the occurrences of the disturbance, electric power utilities and consumers turn to inspect, monitor, record, and analyze the electric power to determine the problem and the proper mitigation technique.

3.5 Types of Power Quality (PQ) Problems

The primary strategy for resolving the PQ issue is to implement an adequate wiring and grounding system for electrical consumers [30]. Technical expertise in electrical systems should be enhanced to avoid major problems caused by PQ. Another factor that may contribute to a PQ problem is the use of electronic devices, particularly non-linear loads. The non-linear loads draw harmonic currents, and as a consequence, harmonic voltages are generated whenever the harmonic current flows through the impedance of the system [31]. Harmonics cause a slew of issues with consumers' electrical systems and equipment [32]. A better understanding of the PQ field is another way to enhance power quality. To improve one's PQ, it helps to have some familiarity with an appropriate electrical wiring system. It's critical to understand the underlying theory behind electrical system behavior and the effects of load usage. The size of the cable in the system, the proper mitigation technique, and the protective system all affect the load's behavior. It's important to remember that the majority of PQ issues stem from an excessive amount of load. Natural causes, such as lightning, animals, and man-made issues, can also have an impact on a person's PQ level. There is no way to keep the system free of these kinds of issues. To prevent the problem from spreading to a larger area, a well-designed protective system should be developed.

3.6 Power Quality (PQ) Phenomena

PQ has been defined in a variety of ways in the relevant field. PQ can be loosely defined as the absence of tripping, high electrical system performance, and fewer system failures

[33]. This definition comes from the point of view of the customer, who is looking at the system application. PQ means how likely the generator is to be able to provide power to the customers. It's important to both of them that the voltage or current in an electrical system can have a sinusoidal characteristic [34]. When current and voltage deviate significantly from their sinusoidal characteristics, this indicates a low PQ in the system. A PQ issue, on the other hand, is any current or voltage deviation, large or small, in magnitude or frequency, that results in system or equipment malfunction or disoperation for users. It means that, if the voltage or current deviation is severe enough, it can cause a serious problem for the utility or the consumers. PQ phenomena can be divided into two main classes, namely; Non-steady state and steady state phenomena are two separate concepts. Certain characteristics, including those listed below, are thought to explain the phenomenon of steady state [7, 13]:

- 1) Amplitude
- 2) Frequency
- 3) Spectrum
- 4) Modulation
- 5) Source Impedance
- 6) Notch Depth
- 7) Notch Area

For the non-steady state phenomena, different characteristic is applied to classify the type of phenomena. The phenomena are as follows [7, 13]:

- 1) Rate of rise
- 2) Amplitude
- 3) Duration
- 4) Spectrum
- 5) Frequency
- 6) Rate of occurrence

7) Energy potential

8) Source impedance

Stone and Collison has stated further description of these phenomena [35]; whereby the phenomena were divided into nine main parts referred to time deviation and frequency deviation. Utility companies, manufacturers, and end users can all benefit from the characterization of PQ phenomena to help them determine the best course of mitigation action. There are five power disturbances that meet the criteria for further investigation in this study. Voltage sag, voltage swell, interruption, oscillatory transient, and impulsive transient are among the five types of disturbances that can occur in a system. Selection of disturbances was influenced by existing research on the waveform of disturbance [8].

3.7 Power Quality Disturbances

The main thing that affects power quality is when voltage or current waveforms don't match up with the ideal signal at a certain frequency and magnitude. In general, any change in the power signal is called a power quality disturbance [9]. In the real world, it is nearly impossible to maintain nominal sinusoidal voltage values when the system is usually disturbed in some way.

The waveforms of each of these disturbances are distinct, so it's important to group or subgroup them. When looking at power quality issues from the perspective of the power electronics industry, events and variations can be distinguished. An interruption is a sudden change in the voltage waveform that has a start and end. A variation is a steady state waveform that requires a continuous measurement such as harmonics and notching [79], as shown in **Fig. 3.1**. Such terminology is found in research publications presented in the power quality field.

Power quality disturbance can be divided into stationary and non-stationary cases based on signal progressing terminology, with the former being the more critical of the two. Most power quality disturbances, in reality, are non-stationary signal.

Disruption characteristics among several voltage power quality disturbances, which are referred to in IEEE Std. [75] and IEC [76].

3.7.1 Pure Sine Signal

Before going into more detail about each power quality disturbance in this thesis, it is important to look at pure voltage signals to better understand how disturbance waves look. When it comes to voltage or current, the pure sine waveform signal is the best

waveform. It can also be called a healthy signal in some publications.

According to the standard IEEE 1159, the voltage signal has a known frequency of 50 or 60 Hz, as shown in **Fig. 3.2**. A pure voltage signal can be modelled by Equation 3.1:

$$f(t) = A\sin(\omega t) \quad (3.1)$$

where the parameters for this equation include the amplitude (A) of the signal, along with the frequency, and they have the conditions: $A = 1.0$ $f = 60$ Hz, $\omega = 2\pi \cdot 60$ rad/sec.

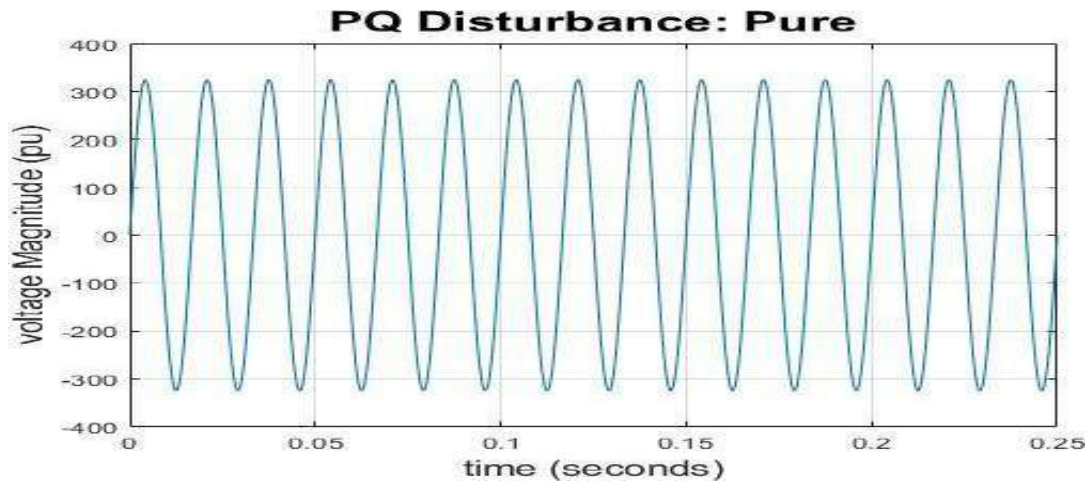


Fig. 3.1 Pure Voltage Signal

In **Fig. 3.1**, a pure sinewave with 0.25sec window is presented here. The sampling frequency is considered 10KHz with 60Hz frequency.

3.7.2 Sag

It is called voltage sag when the voltage drops between 0.1 p.u. and 0.9 p.u. How long does it take for the voltage to go down? It can be anywhere from 0.5 cycles to 1 minute. Motor starting and over current are the most common causes of sagging. But it can also occur as a result of a single line-to-ground (SLG) fault. Voltage sag is a general term for a voltage drop that lasts only a short time. If the voltage drops for more than a minute, the term under voltage is used. Generally, voltage sag is classified into three categories based on the length of time between occurrences. The classes are instantaneous sag, momentary sag and temporary sag [7]. **Fig. 3.2** shows a typical sag magnitude and its duration.

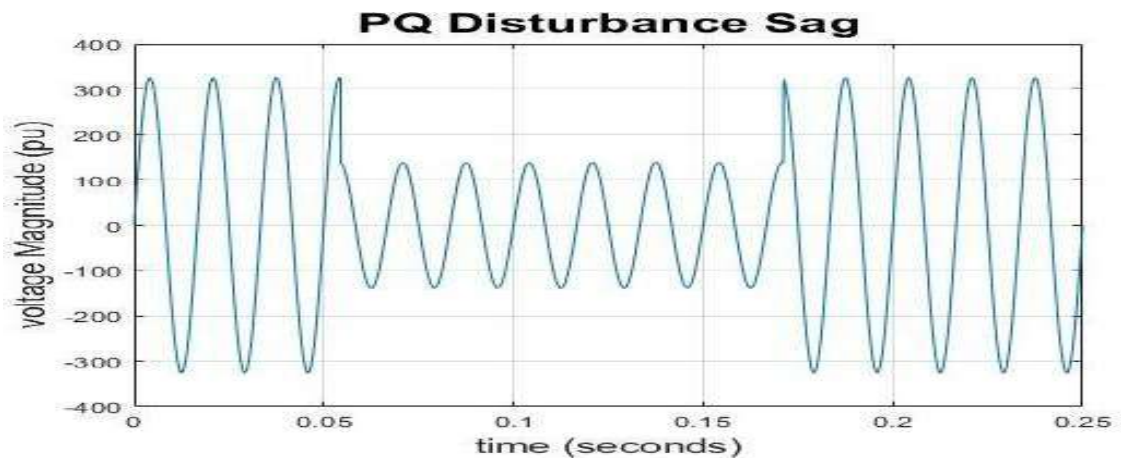


Fig. 3.2 The sag phenomenon caused by single phase fault

Based on the description of the sag phenomenon, and to model this disturbance, the signal specification of sag disturbance is given by Equation 3.2:

$$f(t) = (1 - A(u(t - t_1) - u(t - t_2))) \sin(\omega t) \quad (3.2)$$

where the sag phenomenon described in the above equation shall be within the range of the following parameter limitations: $0 < t < 0.25$ and Amplitude, $A=0.5314$, Disturbance start time, $t_1=0.0587\text{sec}$, Disturbance end time, $t_2=0.1920\text{sec}$.

Motor starting, fault clearing, and initial fault detection are all part of Sag courses. A substation bus voltage sag can be caused by a feeder fault. System sags can be caused by large load changes. When an induction motor is started, a sag can occur if the speed changes even slightly. The sag phenomenon is named by the IEC as ‘dip’, which is more European terminology, whereas the term ‘sag’ is chosen in the North American power quality community.

Voltage sags can cause damage to electronic devices, especially those that are very sensitive. It can also cause the loss of synchronized data or even the loss of stability. It is detected by controllers that have sensors that can tell when there is a problem. Then, the load is shut down [97]. There may be a reduction in lighting during the sag event.

Breaker replacement and large wiring addition are two common sag remedies. A voltage regulator and battery backups are also recommended for short sags in the system in the early stages. There are other solutions for sag as well, such as adding uninterruptible power supply (UPS) or transformers. Moreover, there are effective approaches to prevent sag, such as tree trimming, improving pole grounding and modification of conductor spacing [98].

