"POWER QUALITY DISTURBANCE CLASSIFICATION USING MACHINE LEARNING TECHNIQUES"

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DECLARATION

"We hereby declare that this thesis is our original work and it has been written by us in its entirety. We have duly acknowledged all the sources of information which have been used in the thesis. The thesis (fully or partially) has not been submitted for any degree in any university or institute previously."

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SUPERVISOR'S APPROVAL

This is to certify that this thesis titled **"POWER QUALITY DISTURBANCE CLASSIFICATION USING MACHINE LEARNING TECHNIQUES"** prepared by the following students under my direct supervision. This thesis work has been carried out by them in the laboratories of the Department of Electrical and Electronic Engineering under the Faculty of Engineering, Sonargaon University (SU) in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering.

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ACKNOWLEDGEMENT

There are a number of people who have been significant in the culmination of this paper, both academically and actually. This work, and the time that we have spent in look into the work, would have been a lot less fortunate without them. We owe them with a lot.

Lecturer **Syed Raihan Hossain** has been our supervisor during ours study in the Department of Electrical & Electronic Engineering of SU. He has taught us more about electrical & electronic engineering than has anyone else and his professional and personal standards would be an example to any student. It has been a privilege to work with him. We wishes to thank for his inspiring and invaluable guidance through out the course of this research work. We are highly indebted to his supervisor for his personal care and affection and for making his stay in SU, a memorable one. We are also expresses his deep sense of gratitude to his supervisor for initiating us into the field of machine learning application in electrical & electronic engineering. He took us into the work seriously and contested his ideas and expressions vigorously whenever necessary, and thus has certainly made it a better one.

We also wishes to thank again to the respected **Vice-Chancellor** of SU, **Professor Dr. Md. Abul Bashar** also thanks to Head of Department of SU , Electrical & Electronic Engineering, **Professor Dr. M. Bashir Uddin** because they are designated such an environment for learning through which we got the opportunity to acquire knowledge under BSc in EEE program, and that will be very helpful for our prospective career.

Sincere thanks to the laboratory members for their prompt and generous assistance in every stages during staying at SU. We are gratefully acknowledges the help and friendship received from his colleagues and friends during the course of the study.

At last, we are profoundly obliged to our folks, who needed to help us at each stage and carried us to this level and thus our exceptional thanks are because of them. We might want to thank our family for their getting, consolation, and persistence that they have appeared during the course.

ABSTRACT

The broad utilization of strong state power hardware innovation in industrial, commercial, and residential gear causes corruption of the nature of electric force with the crumbling of the supply voltage. The disturbances results in degradation of the efficiency, decaying the life span of the equipment, increase in the losses, electromagnetic interference, the malfunctions of equipment and other harmful fallout. Generally, the power quality is the measurement of an ideal power supply. More over the power quality is the continuity and characteristics of the supply voltage in terms of frequency, magnitude and symmetry. The mitigation of power quality (PQ) disturbances requires detection of the source and causes of disturbances. The k-NN, DT and SVM algorithm is a suitable method for forecasting of further occurrence of disturbances. However proper and quick detection and localization of the disturbances plays a crucial role in the power quality environment. Hence, in this thesis, a fast detection technique has been proposed along with the k-NN algorithm.

Over the span of the examination, it is discovered that appropriate algorithms are required for the portrayal of the disturbances for smooth relief of the twists. Along these lines, data mining based classifier has been proposed for separation of both single and various disturbances. Further, the reasonable highlights are required for productive portrayal of the disturbances. Henceforth, the appropriate highlights are separated so as to evoke the quantity of raw data. The data standardization likewise assumes an essential job for effective grouping. These order procedures are quick and ready to break down enormous number of disturbances. Right now, quantities of signs are orchestrated both in uproarious and clamor free condition. In the ongoing condition, these methods have been performed sufficiently. This prompts increment in the general effectiveness of the mix of the discovery and grouping technique.

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LIST OF ABBREVIATIONS

ABC	Artificial Bee Colony
AC	Alternating Current
ACO	Ant Colony Optimization
AFD	Amplitude and Frequency Demodulation
AI	Artificial Intelligence
AITC	Artificial Intelligence Technique Classification
ANN	Artificial Neural Network
ANSI	American National Standards Institute
AWN	Adaptive Wavelet Network
AWGN	Adaptive White Gaussian Noise
BFM	Binary Feature Matrix
BFOA	Bacterial Foraging Optimization Algorithm
BPNN	Back Propagation Neural Network
CDEA	Chemotactic Differential Evolution Algorithm
CFL	Compact Fluorescent Light
CI	Computational Intelligence
CPU	Central Processing Unit
CT	Chirp Transform
CWT	Continuous Wavelet Transform
DC	Direct Current
DFT	Discrete Fourier Transform
DG	Distributed Generation
DOST	Discrete Orthogonal Stockwell Transform
DT	Decision Tree
DTFT	Discrete Time Fourier Transform
DWPT	Discrete Wavelet Packet Transform
DWT	Discrete Wavelet Transform
EEMD	Ensemble Empirical Mode Decomposition
EGA	Extension Genetic Algorithm
EKF	Extended Kalman Filter
ELM	Extreme Learning Machine

EMD	Empirical Mode Decomposition
EMTDC	Electromagnetic Transients including Direct Current
EN	European
EPG	Electrical Pattern Generator
FDT	Fuzzy Decision Tree
FES	Fuzzy Expert System
FFT	Fast Fourier Transform
Fk-NN	Fuzzy k-Nearest Neighbour
FL	Fuzzy Logic
FT	Fourier Transform
GA	Genetic Algorithm
GT	Gabor Transform
HHT	Hilbert Huang Transform
HMM	Hidden Markov Model
HOS	Higher-order statistics
HST	Hyperbolic Stockwell Transform
HT	Hilbert Transform
IEC	International Electro-technical Commission
IEEE	Institute of Electrical and Electronics Engineers
IMF	Intrinsic Mode Function
KF	Kalman Filter
LDD	Long Duration Disturbances
LED	Light Emitting Diode
LL	Line-to-Line
LLG	Double Line-to-Ground
LLL	Three phases
LMT	Logistic Model Tree
LS-SVM	Least Square Support Vector Machine
LQE	Linear Quadratic Estimation
LVQ	Learning Vector Quantization
MATLAB	Matrix Laboratory
MCN	Maximum Cycle Number
MODWT	Maximal overlap discrete wavelet transform
MRA	Multi-Resolution Analysis
MSVM	Multiclass Support Vector Machine
MWT	Multi-Wavelet Transform
NE	Norm Entropy
NFC	Neuro-Fuzzy Classifier
NN	Nearest Neighbour
PC	Principle Curves
PNN	Probabilistic Neural Network
PQ	Power Quality
PQD	Power Quality Disturbance

PSCAD	Power System Computer Aided Design
PSO	Particle Swarm Optimization
p.u	per unit
RBF	Radial Basis Function
RES	Renewable Energy Sources
RMS	Root Mean Square
SA	Simulated Annealing
SBS	Sequential Backward Selection
SB-TS	Optimal Subband Tree Structuring
SDD	Short Duration Disturbances
SDV	Short Duration Variation
SFS	Sequential Forward Selection
SI	Swarm Intelligence
SK	Spectral Kurtosis
SLG	Single Line-to-Ground
SOLAR	Self-Organizing Learning Array
SRC	Sparse Representation based Classification
SSD	Sparse-Signal Decomposition
SSE	Sum of Squared Error
ST	Stockwell Transform
ST-ELM	Stockwell Transform with Extreme Learning Machine
STFT	Short Time Fourier Transform
SURE	Stein's Unbiased Risk Estimate
SVD	Singular Value Decomposition
SVM	Support Vector Machine
SWTC	Squared Wavelet Transform Coefficient
TDNN	Time Delay Neural Network
TEO	Teager Energy Operator
TER	Time-Frequency Representation
TTT	Time-Time Transform
UKF	Unscented Kalman Filter
UWT	Un-decimated Wavelet Transform
VSD	Variable speed drives
WEE	Wavelet Energy Entropy
WEW	Wavelet Entropy Weight
WNN	Wavelet Neural Network
WPE	Wavelet Packet Energy
WPT	Wavelet Packet Transform
WT	Wavelet Transform