3.7.3 Swell

Swell disturbance is the opposite phenomenon to sag, where a swell is an increase of RMS voltage of between 1.1 to 1.8 pu at the power frequency for a duration of time (from 0.1 to 1 min) which is typically from 0.5 to 30 cycles. Shown in **Fig. 3.3** is an average swell and its length of time. When the voltage on the swell's line exceeds 1.0 pu, the magnitude of the swell is considered significant in many research.

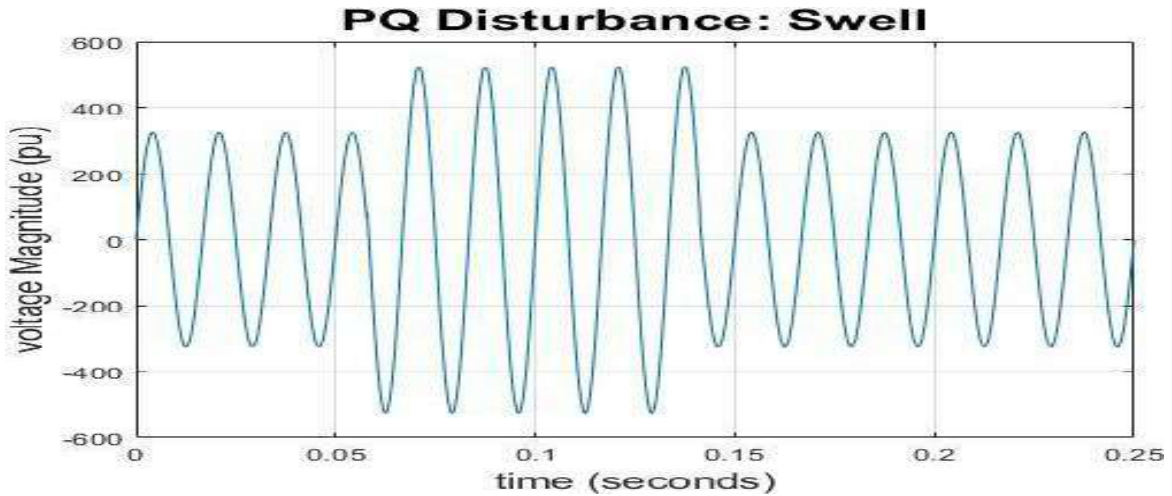


Fig. 3.3 Swell in power systems

A single line to the ground fault can cause swells in power systems, but the phenomenon occurs less frequently than a sag in the system. Loose wiring and sudden load reduction or switching off a heavy load can also cause swelling. As the most common cause of such a disturbance, a large capacitor bank is turned on [78].

Swell's signal formula is provided by Equation 3.3:

$$f(t) = (1 + A(u(t - t_1) - u(t - t_2)))\sin(\omega t) \quad (3.3)$$

where the signal parameters are at the following limits: $A=0.7574$, $0 < t < 0.25$,

Disturbance start time, $t_1= 0.0501$ sec, Disturbance end time, $t_2=0.1835$ sec.

The two main factors in swell characteristics are the magnitude (RMS values) and duration of time. The recognized description of swell in IEEE Std C62.41in [99] is "Temporarily, the voltage delivered by the mains goes up, but it doesn't stay up for long. It usually lasts more than one cycle and doesn't last more than a few seconds".

Swell impact on electrical power systems includes: There could be problems with electronic devices, such as computers and controllers that could cause the whole system to go dark. Normally, switchgears in the bus bars protect power grid components from swell, but they can still be damaged for a short period of time if they are live. Regular

swells on the capacitor bank, on the other hand, result in an individual bulge. There are several possible solutions for voltage swell management, including the use of voltage regulators or motor generators configured to mitigate voltage swells prior to the occurrence of resulting overvoltage to equipment.

3.7.4 Harmonics

Harmonics can be defined as sinusoidal voltages (or currents) having frequencies that are integer multiples of the frequency at which the supply system is designed to operate, according to both IEEE and IEC definitions [71], [72]. The ideal voltage waveform is a sinusoidal wave at a precise fundamental frequency, where the term fundamental frequency is either 50 Hz or 60 Hz, but this case would not exist on a daily basis, due to nonlinear load in power systems, as shown in **Fig. 3.6**.

As one of the main disturbances appearing in power networks, harmonics can be represented by Equation 3.4:

$$f(t) = A(\alpha_1 \sin(\omega t)) + \alpha_3 \sin(3\omega t) + \alpha_5 \sin(5\omega t) + \alpha_7 \sin(7\omega t) \quad (3.4)$$

where the conditions for this complicated equation are: $A=325.2691$,
 $0.0988 \leq \alpha_{7_h}, \alpha_{5_h}, \alpha_{3_h}, \alpha_{1_h} \leq 0.9817$

In power systems, harmonics can come from a variety of sources, but electronic devices are by far the most common contributor. This piece of equipment is a source of harmonics, and as a result, a nonlinear voltage is generated. Harmonic currents are introduced into power systems by these electronic devices with loads acting as current sources. After that, there is a voltage disturbance because these currents are the source of voltage drops in the system impedance that aren't linear. Today, modern lifestyles and the huge use of semiconductor devices are becoming more and more important in many applications.

The magnitudes and phase angles of each harmonic element are listed in the complete harmonic spectrum for each of these distortion levels. It is known in the scientific communities as the total harmonic distortion (THD) as the magnitude of harmonic distortion [75].

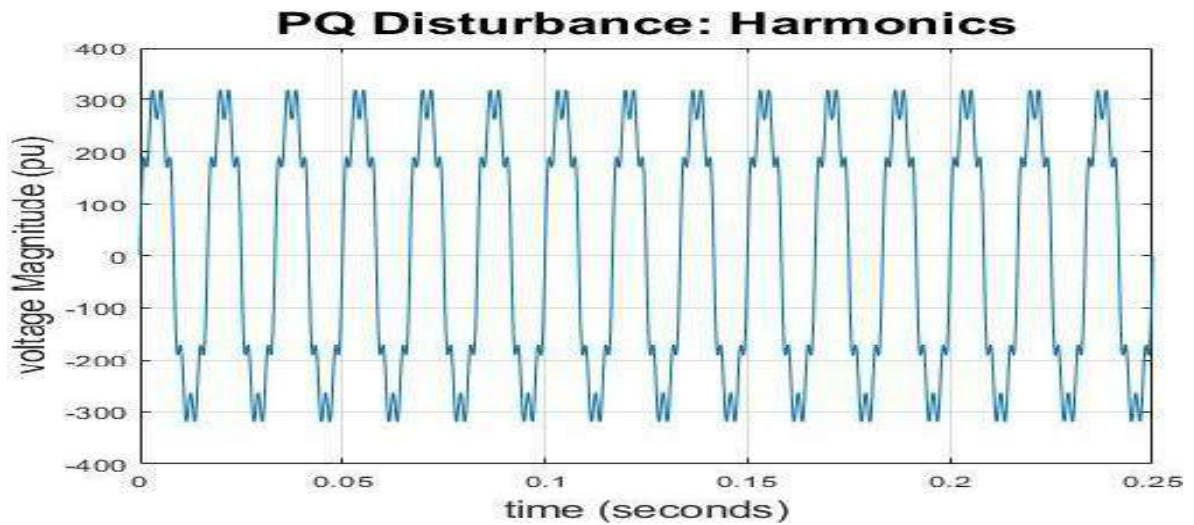


Fig. 3.4 Harmonics in power systems

There are many ways in which customers' loads produce harmonic currents that are injected into power systems, and this results in the appearance of harmonic voltages. In rotating machines, transformers, and the entire system, voltage harmonics cause overshooting. A breakdown in the customer service process may result from these issues. Limits of harmonic voltage and current are presented in the IEEE std 519 to voltage supply [76]. This standard provides control over harmonics to electrical power utilities and their customers, thereby minimizing such a disturbance and its effects.

3.7.5 Harmonics with Sag

Many times in real life, there are more than one problem with a power system at the same time. Such a thing isn't usually talked about in terms of how it's represented as a signal. Sag and harmonics are two types of power quality disturbances that can happen at the same time in power systems. They can be thought of as a multiple disturbance. The occurrences of sag and harmonics happen at the same time. **Fig. 3.5** shows the modelling of multiple disturbance sag with harmonics [71].

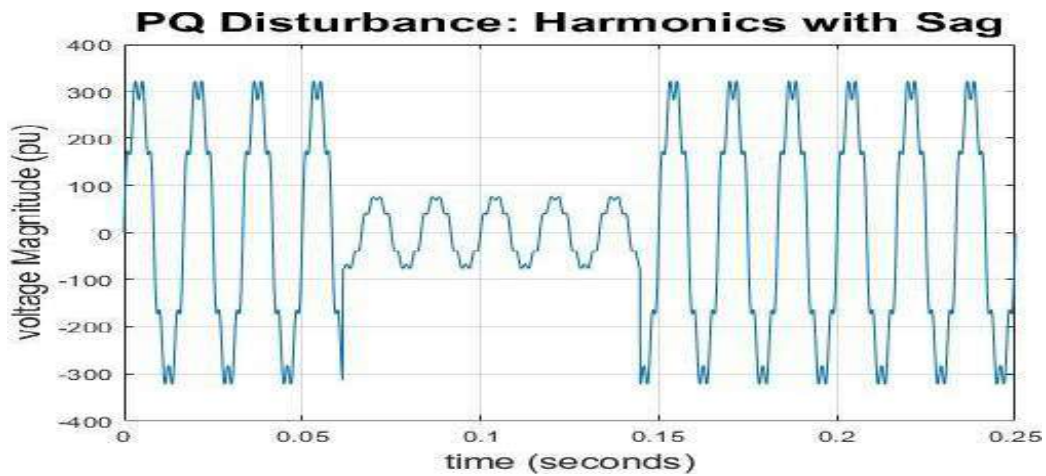


Fig. 3.5 Sag with Harmonics

Equation 3.5 depicts the foregoing phenomenon in terms of sag and harmonics

$$f(t) = (temp_sh)(\alpha_{1_sh} \sin(\omega t) + \alpha_{3_sh} \sin(3\omega t) + \alpha_{5_sh} \sin(5\omega t)) \quad (3.5)$$

where factors in the above mathematical model have the parameters:

$t=0 < t < 0.25$, Disturbance start time, $t_1=0.0634$ sec, Disturbance end time, $t_2=0.1835$ sec and $\alpha_{1_sh}=0.9880$, $\alpha_{3_sh}=0.0784$, $\alpha_{5_sh}=0.0932$

3.7.6 Harmonics with Swell

Swell and harmonics disturbances are another common type of multiple disturbance. A secondary phenomenon to sag and harmonics, this is a multi-disturbance that includes swell as well as harmonics. **Fig.3.6** shows a typical example of swell with harmonics [95].

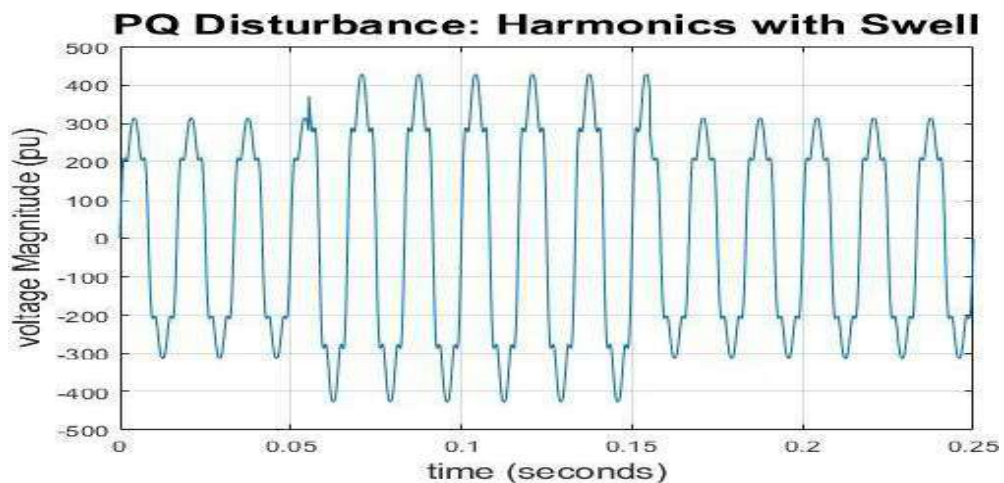


Fig. 3.6 Swell with Harmonics disturbances

In modelling this phenomenon, it is given by Equation 3. in signal processing as:

$$f(t) = (temp_swh)(\alpha_{1_swp_sin}(\omega t) + \alpha_{3_swh_sin}(3\omega t) + \alpha_{5_swh_sin}(5\omega t)) \quad (3.6)$$

where factors in the above mathematical model have the parameters: $0 < t < 0.25$, and $t_1=0.0561$ $t_2=0.1728$

3.7.7 Oscillatory Transient

An oscillatory transient disturbance is when there is a sudden change in the steady state conditions of voltage or current, but the power signal frequency doesn't change at all. Such a disturbance usually moves back and forth between the positive and negative sides. As an oscillatory phenomenon, it has a lot of rapid changes in voltage. As you can see in **Fig. 3.7**, a typical oscillatory transient is shown there. Oscillatory transients are described by their duration, magnitude and spectral content, and have three main subcategories: low frequency oscillatory, medium frequency oscillatory and high frequency oscillatory, based on their spectral content [71].

Low frequency oscillatory transient is normally less than 500 Hz, with a duration less than 30 cycles, and the main cause for this event is capacitor switching. Low frequency oscillatory transient has an impact on power systems, including tripping sensitive equipment, as shown in **Fig. 3.7**.

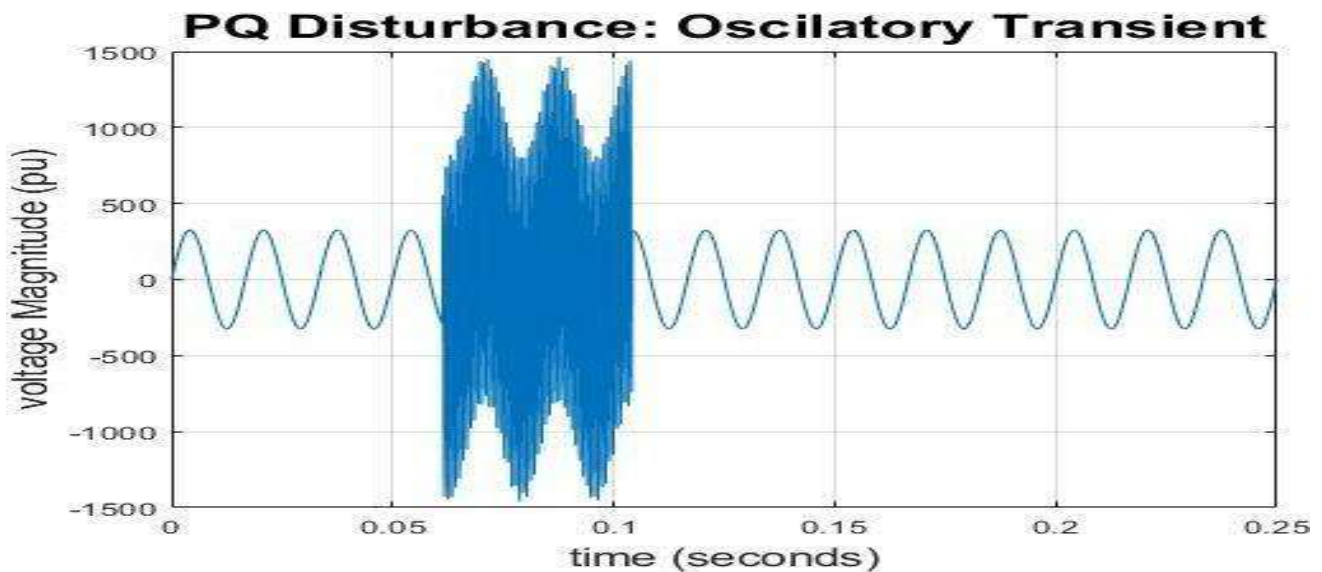


Fig. 3.7 Oscillatory Transient

In this research, it is recognized that low frequency transient and high frequency transient are the two most common disturbances in transient phenomena. Therefore, a deep study will focus on both of them [71].

As high frequency transient is considered as one of the disturbances to be represented in this study, the following formula is provided:

$$f(t) = (\sin(\omega t)) + (\alpha \text{Temp}_o(u(t - t_1) - u(t - t_2)\sin(2\pi f s t))) \quad (3.7)$$

where factors control the representation of this phenomenon are:

$$\alpha_{sh} = 0.1537, t=0 < t < 0.25, t_1 = 0.0634, t_2 = 0.1634 \quad \alpha_{1sh} = 0.9880,$$

$$\alpha_{3sh} = 0.0784, \alpha_{5sh} = 0.0932$$

3.7.8 Voltage Interruption

An interruption is defined as the reduction of RMS voltage to less than 0.1 pu for a time duration of less than 1 minute. When an interruption occurs, it is often after the voltage sag and can be a consequence of a system fault. The interruption disturbance is a result of losing connection, control failures, lightning stroke, severe faults that do not clear, equipment failures and reclosing of the circuit breaker. Interruptions are measured by their duration and magnitude. The voltages are at a minimum magnitude, which is less than 10% or almost zero for most cases, where there is no more power in the system. **Fig. 3.8** shows typical interruption.

In many cases an interruption event occurs following the presence of sag in the system, or it could be the scenario between the sag event and the protective device operation. A protective device must be activated in order for the interruption to be resolved. Most of the time, the healing process is over in less than 30 rounds.

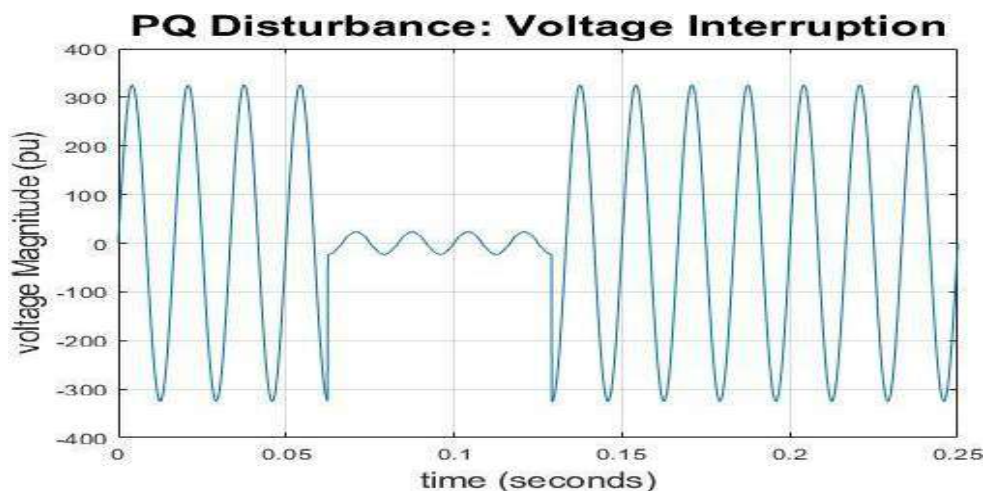


Fig. 3.8 Interruption disturbance

Momentary interruptions, which belong to the category of power quality disturbances that last only a few milliseconds, are the example used in this study; however, there are also two other types of interruptions to consider. The first is temporary interruption, which has the same specifications of momentary interruption, but with duration from 3

to 60 seconds, and the second is long term, which exceeds a 1 minute time duration, as can be seen in **Fig. 3.8**. Therefore, the interruption can be represented according to Equation 3.8 [71]:

$$f(t) = (1 - \alpha(u(t - t_1) - u(t - t_2))) \sin(\omega t) \quad (3.8)$$

where interruption disturbance is represented by the above equation and its limits are:

$$\alpha=0.9997, t_1=0.0598s \quad t_2=0.1264s, 0 < t < 0.25$$

This includes revenue and production losses, as well as operational interruptions, as a result of interruptions. Instantaneous interruptions would cause lighting and electronic equipment to malfunction, resulting in a shutdown or shutdown. Controllers, computers, and any other controls for rotating machines are included in electronic equipment. Most often, a drop-out to the induction motor causes temporary saturations or manometry of interruptions. Interruption recovery scenarios include the use of UPSs and static switches to assist the system in returning to normal operation.

3.8 Summary

In this chapter, ten power quality disturbances including the pure signal were discussed in detail. Each of these disturbances has a distinct definition in scientific, engineering, and standards research, which have all been clearly defined and discussed in this chapter. Following the presentation of the waveform of each disturbance, a precise mathematical expression for PQDs based on the signal processing environment is introduced. The causes of each disturbance were thoroughly discussed in terms of duration and magnitude of time. As a result, remedies and possible solutions for PQDs were also given. International standards that have been approved by international committees that deal with power quality are talked about. These are the foundation for the algorithm's analysis and future development.