LIST OF SYMBOLS

Hz	**Harz**
cA	**Approximation Coefficient**
%	**percentage**
log	**Mathematical function**
N	**data size**
$\mathbf{e^{-1}}$	**exponential**
π	**pi**
***y*k**	**uncertainty**
ψ(t)	**function**
sin(ω*t)	**sinewave**
t	**line-space**
f	**frequency**
ω	**angular velocity**
T	**time period**
=	**equals to**
u	**inline**
1-D	**one dimension**
$\mathbf{(J \cdot K^{-1})}$	**joules per kelvin**
(kB)	**Boltzmann's constant**
(ΔS)	**change in entropy**
(ΔQ)	**change in heat**
T	**temperature**
(U)	**internal energy**
dU	**change in internal energy**
p	**external pressure**
V	**volume**
k(x y)	**kernel function**
$\mathbf{\sum_i \alpha_i k(x_i x)}$	**constant**

C0	**Class 1(Sag)**
C1	**Class 2(Swell)**
C2	**Class 3(Oscillatory Transient)**
C3	**Class 4(Sag with Harmonics)**
C4	**Class 5(Swell with Harmonics)**
C5	**Class 6(Flicker)**
TP_{C1}	**true positive**
FP_{C1}	**false positive**
FN_{C1}	**false negative**
TN_{C1}	**true negative**

CHAPTER ONE

Introduction

1.1 Broad Area of Research

The continuous growth in the application of the microprocessor-based control and the power electronic devices and the adjustable-speed motor drives increases emphasis on the quality of power as these are more sensitive to power quality variations than the traditional equipment's. Hence, the term "power quality" has become a prolific buzzword in the power industry since the late 1980s. Moreover, the power quality (PQ) is like an umbrella which covers various disturbances of the voltage and the current such as the voltage sag, the swell, the harmonics and the oscillatory transients which cause mal-function of the sophisticated equipment's. In other words the "power quality" is a nonstop dynamic variation both in time and space. The concern over quality of power has been increasing rapidly as the present life requires a continuous supply of electrical energy. Similarly, the continuous increase of load demand both in the public sectors as well as the industries has made the PQ a serious issue. The presence of disturbances in the loads is responsible for the deviation of the voltage and the current from the ideal waveform. This declines the performance and the lifespan of equipment's and also creates instability in the system. Hence, the healthy power system operation requires continues supervision, proper monitoring and the optimum control in terms of power quality improvement.
Moreover, the quality of electricity has become an important issue for both the utilities and the end users. The increased use of non-linear loads has made the PQ a pressing issue for the power system engineers unlike some years ago when the loads were linear. Hence, the issue of PQ has become more and more important with each passing day. The proper assessment of the active power, the apparent power and the reactive power is a significant issue in many applications such as the industry, the project, public sector etc. Hence, the improvement of PQ requires proper detection and localization of sources and the cause of disturbances. However, it is aimed at improving PQ with a fast detection and classification technology.

1.2 Power Quality Issues

The power quality is the interaction of the electrical power with the electrical equipment's. In other words, the power quality issue can be defined as "Any power problem manifested in voltage, current or frequency deviations that results in failure or mal-operation of the customer equipment"[1]. However, a disturbance in voltage very often causes a disturbance in current. Hence, PQ includes two aspects such as the quality of voltage and the quality of current. As there is no control over the current that particular loads draw, the power supply can only control the quality of the voltage. However, PQ term used to describe the electric power which drives the electrical load and the loads ability to function properly. The insufficiency of the proper power leads either to malfunction or permanent failure of the electrical equipment's. The poor quality

power also reduces the life span of the electrical equipment's. There are many factors which causes the poor power quality.

According to the International Electro technical Commission (IEC), the power quality is the set of parameter which defines the properties of quality of power as delivered to the end users in normal operating condition. In other words the PQ is the continuity and characteristics of the supply voltage in terms of frequency, magnitude and symmetry[2]. Similarly, PQ is the concept of providing power and grounding of the electronic equipment in such a manner that it can be suitable for the operation and comparable with the wiring system as well as other equipment's in Institute of Electrical and Electronics Engineers (IEEE) Standard[3].

1.3 Types of Power Quality Disturbance Signals

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

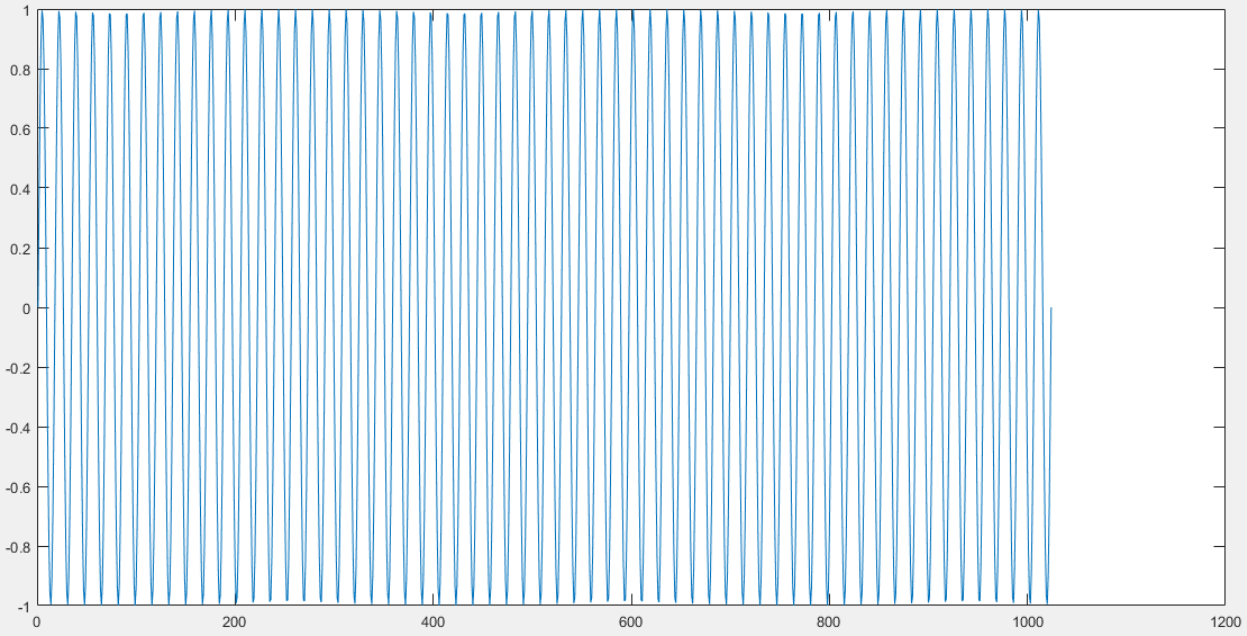


Figure 1.1: Normal Signal

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

1.3.1 Voltage Sag

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

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

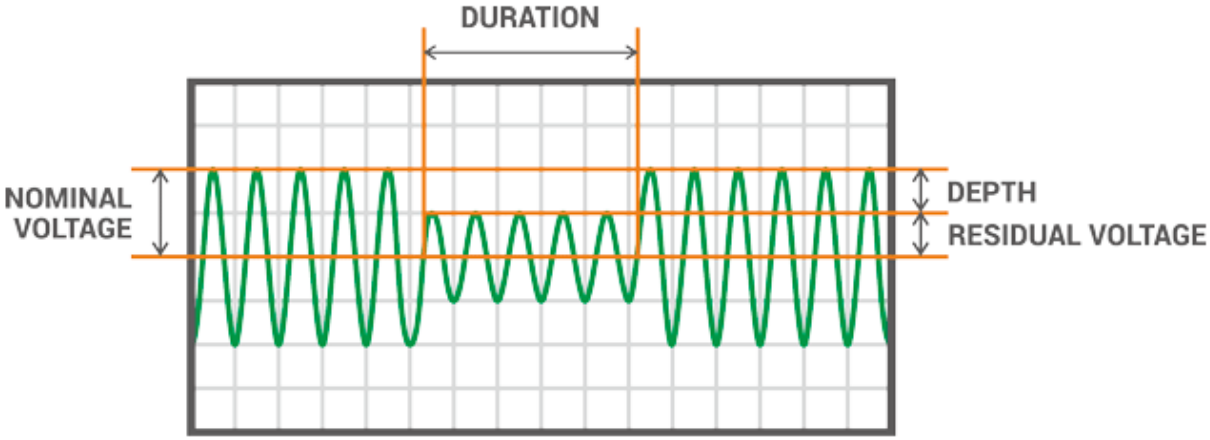


Figure 1.2: Voltage Sag

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

1.3.2 Voltage Swell

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

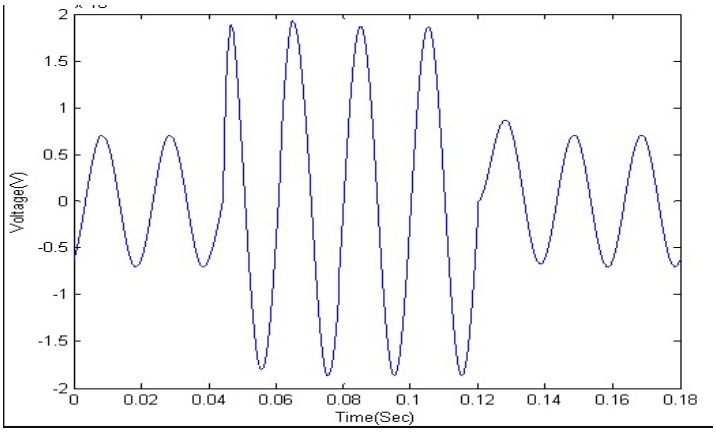


Figure 1.3: Voltage Swell

Main causes of voltage swells include energizing of capacitor banks, shutdown of large loads, unbalanced faults, transients and power frequency surges.
It causes problems with equipment that require constant steady-state voltage. Long-duration voltage variations can be seen in this case.

1.3.3 Voltage Interruption

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

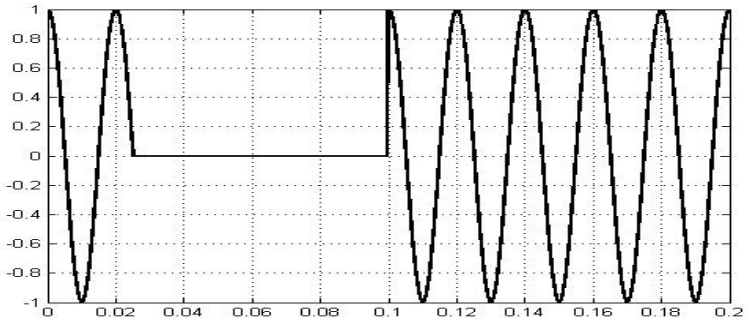


Figure 1.4: Voltage Interruption

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.

1.3.4 Flicker

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

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

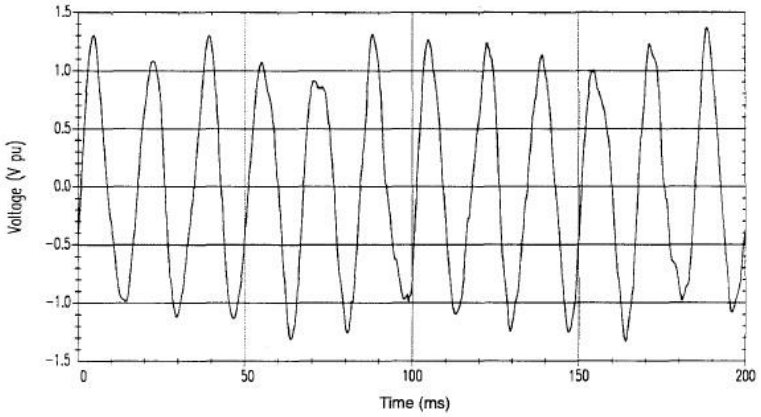


Figure 1.5: Voltage Flicker

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

1.3.5 Voltage Transient

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

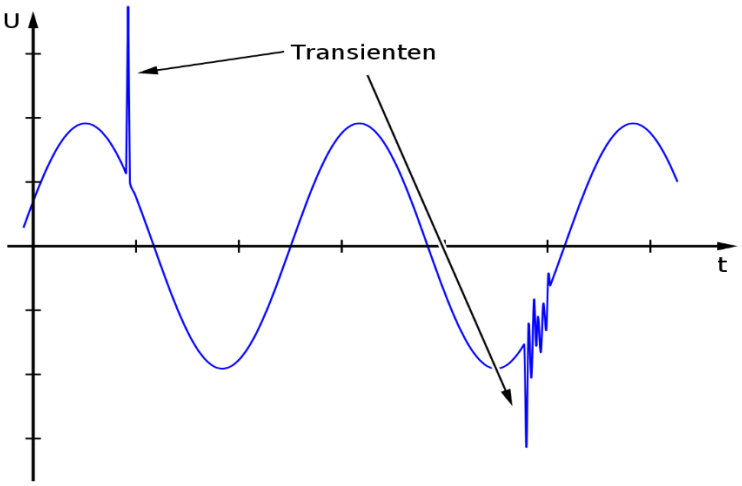


Figure 1.6: Voltage Transient

Main causes for transients are switching on secondary systems, Lightning-induced ringing, Local Ferro resonance etc. Transients with high voltage magnitudes cause insulation breakdown in the power system and transients with high current magnitudes can burn out devices and instruments. Other effects of transients include mal-operation of relays, mal-tripping of circuit breakers,

radiated noise may disrupt sensitive electronic equipment and Voltage magnification at customer capacitors.

1.3.6 Harmonics

Either voltage or current may be distorted by harmonics. When nonlinear loads are connected to normal sinusoidal voltage, the current waveform gets distorted. The distorted current waveform is made up of fundamental sine wave or first order 50Hz current and multiple frequency currents such as 100 Hz, 150 Hz. The harmonic current will then travel upstream, away from the nonlinear loads that produced them and towards the utility source. This will distort the voltage at other nodes separated by appreciable impedance. If the voltage distortion is high, they may affect other power consumers. At low voltage distortion, they will still affect other power system elements and other electrical circuits that are in parallel with the power circuits in the plant that generated them. Nonlinear loads such as computers, laser printers, welders, variable frequency drives, UPS systems, fluorescent lighting, etc., usually have diode-capacitor power supplies at the front end. They draw current in short pulses during the peak of the line voltage thus introducing harmonics. Harmonics in general are often caused by operation of rotating machines, arcing devices, semiconductor based power supply systems, converter-fed AC drives, thyristor controlled reactors, phase controllers, and AC regulators, as well as magnetization nonlinearities of transformers.