CHAPTER 4

DETECTION ALGORITHMS AND CLASSIFICATION TECHNIQUES

4.1 Introduction

The main goal of power quality research is to develop the most appropriate algorithm for detecting and identifying power quality disturbances accurately. The wavelet transform (WT) has recently gained popularity as a useful tool for detecting and identifying PQ disturbances. The basic function of the Wavelet transform is the wavelet function, which scales with frequency. This scheme shows better results because the basic function used in the WT is a wavelet instead of an exponential function used in FT, FFT method, fractal-based method, time-frequency ambiguity plane method, Hilbert transform, Chirp-Z transform and STFT. There are various frequencies that can be broken down using WT and ST. Depending on the types of signal, continuous wavelet transform (CWT) and discrete wavelet transform (DWT) are employed. For continuous time signals, CWT-based decomposition is used, while DWT-based decomposition is used for discrete time signals. However, in this work, all the signals shown are discrete in nature hence DWT and ST based decomposition is employed here in this part of the work for different PQ disturbances such as Sag, Swell, Harmonics, Interruption, Sag with harmonics, Swell with harmonics and Oscillatory Transient are generated using MATLAB 2018b. In addition, the results and overall accuracy of both algorithms are studied and analyzed in a comparison analysis.

4.2 Wavelet Transform (WT)

4.2.1 Introduction

One of the most widely used mathematical tools in power engineering is the Wavelet Transform (WT), a powerful signal processing algorithm. [72].The word "wavelet" means a small wave representation with oscillations. There are a lot of differences between WT and FT. WT can find signals in both the time and frequency domains at the same time, and it can automatically change the width of its window based on how fast it moves. **Fig. 4.1** shows the principle dynamics of wavelet representation, where the signal (a) is a pure sinusoidal wave, (b) is the Gauss function and the summation is the wavelet signal in (c) [112].

The WT algorithm can break down signal data into different parts with different frequency bands. In 1982, Morlet came up with WT as a way to process images. [74]. It was then worked on by many mathematicians, like Meyer and Daubechies.

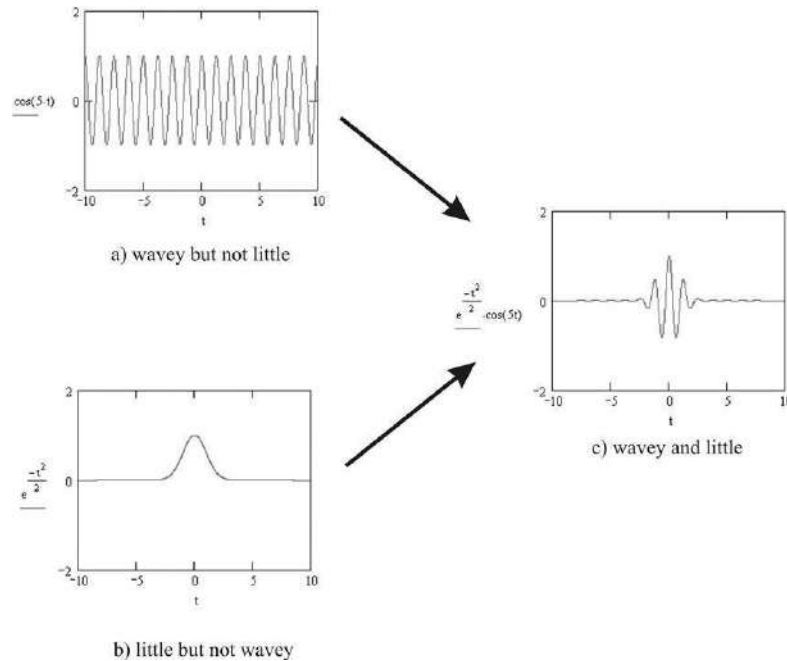


Fig. 4.1 The basic principle of wavelet [73]

It was used to make it easier to look at distorted signals [76]. With these characteristics, it has been used in a lot of different studies, like those about data compression and computing. It also solves complex differential equations [77]. Although WT was initially used in power systems for professional purposes to measure power quantities and provide reliable assessments, [78].

A time-frequency algorithm is one that can analyze signals in both time and frequency.

A wavelet family is used to compute the internal product of a signal as:

$$X_W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (4.1)$$

Where $\psi(t)$ is denoted by continuous mother wavelet for the time and frequency domains. $x(t)$ denotes input signal and ‘a’, ‘b’ represents the translation and scaling factors respectively.

X_W is represented by the correlation between the mother wavelet scaled at ‘a’ and shifted at ‘b’ with the input signal. The mother wavelet is carefully chosen to minimize interference in every output band. DWT is also represented by the signal $f(n)$ with reference to the factor ‘a’ and shifted by ‘b’ versions of mother wavelet $g(n)$ in (2).

$$DWT(m, k) = \frac{1}{\sqrt{a^m}} \sum_n f(n) g\left(\frac{k-nba}{a^m}\right) \quad (4.2)$$

DWT can also be calculated by combining the WT similarity equation with the filter equation. To achieve the required frequency resolution, $x(t)$ is processed by a series of low high pass filters.

4.2.2 Choice of Mother Wavelet

Detection and classification of PQ disturbances are made possible by selecting the appropriate mother wavelet, and this decision is critical in the decomposition process. The original signal is multiplied by the mother wavelet to get the scaled and translated version at various levels. There are several mother wavelets such as Daubechies, Morlet, Haar, Symlet etc. exists in wavelet library but literatures revealed that for power quality analysis Daubechies wavelet gives the desired result. Again the Daubechies wavelet has several orders such as Db2, Db3, Db4, Db5 Db6, Db7 Db8, and Db10 etc. With filter coefficients 4, 6, 8, and 10, Daubechies wavelets have a good performance in most disturbance cases. Detecting and classifying power quality disturbances is difficult. Fast and slow transients can be divided into two categories. The waveforms in the fast transient case have sharp edges, abrupt and rapid changes, and a relatively short time duration. Because of their compactness, Daub4 and Daub6 produce good results in this case. In slow transient case Daub8 and Daub10 shows better performance as the time Interval in integral evaluated at point n is long enough to sense the slow changes.

4.2.3 Feature Extraction

The internal process of feature extraction is to convert the original distorted signal to the DWT domain prior to collecting and building the database, which can then be used as an input to any classification system technique. The DWT coefficients are obtained through multiresolution analysis of power quality disturbances. Due to the non-stationary nature of PQDs, each distorted signal has a distinct frequency component and, as a result, a distinct energy distribution.

Fig. 4.2 shows the seven-level decomposition process for sag signal [54]. The parameter (a7) is the approximation level, and considered the parameter with the lowest frequency band. On the other hand, approximation levels from (d1) to (d7) are high frequency bands. Each of these bands is looked at on its own, and then they can be put together to make a new signal.

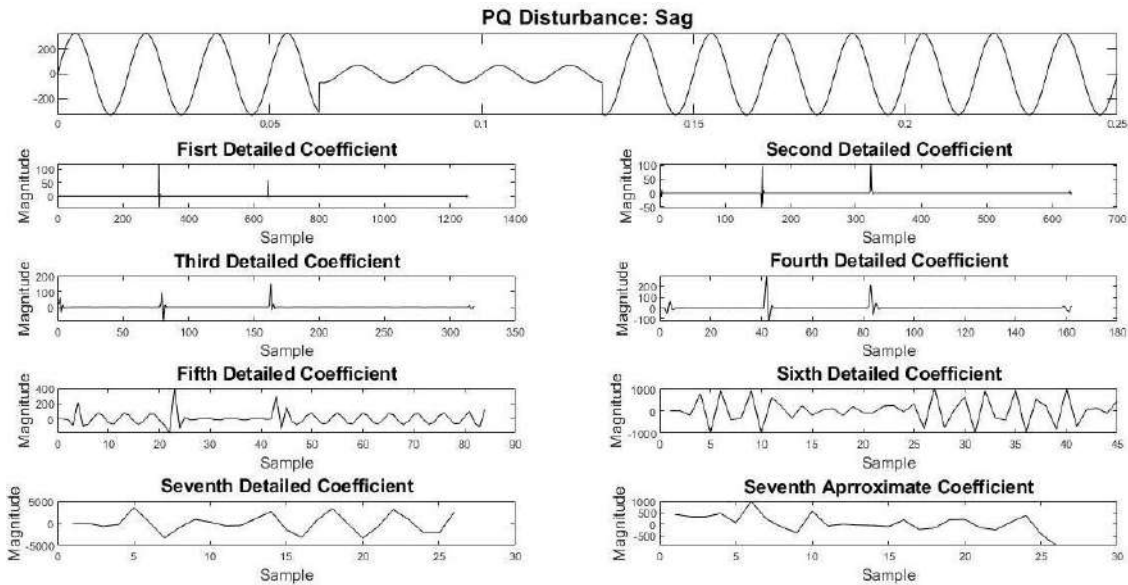


Fig. 4.2 7 level decomposition of PQ disturbance

4.3 Stockwell Transform (ST)

4.3.1 Introduction

As time went on, the Stockwell transform was used to look at geophysical data. The Stockwell transform is a more generalized version of the Fourier transform for short time intervals. It is also a version of the continuous wavelet transform (CWT), which has more advantages than the wavelet transform. In the case of S-transform modulation, the sine waves stay the same with respect to the time axis. These modulation sine waves help to keep the scalable Gaussian window in place. S-transform doesn't have a problem with cross-terms. In this case, the S-transform makes the signal clearer than the Gabor transform. But, the Stockwell transform has some downsides, like it takes a lot more work to do. When the Stockwell transform algorithm came out in 2010, it was very new. The Stockwell transform cuts the amount of time and resources it takes to do something by at least 4 orders of magnitude.

- When there is a lot of noise, the wavelet transform's ability to

find and pinpoint power quality problems is often reduced. But with S-transform, it can be found even when there is a lot of noise.

- Wavelet transforms need to be tested with different types of wavelets in order to get a better classification, but the S-transform doesn't need this many steps.
- An FFNN was used in this paper to classify the signals that were found. The features from the S-transform are given to the ANN. To classify the seven types of PQD, only seven things need to happen. It will also take less time to do calculations as a result.