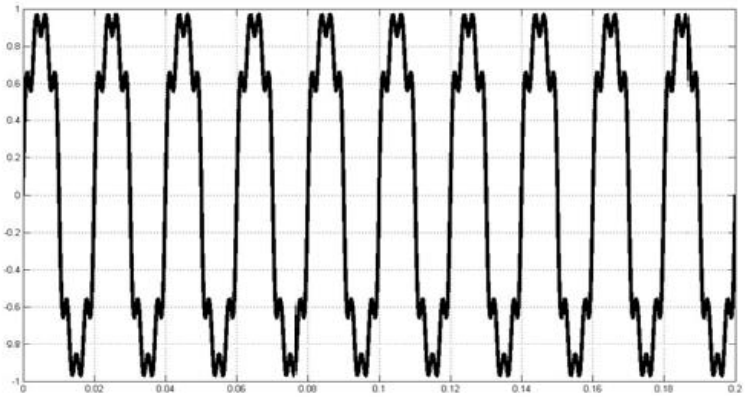


Figure 1.7: Voltage Harmonics

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

1.3.7 Sag with Harmonics

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

seen for this distortion.

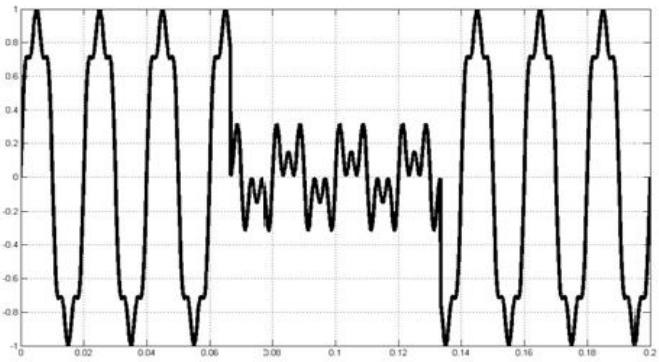


Figure 1.8: Voltage Sag with Harmonics

1.3.8 Swell with Harmonics

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

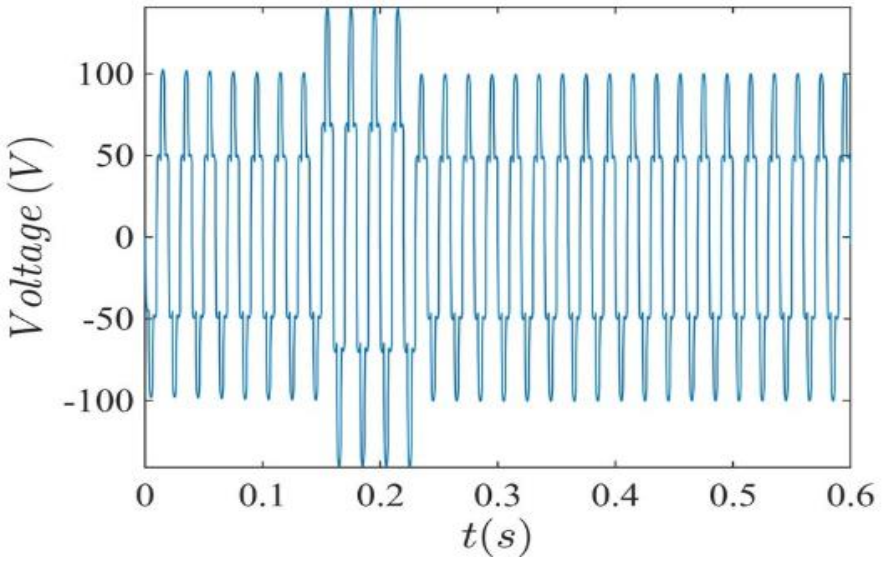


Figure 1.9: Voltage Swell with Harmonics

1.3.9 Notch

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

This event causes negative operational effects, such as signal interference introduced into logic and communication circuits. Also, when of sufficient power, the voltage notching effect may

overload electromagnetic interference filters, and other similar high-frequency sensitive capacitive circuits.

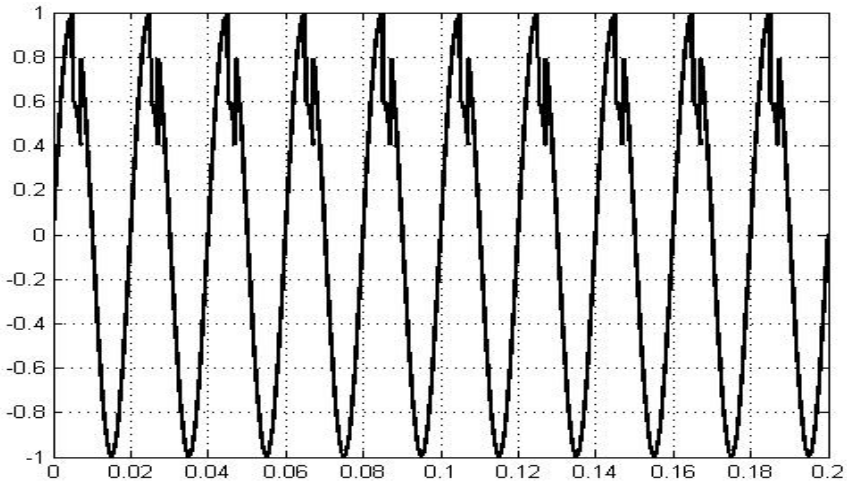


Figure 1.10: Voltage Notch

1.4 Importance of the classification of Power Quality Disturbances

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

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

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

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

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

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

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

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

1.5 Difficulties in classification of Power Quality Disturbances

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

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

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

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

- Another issue of concern is the number of decomposition level required to avoid possible loss of some important information and to have accurate classifier since PQ disturbances cover a wide range of frequency.

- Effort should be aimed at incorporating knowledge and expertise of power system engineers in statistical classifiers also.

- To properly monitor the PQ events, the power quality monitors are installed in the system. Since, it is not possible to install the PQ monitor at all the nodes in the system due to

technical and economical reasons, the optimal number of monitoring devices are to be placed in the system to get complete information about the PQ events.

- Most of the studies have done training and testing on synthetic data. There-fore, accumulation of a comprehensive standard PQ database similar to that of many other signal processing fields, for testing and comparisons of the state of the art techniques are also needed.

- Noise present in the signal has been a major hurdle in the accurate feature extraction and classification of PQ events.

1.6 Problem Definition

The increasing pollution of power signals and its impact on the power quality supplied by power plants to customers are pushing forward the development of signal processing tools to monitor and control of PQ disturbances. Recently, for the detection, localization and classification of PQ disturbances, researchers become interested to use efficient and appropriate signal processing methods that always try to model all information into a set of features from where decision making becomes easier and more accurate than the conventional methods of visual inspection [4-6]. Most of the signal processing techniques reported in the literature use time, frequency and time-frequency domain representation of the PQ disturbance waveforms, on the basis of which many specific features are derived in order to classify different types of PQ disturbances. The most difficult problem faced by today's PQ disturbances classification method is the large variation in the morphologies of PQ disturbance waveforms. It is to be noted that methods capable of classifying PQ disturbances in stringent conditions, such as multiclass PQ [7]disturbances, and presence of noise have been limitedly reported. Thus, in order to handle the practical situations of real life applications as mentioned above, development of a method with an effective feature set for multiclass PQ disturbances classification that is capable of providing performance with greater accuracy with simplicity in computation is indeed a difficult problem[8, 9].

1.7 Objective of the Thesis

- To synthesize different types of power quality disturbance signals and propose simple, suitable and fast analysis technique in order to detect and localize the disturbances.
- To extract suitable features from the signal analysis and propose a fast automatic classifier in order to classify large classes of data set. The testing of the proposed method in the noisy environment.
- To implement the proposed detection and the classification methods in real time environment for validating its suitability.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction:

Poor power quality (PQ) may cause some major problems to the use of the electronic equipment and furthermore may damage its efficiency and lifespan. The main reason of poor PQ is the disturbance events created along power line, such as voltage sag, voltage swell, voltage harmonics, voltage impulse, and interruption.[10] There are a lot of PQ disturbance sources, such as adjustable speed drivers, electronic lamps blasts, power supplies, green energy devices like LED, and so on.

In smart grid (SG), power quality disturbance detection is a very big issue since various and incompatible power resources are connected together over the power grid. Voltage sags are caused by abrupt increase in load or source impedance. Voltage swells are induced by abrupt reduction in load, by lightening, faulting in circuits, or switching of capacitors. Harmonic current may be induced due to various non-linear loads. Also the fault clearing and utility switching often create various disturbances which degrade PQ. Hence, the mitigation of these disturbances becomes a big concern, even after the introduction of SG utilizing various kinds of power resources[11]. Until now, for the PQ disturbance detection, Fourier transform (FT), short-term Fourier transform (STFT), neural networks (NN), and wavelet transform (WT) have been used. However, FT is not a reliable tool for the analysis of PQ events because it deals with only spectral information of signal such that the starting and ending time of PQ disturbances appearing along the time axis is not well monitored. Furthermore, FT does not work well for nonstationary signals like PQ disturbances. STFT, also called windowed FT, is reliable for stationary signals and overcomes the limitations of FT by segmenting the signal into narrow time intervals but cannot simultaneously provide good frequency and time resolutions. NN is typically used with the WT, especially for the classification of disturbance patterns. WT has two favorable characteristics over FT and STFT. First, WT allows simultaneous signal localization in time and frequency domain. Second, WT is able to separate the fine details representing transient signal components from coarse details such that the PQ disturbance detection is easily performed. For the time frequency analysis of non-stationary signals, WT is more suitable because it provides time information along with spectral information. Discrete WT (DWT) is better for the PQ disturbance detection because it provides a flexible window where time-frequency variations are easily detectable. For the evaluation of the PQ detection, we generate various PQ disturbance signals including voltage sag, voltage swell, interruption, and the combined effect of sag-harmonics or swell-harmonics, on the basis of IEEE-1159 standard [12].

2.2 Architecture of Automatic Classification of Power Quality Disturbances

2.2.1 Understanding the sources of power-quality disturbances:

Poor power quality can cause innumerable problems in industrial facilities. While a facility owner's first inclination might be to blame their electric utility for such problems, it's much more likely that their own equipment is it fault. In fact, it's generally accepted that up to 80% of power disturbances originate within facilities, rather than from utility-supplied electricity.[13]

Industrial facilities are particularly prone to power-quality problems because of the density and complexity of electrical equipment involved in their daily operations.

What to look for

Certainly, improper wiring, defective equipment and installation or operation errors play a role in such disturbances. However, there are also specific devices common to industrial plants that can cause power quality issues just through their everyday use.

Electric motors

Electric motors are everywhere in many modern industrial plants, comprising up to 80% of facilities' electrical load in some industries, and they also can be the cause of several types of power-quality problems commonly seen in these operations. These problems can include:

Voltage sags can result in local or adjacent areas from the direct starting of large electric motors, either individually or in groups.[14]
Harmonics can be generated by saturation of the magnetic core of electric motors.
Low power factor – at rates of 0.85 to 0.90 at full load, down to 0.35 at no-load – can be created by the reactive energy required by induction motors.

Variable speed drives

Variable speed drives (VSDs) have become go-to devices for facilities seeking to improve the efficiency of induction motors. Common applications include variable-torque centrifugal fans, pumps conveyors and compressor. However, VSDs also have become a major source of harmonic distortion if they aren't associated with a harmonic filtering solution.

Lighting systems

Lighting typically represents between 5% and 8% of an industrial facility's electrical load. Power-quality problems associated with this equipment can include:

Harmonics, which can be caused by energy-efficient compact fluorescent lamps (CFLs).
Low power factor resulting from fluorescent high-intensity discharge lamps and CFLs.
Harmonic distortion and a power factor less than 1 also can be caused by increasingly popular high-efficiency LED lighting.

Transformers
Transformers are critical pieces of equipment in industrial plants, given the high volumes of electricity that can be moved around such facilities. They also can compromise power quality through such problems as:

Harmonics resulting from saturation of their magnetic core.
Low power factor, which can follow from their need for reactive energy. The reactive power absorbed by a transformer can total up to 5% of its rating at full load.

Capacitors
While they don't, themselves, create harmonics, capacitors can create resonance that can amplify the magnitudes of harmonic voltages and currents. For this reason, a project-specific study should be done to properly size the reactive power compensation system. Additionally, capacitor-bank switching can cause small voltage transients, usually with no impact on the system.

Uninterruptible Power Supplies (UPS)
Old-generation UPS were characterized by significant harmonic distortion. In new generation UPS the total harmonic distortion is reduced. However, attention should be paid to the high frequency harmonics these devices may generate.

Office Equipment
Business and office equipment based on power electronics, such as PCs, copiers and printers, draw a non-sinusoidal current and are a source for harmonic distortion.

2.2.2 Feature Extraction
At the point when the information to a calculation is too enormous to possibly be handled and it is suspected to be repetitive (for example a similar estimation in the two feet and meters) at that point the information will be changed into a diminished portrayal set of highlights (likewise named highlights vector). Changing the information into the arrangement of highlights is called Highlight Extraction. In the event that the highlights separated are painstakingly picked, it is normal that the highlights set will remove the important data from the info information to play out the ideal assignment utilizing this decreased portrayal rather than the full-size information. Highlight extraction is performed on crude information preceding applying the k-NN calculation on the changed information to include space.

2.2.3 Classification Techniques
The K-NN algorithm is a nonparametric method in that no parameters are estimated as, for example, in the multiple linear regression model. Instead, the proximity of neighboring input (x) observations in the training data set and their corresponding output values (y) are used to predict (score) the output values of cases in the validation data set. These output variables can either be interval variables in which case the KNN algorithm is used for prediction while if the output variables are categorical, either nominal or ordinal, the K-NN algorithm is used for classification purposes.

2.2.4 Feature Selection Stage

The algorithm can be summarized as:

1. A positive integer k is specified, along with a new sample
2. We select the k entries in our database which are closest to the new sample
3. We find the most common classification of these entries
4. This is the classification we give to the new sample

A few other features of KNN:

- KNN stores the entire training dataset which it uses as its representation.
- KNN does not learn any model.
- KNN makes predictions just-in-time by calculating the similarity between an input sample and each training instance.

2.3 Categories of Power Quality Disturbances:

2.3.1 Transient disturbances

Transients are power quality disturbances that involve destructive high magnitudes of current and voltage or even both.[15] It may reach thousands of volts and amps even in low voltage systems. However, such phenomena only exist in a very short duration from less than 50 nanoseconds to as long as 50 milliseconds. This is the shortest among PQ problems, hence, its name. Transients usually include abnormal frequencies, which could reach to as high as 5 MHz.

In addition, transients[15] are also known as surge. According to IEEE 100, surge is a transient wave of voltage, current or power in an electric circuit. Other IEEE definitions suggest that it is the part of the change in a variable that disappears during transition from one steady-state operating condition to another. Such description is too vague, which could be used to describe just about any unusual events occurring in the electrical system. Moreover, most electrical engineers would refer to the damped oscillatory transient phenomena in a RLC[16] circuit when hearing such term.

Effects of Transients:

Electronic Equipment

- Equipment will malfunction and produces corrupted results[15]
- Improper specification and installation of TVSS can aggravate the failures
- Efficiency of electronic devices will be reduced

Motors

- Transients will make motors run at higher temperatures
- Result in micro-jogging leading to motor vibration, excessive heat and noise
- Degrades the insulation of the motor winding resulting to equipment failure.
- Increases the motor's losses (hysteresis) and its operating temperature[15]

Lights

- Fluorescent bulb and ballast failure
- Appearance of black rings at the fluorescent tube ends (indicator of transients)[15]
- Premature filament damage leading to failure of the incandescent light.