4.3.2 *The Discrete S- Transform*

Moving and scalable Gaussian windows are used to establish the GT and WT ideas in S-Transform. In transposable and scalable Gaussian window, the inverse function of frequency related to standard deviation, the S-transform belongs to the broad category of multiresolution spectral analysis. It's now possible to use the localizing Gaussian function illustrated in,

$$g(t) = \left(\frac{1}{\sigma\sqrt{2\pi}}\right) \exp\left(-\frac{t^2}{2\sigma^2}\right) \quad (4.3)$$

The standard deviation is denoted by the σ . Because it has the lowest level of uncertainty, the Gaussian function is used as the window. By using the multiresolution -transform,

$$S(f, r) = \int_{-\infty}^{\infty} h(t)g(r - t, \sigma) e^{-i2\pi ft} dt \quad (4.4)$$

The primary purpose of the parameters related to dilation (or scaling) is to improve the "width" of the window function $g(t)$ at lower frequencies. It is manipulated through specifying a certain functional relationship between the frequency, f .

$$\sigma(f) = T = \frac{k}{|f|}, \quad \text{and } k = 1 \quad (4.5)$$

Here T=Time period; the Gaussian window in Eq. (3) is the smallest in the time domain because the constant in Eq. (5) is designated to unity. Now, the continuous -transform changes to,

$$s(f, t) = \int_{-\infty}^{\infty} h(t) \times \frac{|f|}{\sqrt{2\pi}} \exp\left(-\frac{(c-t^2)f^2}{2}\right) \times e^{-i2\pi ft} dt \quad (4.6)$$

The signal can express in discrete form as, it is varied between 0 and 1, which is referred

to as the signal's discrete time series. A time series' discrete Fourier transform is written as,

$$H\left[\frac{n}{NT}\right] = \frac{1}{N} \sum_{p=0}^{N-1} h[pT] \exp\left(-\frac{i2\pi nk}{N}\right) \quad (4.7)$$

Here 0, 1, 1 and the inversion of DFT is

$$h[pT] = \sum_{n=0}^{N-1} H\left[\frac{n}{NT}\right] \exp\left(\frac{i2\pi nk}{N}\right) \quad (4.8)$$

The ST in the discrete case is the projection of the time series vector onto a comprising set of vectors. The discrete-time series of S transform is

$$S\left[\frac{n}{NT}, jT\right] = \sum_{m=0}^{N-1} H\left[m + \frac{n}{NT}\right] \times \exp\left(-\frac{2\pi^2 m^2}{n^2}\right) \exp\left(\frac{i2\pi mj}{N}\right) \quad (4.9)$$

4.4 Classification Technique Using Artificial Neural Networks

4.4.1 Introduction

Artificial Intelligence (AI) is the ability of a machine to perform tasks that are similar to those performed by humans. It also refers to computer programs capable of performing complex tasks. Expert systems and artificial neural networks are the two primary branches of artificial intelligence. Expert systems are permitted to make decisions based on the interpretation of roles and the selection of a rule or a process from a set of alternatives, a technique known as rule-based inference.

An Artificial Neural Network (ANN) is one of the widely accepted techniques for solving complex and difficult problems. ANNs are capable of learning from samples and coping with a noisy environment. It is capable of processing incomplete data and non-linear problems, which are prevalent in power systems. Prediction and estimation can be accomplished during the training stage. ANN is particularly useful in system modeling for implementing complex mappings and parameter identification.

A neural network is a collection of independent processing units. These units receive inputs in the form of signal representations or formulas. Each of these inputs contains two characters: a value for the input and a weight. They are then trained until they understand the patterns that these inputs have in relation to data sets. Following that, novel patterns are created for the classification stage [78]. The neurons that make up the ANN process construction connect together to make it work well. Many industries, including medical science, automotive manufacturing, and electrical power systems have found success with it [79].

ANN is made up of numerous nodes that are connected via layers. The connections between these nodes are referred to as neurons, and they have weights that contribute to the achievement of desired targets. Due to its non-linear mapping mechanism, ANN is an efficient mathematical technique for detecting, identifying, and controlling complicated processes. The primary advantages of using ANN are related to three factors. To begin, it is capable of dealing with random fluctuations in operating points as a result of the accumulation of data. Second, ANN significantly accelerates classification and online processing performance.

Thirdly, it aids in the development of functions required for filtering the system's data through its non-linear modeling [80]. Other AI techniques, like fuzzy logic systems, expert systems, and optimization techniques, can also be used with ANN to build a hybrid intelligent system that can help you get the results you want.

4.4.2 Structure of a Neural Network

Several publications have described the mechanism of processing information using ANN, as in [81], [82]. There are a lot of connectors for neurons, which are the input parts. Every time one of these connections is made, it is then linked to a weight these weights

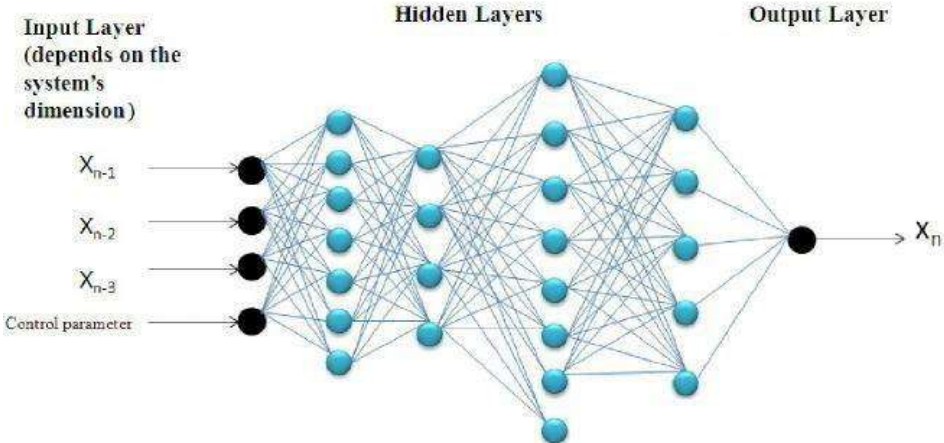


Fig. 4.3 Typical example of Artificial Neural Networks [83]

show how big and strong the connection is. Within each neuron, there is a non-linear transformation function called the activation function, which is what makes the neuron work. This activation function is used on input neurons to make outgoing signals. However, neurons are organized into a series of layers, as can be seen from **Fig. 4.3**.

An ANN is composed of three layers: input, hidden, and output, all of which are connected by complex connections called neurons. As illustrated in **Fig. 4.4**, neurons in an ANN system are connected via weights, and the learning algorithm updates the relationship between these weights in the network.

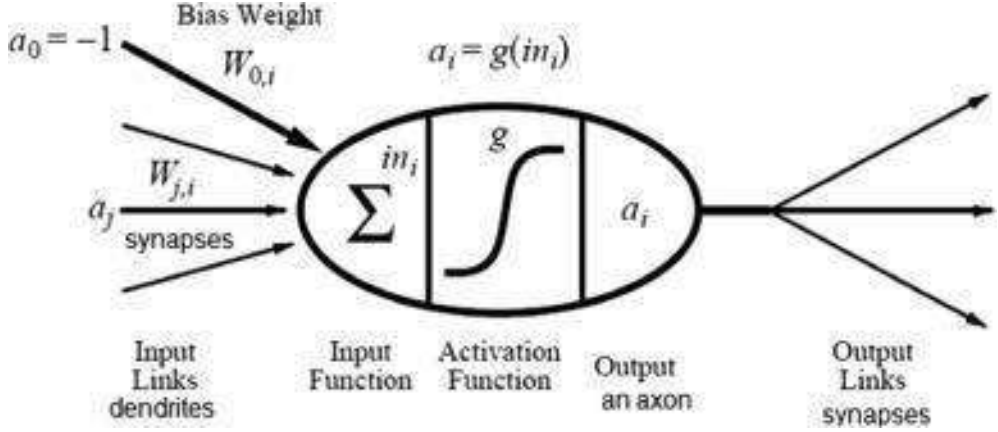


Fig. 4.4 Typical architecture of a neuron [84]

The activation function generates outputs by first processing weighted inputs. Finally, the weights and biases of the network are adjusted to reduce the discrepancy between the activation function's outputs and the network's desired outputs. In this procedure.

For precise mapping of input-to-output relationships, training is needed. During the testing stage, the system investigates and recognizes the taught input patterns precisely when it generates outputs. For this reason, if any of the network's outputs are incorrect or do not match the trained inputs, it will go back and redo the training process. Until a certain desired value is met, the process continues in this manner.

4.4.3 Activation Function

An important part of a neural network is called the activation function. It helps to speed up the process of weighted inputs being used to make outputs. These functions can be linear, step, logistic, or sigmoid. They change based on how the neural network is set up and the type of problem it's trying to solve, so they look different. According to studies, the activation function may influence the outputs [85]. The activation function also has two stages: the linear combination and the transfer function, the latter of which converts the weighted inputs into target units. The nature of the problem determines which transfer functions are used, as in [86].

4.4.4 Types of Artificial Neural Networks

Recurrent neural networks and feed forward neural networks are the two main types of ANNs that you can find. In the first type, information moves from inputs to outputs through layers that have been planned. There are no loops. In the second type, the network has loops in the way it works.

4.4.4.1 Feed Forward Neural Network

There are two major divisions of the Feed Forward Neural Network (FFNN): single or multi-layer networks between input and output. The weights of inputs and outputs determine the connections in the signal layer. The activation function is activated by adding the inputs and weights together. The output is either +1 or -1 depending on the input value and whether or not it falls below or exceeds the threshold. When the multi-layer type is used, which includes input layers, output layers, and hidden layers, the procedure becomes more complicated [87]. Through hidden layers, information is only transmitted in a forward direction from inputs to outputs. Because there is no interaction or loop cycle in this process, FFNN has no effect on the process between hidden layers.

4.5 Experimental Results

4.5.1 Detection and Features Extraction Based on the DWT and ST Algorithm

In this stage, a characterization of a pure sine wave among seven power quality disturbances, is conducted. These disturbances are sag, swell, harmonics, harmonics with sag, harmonics with swell, oscillatory transient and interruption and its parameters for each signal is also discussed here.

The strategy used to achieve targets in this research is shown in **Fig. 4.5**.

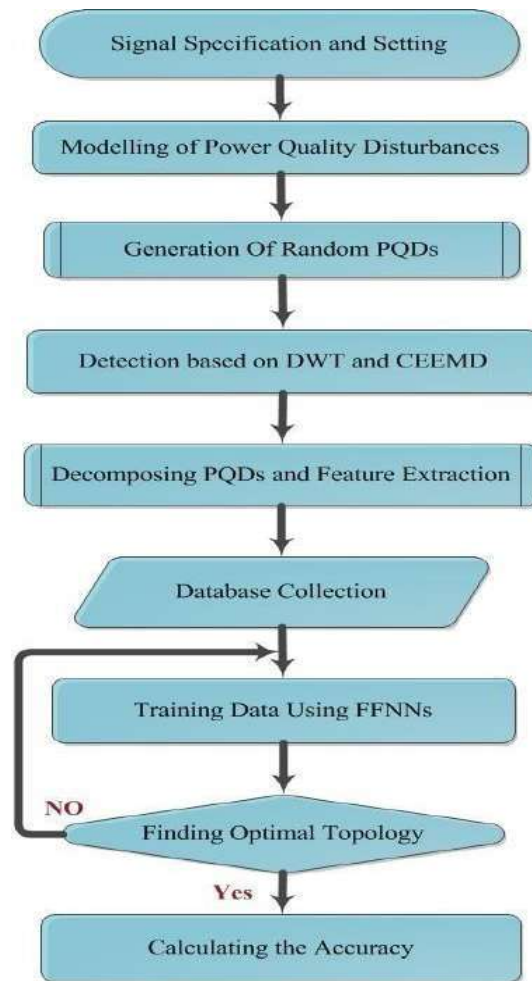


Fig. 4.5 Flowchart of the detection algorithm and classification technique

To achieve this, it is necessary to design the signal specifications as:

T_s (time period) = 0.5 seconds, and f (frequency) = 60 Hz. Modelling of PQDs is generated according to their parametric equations, explained in **Chapter 3** and summarized in **Table 4.1**.