Electrical Equipment

- Transients degrade the contacting surfaces of circuit breakers and switches
- Nuisance tripping of breakers due to false activation to a non-existent current demand
- Reduce transformer efficiency because of increased hysteresis losses[15]

Damages due to such PQ problems are uncommon as compared to voltage sags and interruptions, but when it does occur it is more destructive. To protect against transients, end-users may use Transient Voltage Surge Suppressors (TVSS), while utilities install surge arresters.[17]

2.3.2 Short-Duration Disturbances

PQ problems deal with events lasting for short duration, typically from less than one cycle to few seconds. The sources of poor PQ[18] are power line disturbances such as voltage sags, swells, interruptions, impulses, outages and harmonic distortion. To improve the PQ, various types of equipment are used[19]. Detection and classification of short and long duration disturbances in power system has been proposed in[20] by Zaid, Malik Muhammad, Malik, Muhammad Usama, Bhatti, Muhammad, Sibtain, Razzaq, Hamid, Aslam, Muhammad Umair. Symmetrical components-based modified technique for power-quality disturbances detection and classification has been proposed in[21] by Shahani, DT.

2.3.3 Long Duration Disturbances

Detection of power quality disturbances using wavelet transform technique has been proposed in[22] by Lachman. Detection and classification of short and long duration disturbances in power system has been proposed in[20] by Zaid, Malik Muhammad, Malik, Muhammad Usama, Bhatti, Muhammad, Sibtain, Razzaq, Hamid, Aslam, Muhammad Umair.

2.3.4 Voltage Unbalance

Voltage unbalance is a condition in which the three-phase voltages differ in amplitude or are displaced from their normal 120° phase relationship. Negative-phase sequence (NPS) unbalance appears in networks supplying such single-phase loads as modern 25 kV traction systems. G Burchi, C Lazaroiu, N Golovanov presented ‘Estimation of voltage unbalance in power systems supplying high speed railway’[23]. MJ Ortega, JC Hernández, OG García presented ‘Measurement and assessment of power quality characteristics for photovoltaic systems: harmonics, flicker, unbalance, and slow voltage variations’[24]. R Omar, NA Rahim presented ‘Voltage unbalanced compensation using dynamic voltage restorer based on supercapacitor’[25].

2.3.5 Waveform Distortion Disturbances

A waveform distortion is any power quality variation affecting the wave shape of the voltage or current. There are five primary types of waveform distortion: direct current offset, harmonic distortion, interharmonics, notching and noise. To varying degrees, they can all cause damage or disruption to IT equipment.[26]

2.3.5.1 Direct current offset

Direct current offset occurs as a result of two natural laws: Current cannot change instantaneously in an inductance and. Current must lag the applied voltage by the natural power-factor. MA Nitsche, W Paulus presented Excitability changes induced in the human motor cortex by weak transcranial direct current stimulation[27]. Blood, Ernest B presented 'Device for quantitatively measuring the relative position and orientation of two bodies in the presence of metals utilizing direct current magnetic fields'[28].

2.3.5.2 Harmonics

Harmonics are unwanted higher frequencies which superimposed on the fundamental waveform creating a distorted wave pattern. In an AC circuit, a resistance behaves in exactly the same way as it does in a DC circuit. That is, the current flowing through the resistance is proportional to the voltage across it. J Barros, RI Diego, M De Apraiz presented 'Applications of wavelet transform for analysis of harmonic distortion in power systems: A review'[29]. VL Pham, KP Wong presented 'Antidistortion method for wavelet transform filter banks and nonstationary power system waveform harmonic analysis'[30]. MJ Ortega, JC Hernández, OG Garcia presented 'Measurement and assessment of power quality characteristics for photovoltaic systems: harmonics, flicker, unbalance, and slow voltage variations'[24].

2.3.5.3 Inter-harmonics and sub-harmonics

Power signals can also contain components which have frequencies which are non-integer multiples of the fundamental frequency. These components are referred to as inter-harmonics. Sub-harmonics are components of a power signal which have a frequency that is a fraction of the fundamental frequency.[31] Y Zhang, G Jin, T Li presented A Method to Detect Fundamental Component by Symmetrical Component under Inter-Harmonics[32]. S DENG, L LUO, Y Li, J SHI, Y LIANG presented Characteristic analysis on inter-harmonics and sub-harmonics in the new type of industry converting system[33].

2.3.5.4 Periodic notch

A periodic voltage disturbance caused by line-commutated thyristor circuits is called notching. The notching appears in the line voltage waveform during normal operation of power electronic devices when the current commutates from one phase to another. The notching appears in the line voltage waveform during normal operation of power electronic devices when the current commutates from one phase to another. During this notching period, there exists a momentary short-circuit between the two commutating phases, reducing the line voltage; the voltage reduction is limited only by the system impedance.

Notching is repetitive and can be characterized by its frequency spectrum. The frequency of this spectrum is quite high. Usually it is not possible to measure it with equipment normally used for harmonic analysis. Notches can impose extra stress on the insulation of transformers, generators,

and sensitive measuring equipment. E Fuchs, MAS Masoum presented 'Power quality in power systems and electrical machines'[34]. M Malekpour, M Farshadnia presented 'Monitoring and measurement of power quality indices using an adaptive notch filter'[35]. M Mojiri, AR Bakhshai presented 'An adaptive notch filter for frequency estimation of a periodic signal'[36].

2.3.5.5 Noise

Noise is a high-frequency distortion of the voltage waveform caused by disturbances on the utility system or by equipment such as welders, switchgear and transmitters. Noise frequently goes unnoticed. Frequent or high levels of noise can cause equipment malfunction, overheating, and premature wear.[37]

2.3.6 Voltage Fluctuation Or Flicker

Voltage Fluctuations are described by IEEE as systematic variations of the voltage waveform envelope, or a series of random voltage changes, the magnitude of which falls between the voltage limits set. Generally, the variations range from 0.1% to 7% of nominal voltage with frequencies less than 25 Hz. Subsequently, the most important effect of this power quality problem is the variation in the light output of various lighting sources, commonly termed as Flicker. This is the impression of instability of the visual sensation brought about by a light stimulus, whose luminance fluctuates with time. Voltage fluctuation and light flicker are technically two distinct terms, but have been erroneously referred to the same meaning. Aggravating the confusion is the use of the expression "voltage flicker", which does not actually exist, even though it is often heard. In fact, IEEE has cautioned on the incorrect usage of these terms.[38]

Nevertheless, voltage fluctuation and flicker are closely related to each other. This is because flicker is derived from the impact of voltage fluctuation on lighting intensity due to large loads that have rapidly changing active and reactive power demand. In fact, voltage variations as low as 0.5% could result in perceptible light flicker if the frequencies are in the range of 6 to 8 Hz. In other words, voltage fluctuation is the response of the power system to fast changing loads. On the other hand, light flicker is the response of the lighting system to such load variations as observed by the human eye. Moreover, International standards have been developed for characterizing the voltage fluctuations based on the potential effects on lighting and the human perception of the lighting variations. MJ Ortega, JC Hernández, OG García presented 'Measurement and assessment of power quality characteristics for photovoltaic systems: harmonics, flicker, unbalance, and slow voltage variations'[24]

2.3.7 Power Frequency Variations

Power frequency varieties are a deviation from the ostensible inventory frequency. The stockpile frequency is a component of the rotational speed of the generators used to create the electrical vitality. At any moment, the frequency relies upon the harmony between the heap and the limit of the accessible age.

2.4 Signal Processing Techniques For Feature Extraction:

2.4.1 Fourier Transform

The Fourier transform (FT) decomposes a function of time (a signal) into its constituent frequencies. This is similar to the way a musical chord can be expressed in terms of the volumes and frequencies of its constituent notes.[39] The most used classical signal processing is the Fourier transform (FT). This transform represents a signal as a sum of sinusoidal terms of different frequencies, named frequency spectrum[40]. This technique is suitable for stationary signals and extracting spectrum components of the signals at specific frequencies, but it is not efficient when the signal contains short-term transient disturbances[41]. P. Kailasapathi et al.[42] described that FT can be applied to both continuous signal and discrete signal. It can be either periodic or aperiodic. Anton et al.[43] presented that the FT based signal processing techniques are Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT).

The DFT is the widely used discrete signal processing algorithm. An approach to compute the DFT is to use a recursive computation scheme. The most popular approach is the Goertzel's Algorithm. Goertzel algorithm is used to implement the non-uniform discrete fourier transform[44]. Rosendo et al.[45] described that in the windowed discrete Fourier transform (WDFT), the amplitude for any given spectral component of the DFT gives the average of windowed tie series. The choice of window size is, however, completely arbitrary.

An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the only difference is that an FFT is much faster. The radix is the size of FFT decomposition. Radix-2, radix-4, radix-8, spilit radix are the types of radix. The FFT algorithms are found to be more accurate than evaluating the DFT definition direct computation when round-off error is present[46].

The STFT is the classical method of time frequency analysis. It is a Fourier related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. In essence, STFT extracts several frames of the signal to be analyzed with a window that moves with time. If the time window is sufficiently narrow, each frame extracted can be viewed as stationary so that Fourier transform can be used. With the window moving along the time axis, the relation between the variance of frequency and time can be identified [47-49]. Non-stationary signals characterized by wide range of frequency spectrum with transient and sub-harmonic components are difficult to analyze with STFT[50]. For non-stationary signals, the STFT does not track the signal dynamics properly due to the limitations of a fixed window width chosen a priority[48].

2.4.1.1 Discrete fourier transform

In mathematics, the discrete Fourier transform (DFT) converts a finite sequence of equally-spaced samples of a function into a same-length sequence of equally-spaced samples of the discrete-time Fourier transform (DTFT), which is a complex-valued function of frequency. The interval at which the DTFT is sampled is the reciprocal of the duration of the input sequence. An inverse DFT is a Fourier series, using the DTFT samples as coefficients of complex sinusoids at the corresponding DTFT frequencies. It has the same sample-values as the original input sequence. The DFT is therefore said to be a frequency domain representation of the original input sequence. If the original

sequence spans all the non-zero values of a function, its DTFT is continuous (and periodic), and the DFT provides discrete samples of one cycle. If the original sequence is one cycle of a periodic function, the DFT provides all the non-zero values of one DTFT cycle.

The DFT is the most important discrete transform, used to perform Fourier analysis in many practical applications. In digital signal processing, the function is any quantity or signal that varies over time, such as the pressure of a sound wave, a radio signal, or daily temperature readings, sampled over a finite time interval (often defined by a window function). In image processing, the samples can be the values of pixels along a row or column of a raster image. The DFT is also used to efficiently solve partial differential equations, and to perform other operations such as convolutions or multiplying large integers.

Since it deals with a finite amount of data, it can be implemented in computers by numerical algorithms or even dedicated hardware. These implementations usually employ efficient fast Fourier transform (FFT) algorithms;[3] so much so that the terms "FFT" and "DFT" are often used interchangeably. Prior to its current usage, the "FFT" initialism may have also been used for the ambiguous term "finite Fourier transform".

2.4.1.2 Fast Fourier Transform

A fast Fourier transform (FFT) is an algorithm that computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IDFT). Fourier analysis converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa. The DFT is obtained by decomposing a sequence of values into components of different frequencies. This operation is useful in many fields, but computing it directly from the definition is often too slow to be practical. An FFT rapidly computes such transformations by factorizing the DFT matrix into a product of sparse (mostly zero) factors. As a result, it manages to reduce the complexity of computing the DFT from $O(N^2)$, which arises if one simply applies the definition of DFT, to $O(N \log N)$ where N is the data size. The difference in speed can be enormous, especially for long data sets where N may be in the thousands or millions. In the presence of round-off error, many FFT algorithms are much more accurate than evaluating the DFT definition directly or indirectly. There are many different FFT algorithms based on a wide range of published theories, from simple complex-number arithmetic to group theory and number theory.

The best-known FFT algorithms depend upon the factorization of N, but there are FFTs with $O(N \log N)$ complexity for all N, even for prime N. Many FFT algorithms only depend on the fact that $e^{-2\pi i/N}$ is an N-th primitive root of unity, and thus can be applied to analogous transforms over any finite field, such as number-theoretic transforms. Since the inverse DFT is the same as the DFT, but with the opposite sign in the exponent and a $1/N$ factor, any FFT algorithm can easily be adapted for it.

2.4.1.3 Shot-time fourier transform

The short-time Fourier transform (STFT), is a Fourier-related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. In practice, the procedure for computing STFTs is to divide a longer time signal into shorter segments

of equal length and then compute the Fourier transform separately on each shorter segment. This reveals the Fourier spectrum on each shorter segment. One then usually plots the changing spectra as a function of time.[51]

2.4.2 Kalman Filter

In statistics and control theory, Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe. The filter is named after Rudolf E. Kálmán, one of the primary developers of its theory.

The Kalman filter has numerous applications in technology. A common application is for guidance, navigation, and control of vehicles, particularly aircraft, spacecraft and dynamically positioned ships. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics. Kalman filters also are one of the main topics in the field of robotic motion planning and control, and they are sometimes included in trajectory optimization. The Kalman filter also works for modeling the central nervous system's control of movement. Due to the time delay between issuing motor commands and receiving sensory feedback, use of the Kalman filter supports a realistic model for making estimates of the current state of the motor system and issuing updated commands[52].

The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. The algorithm is recursive. It can run in real time, using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required.

Extensions and generalizations to the method have also been developed, such as the extended Kalman filter and the unscented Kalman filter which work on nonlinear systems. The underlying model is similar to a hidden Markov model except that the state space of the latent variables is continuous and all latent and observed variables have Gaussian distributions. Also, Kalman filter has been successfully used in multi-sensor fusion[4], and distributed sensor networks to develop distributed or consensus Kalman filter.

The Kalman filter keeps track of the estimated state of the system and the variance or uncertainty of the estimate. The estimate is updated using a state transition model and measurements. denotes the estimate of the system's state at time step $\boldsymbol{k}$ before the $\boldsymbol{k}$-th measurement $\boldsymbol{y}_k$ has been taken into account; is the corresponding uncertainty.

2.4.3 Wavelet Transform

A wavelet transform (WT) is the decomposition of a signal into a set of basis functions consisting of contractions, expansions, and translations of a mother function $\psi(t)$, called the wavelet. Wavelet Transform (WT) is used as a feature extraction tool to identify power quality disturbances.[53] The wavelet transform traces the signal changes in time domain and simultaneously decomposes the signal in frequency domain. In the wavelet transform based approach, a mother wavelet is employed for finding the wavelet coefficients of the signal which affects the effectiveness in identifying the disturbance present in the signal.[54] The mathematics of wavelet transform was extensively studied and can be referred in papers[55] & .[56] Wavelet transforms are classified into discrete wavelet transform (DWT) and continuous wavelet transforms (CWT). Lalit Behera et al.[57] presented the theory of CWT and DWT and used DWT for time series data mining of power quality events occurring due to power signal disturbances. The wavelet transform has been introduced as powerful tool for voltage flicker signal extraction and harmonic detection[58]. The main disadvantage of WT is its batch processing, which in turn, results in some delay. Feature extraction technique using the standard deviation of the wavelet coefficients is discussed in[59]. Perumal et al.[6] employed multi-resolution analysis (MRA) based modified wavelet transforms for detection and classification of power quality disturbance waveform. The use of continuous wavelet transform (CWT) to analyze non-stationary harmonic distortion has been proposed in.[60] Classification of power quality disturbances using Wavelet Transform and Optimized ANN has been proposed in[61] by Ijaz, Muhammad, Shafiullah, Md.Abido, MA.