Table 4.1: Modelling of PQD and Their Parameters

| PQD | Mathematical Models | Parameter of models |
|-----------------------|--|--|
| Pure Signal | $f(t) = A\sin(\omega t)$ | $A=1, f=60\text{Hz}, \omega=2\pi f \text{ rad/sec}$ |
| Sag | $f(t)=(1-A(u(t-t_1)-u(t-t_2)))\sin(\omega t)$ | $A=0.5314, 0 < t < 0.25, t_1=0.0587\text{s} \ t_2=0.1920\text{s}$ |
| Swell | $f(t)=(1+A(u(t-t_1)-u(t-t_2)))\sin(\omega t)$ | $A=0.7574, 0 < t < 0.25, t_1=0.0501\text{s} \ t_2=0.1835\text{s}$ |
| Harmonic | $f(t) = A(\alpha_1\sin(\omega t)) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t) + \alpha_7\sin(7\omega t)$ | $A=325.2691, 0.0988 \leq \alpha_7_h, \alpha_5_h, \alpha_3_h, \alpha_1_h \leq 0.9817$ |
| Voltage Interruption | $f(t)= (1 - \alpha(u(t-t_1)- u(t-t_2))) \sin(\omega t)$ | $\alpha=0.9997, t_1=0.0598\text{s} \ t_2=0.1264\text{s}, 0 < t < 0.25$ |
| Oscillatory Transient | $f(t)=(\sin(\omega t) + (\alpha\text{Temp}_o((u(t-t_1)-u(t-t_2))\sin(2\pi f_s t))))$ | $\alpha = 1.2676 \times 10e3,$ $\text{temp}_o= \exp(-(t / t_1)^*\text{To}_w), t=0 < t < 0.25, t_1 = 1.2676 \times 10e^3$ $\text{To}_w = 1.3821 \times 10e^{-3}, 0 < t < 0.25$ $t_1=0.0636\text{s}, t_2=0.808\text{s}, f_s= 1.2676 \times 10e^3$ |
| Harmonic with Sag | $f(t)=(\text{temp_sh}) (\alpha_{1_sh} \sin(\omega t)+\alpha_{3_sh} \sin(3\omega t) + \alpha_{5_sh} \sin(5\omega t))$ | $\omega=2\pi f, f=60\text{Hz}$ $\text{temp_sh}=(1-\alpha_{_sh} (u(t-t_1) -u(t - t_2)))$ $\alpha_{_sh} = 0.1537, t=0 < t < 0.25, t_1 =0.0634, t_2= 0.1634$ $\alpha_{1_sh}=0.9880, \alpha_{3_sh}=0.0784, \alpha_{5_sh}=0.0932$ |
| Harmonic with Swell | $f(t)=(\text{temp_sw}_h) (\alpha_{1_sw}_h \sin(\omega t)+\alpha_{3_sw}_h \sin(3\omega t) + \alpha_{5_sw}_h \sin(5\omega t))$ | $\omega=2\pi f, f=60\text{Hz}$ $\text{temp_sw}_h=(1+\alpha_{_sw}_h (u(t-t_1) -u(t - t_2)))$ $0 < t < 0.25, t_1=0.0561 \ t_2=0.1728$ $\alpha_{_sw}_h=0.5023, \alpha_{1_sw}_h=0.9783$ $\alpha_{3_sw}_h=0.1044, \alpha_{5_sw}_h=0.1130$ |

DWT is used to generate and detect a list of the most common power quality disturbances. **Fig. 4.6** shows the results of this stage.

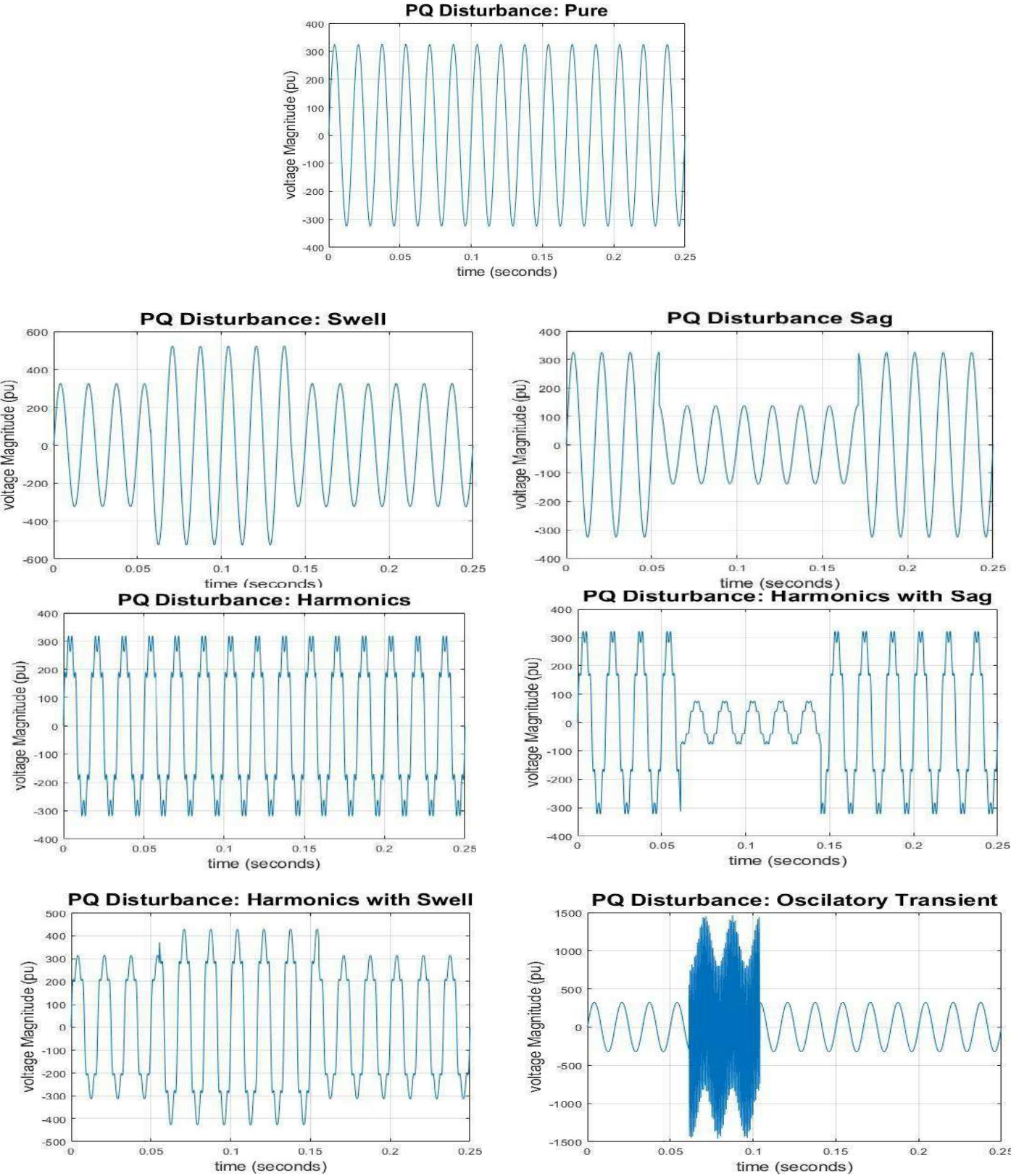


Fig. 4.6 Different PQDs signals

For each power quality disturbance, the goal of decomposition and extraction is to convert the original distorted signal from its time domain to its energy form. The DWT filter (db7) is used to decompose each PQD generated in this study, and the results for selected PQDs are shown in **Fig. 4.7 to 4.15**.

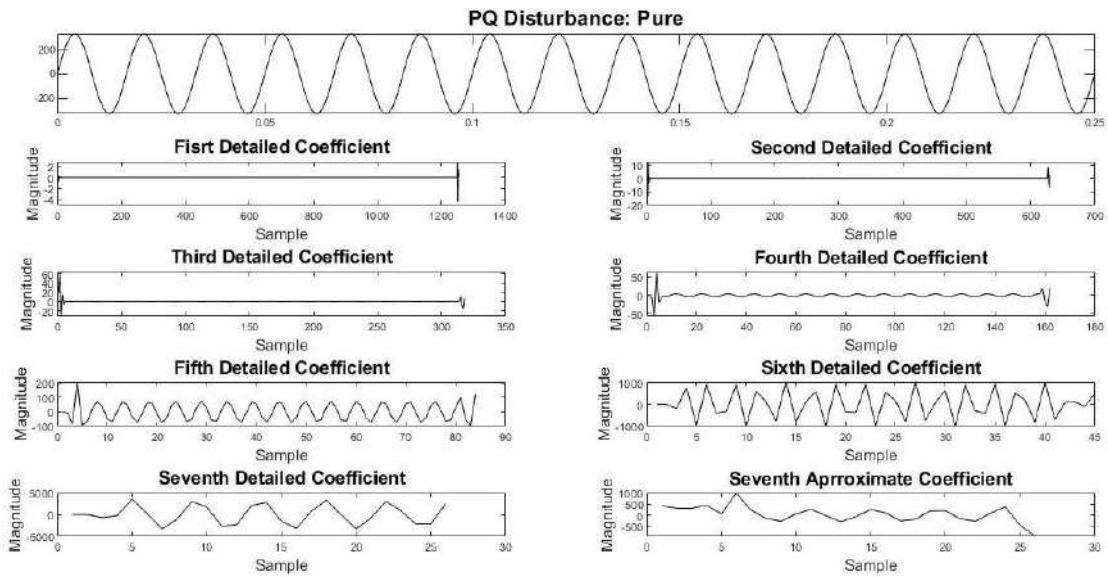


Fig. 4.7 Decomposition and features extracted from pure voltage signal

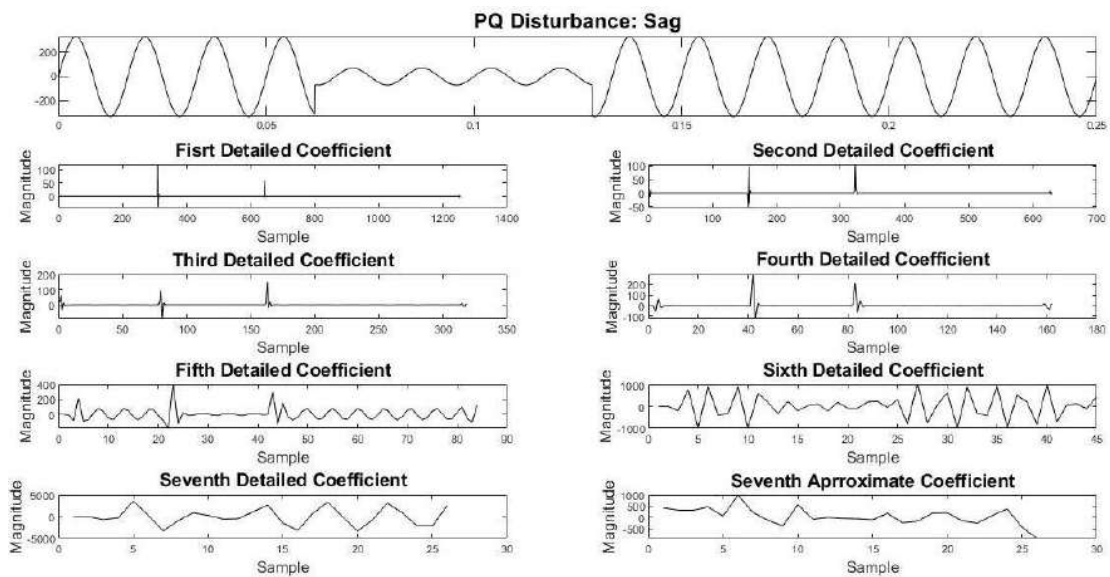


Fig. 4.8 Decomposition and features extracted from sag signal

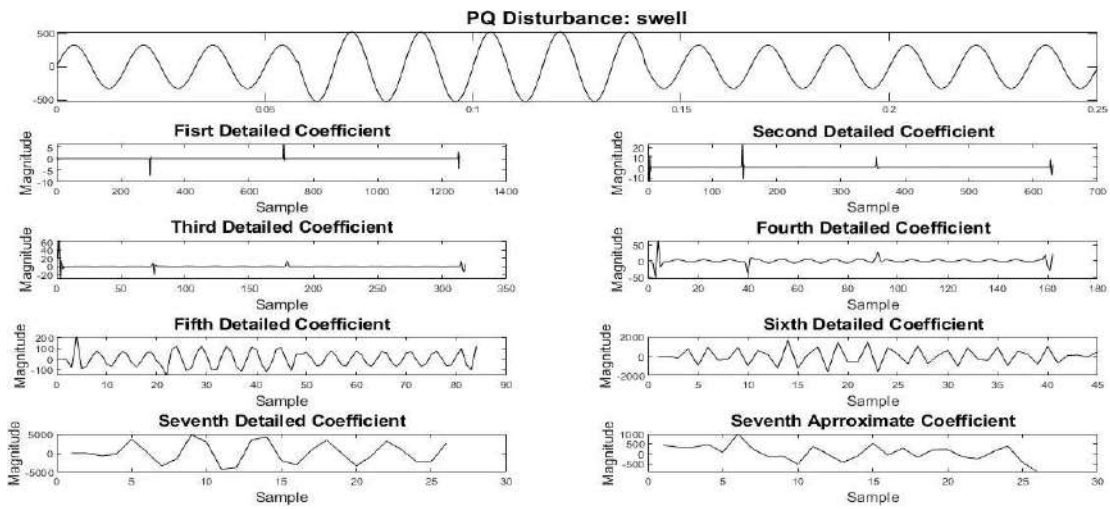


Fig. 4.9 Decomposition and features extracted from swell signal

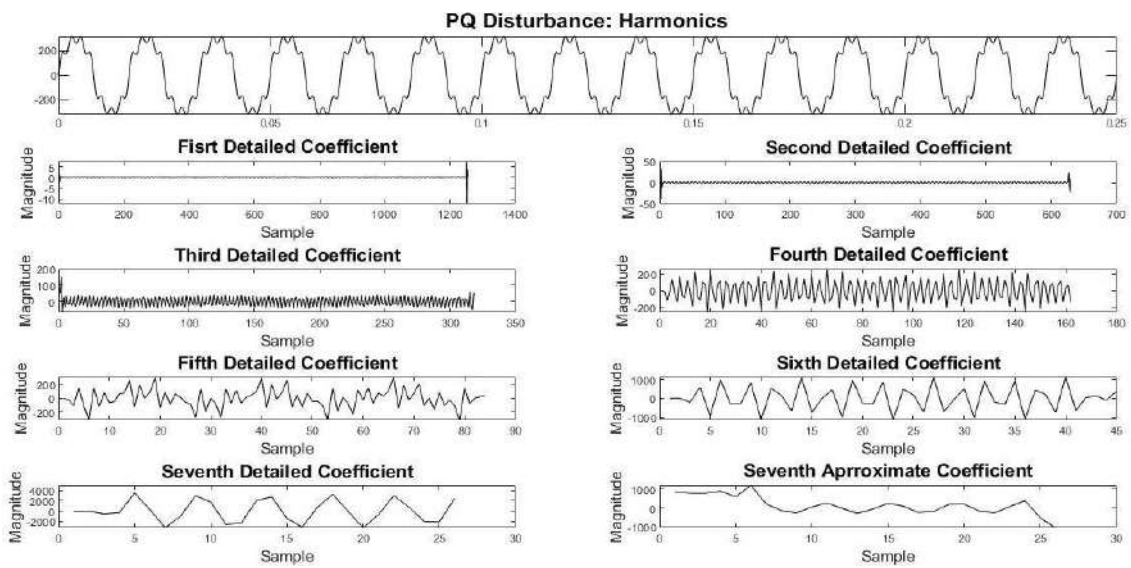


Fig. 4.10 Decomposition and features extracted for harmonic signal

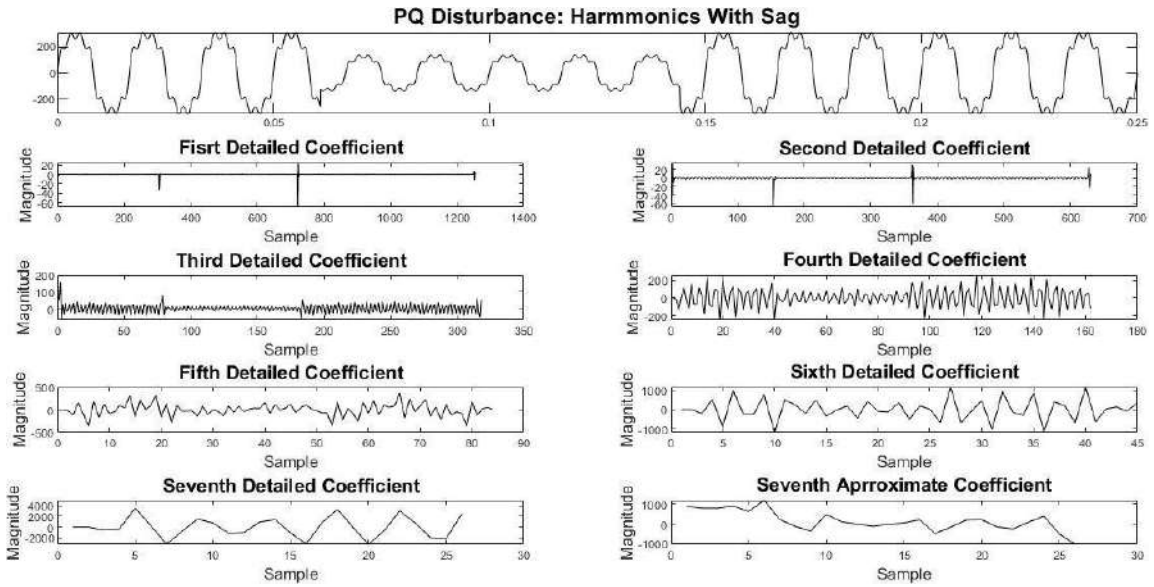


Fig. 4.11 Decomposition and features extracted for harmonics with sag signal

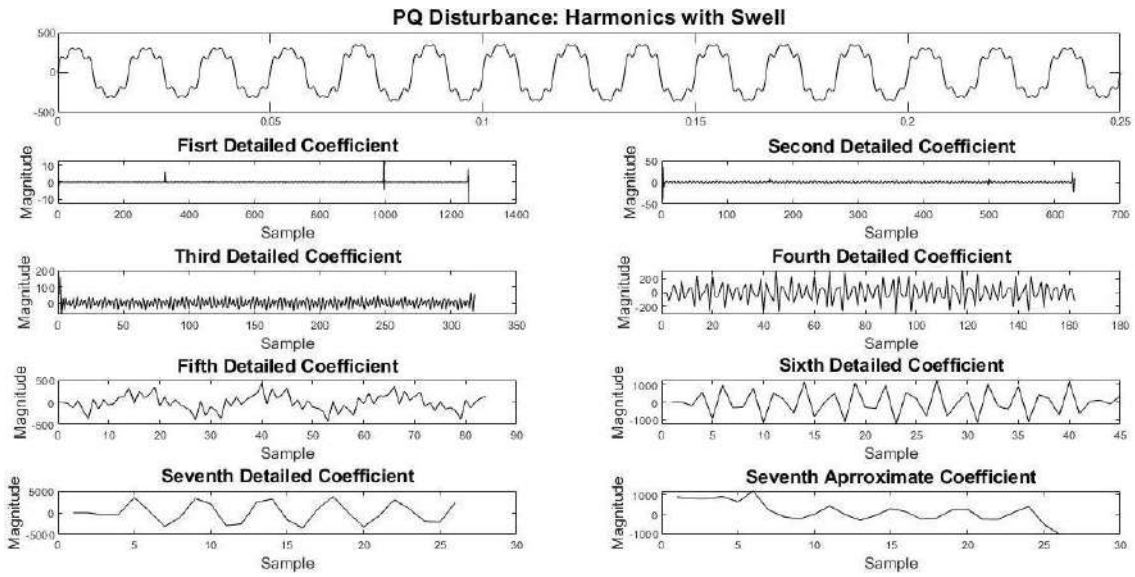


Fig. 4.12 Decomposition and features extracted for harmonics with swell signal

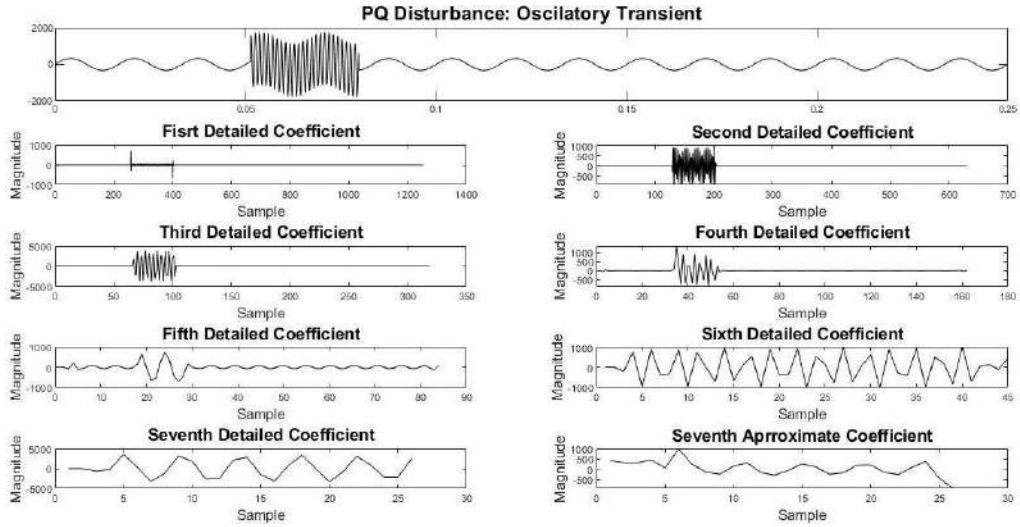


Fig. 4.14 Decomposition and features extracted for oscillatory transient signal

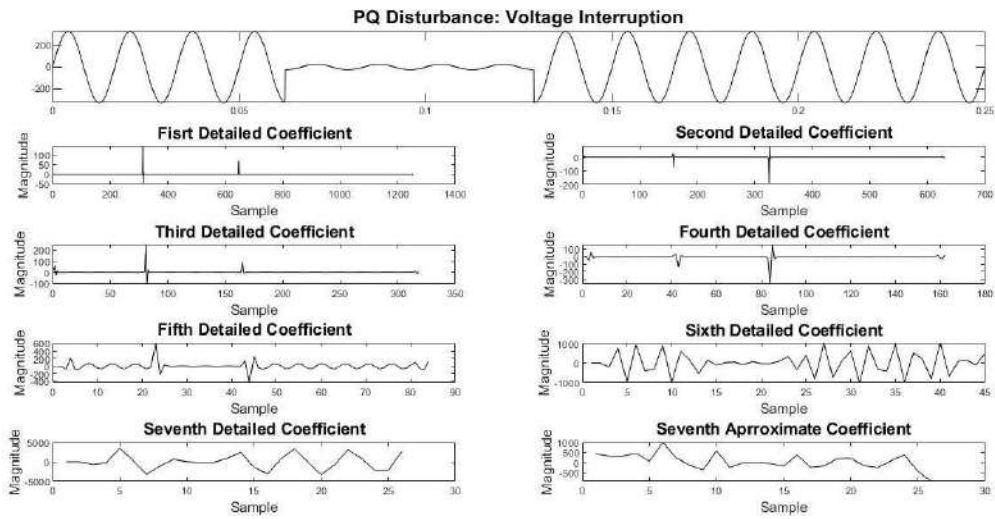


Fig. 4.15 Decomposition and features extracted for interruption signal

As mathematically explained, results of eight features set are displayed for both DWT coefficients: the approximation coefficient (a) and the detailed coefficient (d) with a total of 16 signals of feature sets for each disturbance. Each high-frequency feature comes first, and the low-frequency features come last, when these are grouped and sorted by frequency. The classifier uses the most detailed feature sets during the training phase. In each generation step, 7 x 8 types (1 normal and 7 distorted signals) yield 56 features. Based on its numerical parameters, each of these disturbances has a random value at every generation.

4.5.2 Detection Stage Results

A classification system technique is required to evaluate and examine the detection algorithm's performance. FFNN data training consists of three stages. This phase begins by creating a database of inputs for the classifier.

In **Table 4.1**, each of these PQDs is decomposed into seven features by a seven-step decomposition process at each generation. The final product is a 4500-sample dataset that can now be used for training and learning purposes. The FFNN is fed with the results of the disturbance features extracted.

The second phase involves data validation, which is accomplished by assessing network efficiency. The FFNN is designed to measure and classify power quality disturbances, with each disturbance having its own neural network. This system's main benefit is network learning. Following that, the learning process is carried out in order to correct data errors and to apply the principle of multiplying inputs by their weights. The activation function of the neural is then calculated using a mathematical procedure. The outputs are then calculated by a different mathematical model, which sets in motion a set of rules to classify new inputs.

The network's accuracy is tested in the third phase to ensure optimal performance. Furthermore, one, two, and three hidden layers of 3 to 9 neurons are used to improve accuracy and investigate the classifier's best performance. **Tables 4.2 to 4.4** show the detection and classification results. For each PQD signal, the accuracy is detailed.

Table 4.2: Detection result with different SNR values

| Detection Result | | | | | | |
|--------------------------------|-------|-------|-------|-------|-------|-------|
| Successfully Classified Sample | | | | | | |
| SNR (dB) | 20 | | 30 | | 40 | |
| Item | DWT | ST | DWT | ST | DWT | ST |
| For PQD | 4454 | 4494 | 4495 | 4487 | 4496 | 4485 |
| For Non PQD | 5213 | 5232 | 5211 | 5225 | 5199 | 5213 |
| Accuracy (%) | 99.55 | 99.75 | 99.54 | 99.61 | 99.35 | 99.47 |

Table 4.3: WT-based confusion matrix for PQ classification using ANN

| Symbol | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|--------------|-------------------------|------------|---------------|------------|------------|------------|------------|
| C1 | 793 | 0 | 2 | 5 | 0 | 0 | 0 |
| C2 | 0 | 791 | 0 | 0 | 0 | 9 | 0 |
| C3 | 2 | 0 | 797 | 1 | 0 | 0 | 0 |
| C4 | 11 | 0 | 1 | 788 | 0 | 0 | 0 |
| C5 | 0 | 0 | 0 | 0 | 800 | 0 | 0 |
| C6 | 0 | 22 | 0 | 0 | 0 | 778 | 0 |
| C7 | 00 | 0 | 0 | 1 | 0 | 0 | 799 |
| Accuracy (%) | Overall Accuracy | | 98.08% | | | | |

Table 4.4: ST-based confusion matrix for PQ classification using ANN

| Symbol | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|--------------|-------------------------|----------|---------------|------------|------------|------------|------------|
| C1 | 728 | 0 | 72 | 0 | 0 | 0 | 0 |
| C2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| C3 | 26 | 0 | 771 | 0 | 0 | 0 | 3 |
| C4 | 0 | 0 | 0 | 800 | 0 | 0 | 0 |
| C5 | 0 | 0 | 2 | 2 | 796 | 0 | 0 |
| C6 | 0 | 1 | 0 | 0 | 0 | 799 | 0 |
| C7 | 0 | 0 | 3 | 0 | 0 | 0 | 797 |
| Accuracy (%) | Overall Accuracy | | 99.05% | | | | |

4.6 Result Comparison Analysis

In order to examine the effectiveness and evaluate the feasibility of the proposed detection algorithm and classification technique, a comparison analysis is constructed for the classification technique based on the following factors:

- Both detection algorithms are capable of analyzing and detecting signals in the

time-frequency domain, as well as non-stationary signals.

- The feature extraction process, which was 8 features for each disturbance, is a function provided by both algorithms.
- Each algorithm models power quality disturbances the same way, and the same number of random values are made.
- ST is more accurate at detecting samples as the SNR increases, whereas WT is more accurate at classifying the detected samples.

4.7 Summary

This chapter talks about the two main ways to find problems with power quality. The first thing that was done was to show how these disturbances could be modelled, based on each formula and on international standards that describe the characteristics and limits of each one. Furthermore, DWT was used to look for problems with power quality. It was shown in this work that DWT can work around Fourier transform limitations, especially when there aren't any steady waves. PQDs are then broken down into seven levels and energy values are calculated for each distorted signal. This information is used to build the database that will be used by a computer program to classify them.

A random sample of 4500 PQDs is used to create an FFNN classifier and a database. In order to discover the overall accuracy of these signals' features, they are trained, analyzed, and tested. As a result, the accuracy of the classifier of power quality disturbances was more than 98% for each disturbance and for overall accuracy, which shows the success of DWT-FFNNs for power quality disturbances. For each power quality disturbance, the classifier was more than 98% correct. This shows that DWT- FFNNs are good at classifying power quality disturbances.

A database of PQD-generated signals is classified using the FFNN classifier. The results of this data are then analyzed, trained, and tested to see how well the detection method and classification method work. Because the FFNN classifier has an overall accuracy rate of more than 98%,

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Introduction

The main contributions and results of this research are discussed in this chapter. In this thesis, a new detection algorithm and classification technique is proposed for electrical power quality disturbances. Moreover, a validation methodology is conducted based on DWT. Compared with existing algorithms, the proposed methodology showed a better performance based on the accuracy achieved. The novelties of the proposed methodology of the detection algorithm and classification technique can be categorized into four major aspects.

5.2 Conclusion

In this chapter, we'll go over the study's most important findings and contributions. Detection and classification of electrical power quality disturbances are proposed in this thesis. Furthermore, a method for testing DWT is used to make sure it works. Compared to other algorithms, the proposed method did better because it was more accurate. The new ideas in the proposed detection algorithm and classification technique can be broken down into four main groups. The first step is to figure out what is causing power quality problems. This is accomplished by modeling these issues in accordance with international standards for power quality. In the characterization stage, mathematical equations are implemented, considering equation parametrical limits in IEEE 1159 and IEC 61000-4-30. These disturbances include pure, voltage sag, voltage swell, harmonics, harmonics with sag, harmonics with swell, oscillatory transients and voltage interruption. **Chapter 3** illustrates the phenomena associated with these events in both their singular and multiple manifestations. In order to get to the second stage, two powerful signal processing algorithms are used to create an environment that can automatically detect and analyze power quality disturbances. First, the requirement outlined in Chapter 3 and signal specifications required in this field cause power quality disturbances. To detect and identify distorted power signals, DWT is then used. On the time-frequency domain, DWT proved its ability to distinguish between non-stationary disturbances and to overcome Fourier Transform limitations. After that, the decomposition process extracts 7 levels of features from the disturbances. In order to test the detection algorithm's accuracy and sturdiness, 4500 samples of database features are generated and tested.

After obtaining the feature vector, the strong classifier MFNN is applied to the classification stage, yielding an average performance of 98.05 percent. For the disturbance types considered in this thesis, two types of classification algorithms were proposed, and one of those algorithms was successfully used to achieve a very high error classification rate.

5.2 Future Work

- ❖ The main parts of this thesis have been about the most common problems with power quality. This thesis didn't include all power quality disturbances in power systems because they didn't have a big effect or because they were more common in power systems than they were in other places.
- ❖ The statistics on how important research is in this field are still very limited. It should also be done in a lot of different places around the world to help the research community deal with losing money.

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