2.4.3.1 Wavelet Transform for Disturbance Detection

The wavelet transform is a signal processing algorithm which is useful in detection of abnormal operating conditions[62] based on decomposition of the power signals into different ranges of frequencies by the help of a series of low-pass and high-pass filters.

This usually provides us a time-frequency multi-resolution analysis that greatly useful for identifying any short of abrupt variations in the electrical parameters such as voltage, phase, current, frequency etc.[63]

2.4.3.2 Discrete wavelet transform for feature extraction

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled.

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules.[64] The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules.

2.4.3.3 Wavelet neural network

Wavelet neural networks combine the theory of wavelets and neural networks into one. A wavelet neural network[65] generally consists of a feed-forward neural network, with one hidden layer, whose activation functions are drawn from an orthonormal wavelet family.

2.4.3.4 Wavelet packet transform

Originally known as Optimal Subband Tree Structuring (SB-TS) also called Wavelet Packet Decomposition (WPD) (sometimes known as just Wavelet Packets or Subband Tree) is a wavelet transform where the discrete-time (sampled) signal is passed through more filters than the discrete wavelet transform (DWT).

Optimal feature selection for classification of power quality disturbances using wavelet packet-based fuzzy k-nearest neighbour algorithm.[66]

2.4.4 Stockwell-Transform

Stockwell et al.[67] introduced the S-Transform (ST) to track the dynamics properly. The S-transform is a time-frequency spectral localization method, similar to the STFT and continuous wavelets. The S-transform is conceptually a hybrid of STFT and wavelet analysis, bridges the gap between them, containing elements of both but having its own characteristic properties. Just like the STFT, the S-transform uses a window to localize the complex Fourier sinusoid, but unlike the STFT, the width and height of the window scale with frequency in analogy with wavelets. S-transform employs a moving and scalable localizing Gaussian window. It combines a frequency dependent resolution with simultaneous localizing the real and imaginary spectra[68, 69]. Leonowicz et al.[43] stated that the basic functions for the S-transform are Gaussian modulated cosinusoids whose width varies inversely with the frequency. Ming He Zhang et al.[70] employed S-Transform for the analysis and detection of power quality disturbances. Ameen M. Gargoom et al.[71] proposed the analysis of power quality events using amplitude and phase spectrum derived from the S-Transform of signal. Nguyen et al. [72] presented Discrete S-Transform (DST) for feature extraction. Yokeeswaran et al.[69] presented Discrete Orthogonal S-Transform (DOST) using time series for representation. The transformation matrix is orthogonal, meaning that the inverse matrix is equal to the complex conjugate transpose. An orthogonal transform is referred to as an energy preserving transform. R Kumar, B Singh, DT Shahani et al.[73] presented Recognition of single-stage and multiple power quality events using Hilbert–Huang transform and probabilistic neural network. Mahela, Om Prakash, and Abdul Gafoor Shaik et al. presented "Power quality recognition in distribution system with solar energy penetration using S-transform and Fuzzy C-means clustering." [74] A rule-based S-Transform and AdaBoost based approach for power quality assessment has been proposed in[75] by Reddy, Motakatla Venkateswara, Sodhi, Ranjana.

2.4.5 Hilbert-Huang Transform

The development of the Hilbert Huang Transform (HHT) was motivated by the need to describe nonlinear distorted waves in detail, along with the variations of these signals that naturally occur in nonstationary processes.[76] The Hilbert Huang Transform is an adaptive data analysis method designed for analyzing non-stationary signals. In HHT, the signal is decomposed into a finite small number of components, called Intrinsic Mode Functions (IMF). This process of decomposition is called Empirical Mode decomposition(EMD). The EMD decomposes the signal in terms of IMFs each of which is a mono-component function. A signal can be analyzed in details for its frequency, amplitude and phase contents by using EMD followed by HT[77]. The method has been applied to many important problems in various fields including medical[78], geophysics[79], and power

engineering[80]. Jayasree et al.[81] employed automated classification of power quality disturbances using HHT and RBF neural networks. Nilanjan Senroy et al.[82] presented an innovative algorithm of improved Hilbert Huang method based on masking signals for power quality applications. The rationale for the improvements is that the original EMD method is unable to separate frequency modes lying within one octave. The proposed method is shown to efficiently separate modes existing in distorted signals typically encountered in power quality applications. Elango et al.[43] presented performance comparisons of Back Propagation Algorithm (BPA) network and Radial Basis Function (RBF) network for power quality disturbance classification. Features are extracted from the electrical signals by using Hilbert Huang Transform. LI Peng, GAO Jing, XU Duo, W Chang presented Hilbert-Huang transform with adaptive waveform matching extension and its application in power quality disturbance detection for microgrid. With the significant improvement of microgrid technology, microgrid has gained large-scaleapplication. However, the existence of intermittent distributed generations, nonlinear loads and various electrical and electronic devices causes power quality problem in microgrid[83]. M Sahani, PK Dash[84] presented Automatic power quality events recognition based on Hilbert Huang transform and weighted bidirectional extreme learning machine.

2.5 Artificial Intelligence Techniques for Classification

A comprehensive overview on signal processing and artificial intelligence techniques applications in classification of power quality disturbances has been proposed in[10] by Khokhar, Suhail.

2.5.1 Artificial neural network

An artificial neural network is an interconnected group of nodes, inspired by a simplification of neurons in a brain. Here, each circular node represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another.[85]

2.5.1.1 Multi-Layer perceptron neural network

A multilayer perceptron (MLP) is a class of feedforward artificial neural network (ANN). The term MLP is used ambiguously, sometimes loosely to refer to any feedforward ANN, sometimes strictly to refer to networks composed of multiple layers of perceptrons (with threshold activation). Multilayer perceptrons are sometimes colloquially referred to as "vanilla" neural networks, especially when they have a single hidden layer.[86] An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable.

2.5.1.2 Radial basis function neural network

In the field of mathematical modeling, a radial basis function network is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks have many uses, including function approximation, time series prediction, classification, and system control. They were first formulated in a 1988 paper by Broomhead and Lowe, both researchers at the Royal Signals and Radar Establishment.[87]

2.5.1.3 Probabilistic neural network

A probabilistic neural network (PNN) is a feedforward neural network, which is widely used in classification and pattern recognition problems. In the PNN algorithm, the parent probability distribution function (PDF) of each class is approximated by a Parzen window and a non-parametric function. Then, using PDF of each class, the class probability of a new input data is estimated and Bayes' rule is then employed to allocate the class with highest posterior probability to new input data. By this method, the probability of mis-classification is minimized. This type of ANN was derived from the Bayesian network and a statistical algorithm called Kernel Fisher discriminant analysis.[88]

2.5.2 Support Vector Machine

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples.[89]

2.5.3 Fuzzy Expert System

A fuzzy expert system is a collection of membership functions and rules that are used to reason about data. Unlike conventional expert systems, which are mainly symbolic reasoning engines, fuzzy expert systems are oriented toward numerical processing.[90]

2.5.4 Neuro-Fuzzy Classifier

Neuro-fuzzy classification systems offer means to obtain fuzzy classification rules by a learning algorithm. It is usually possible to find a suitable fuzzy classifier by learning from data, but it can be hard to obtain a classifier that can be interpreted conveniently.[91]

2.6 Optimization Techniques for Feature Selection

In machine learning and statistics, feature selection, also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant features (variables, predictors) for use in model construction.[92]

2.6.1 Genetic Algorithm

A genetic algorithm is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation.[93]

2.6.2 Particle Swarm Optimization

In computational science, particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality.[94]

2.6.3 Ant Colony Optimization

An ant colony is the basic unit around which ants organize their lifecycle. The typical colony consists of one or more egg-laying queens, a large number of sterile females (workers, soldiers) and, seasonally, a large number of winged sexual males and females.[95]

In computer science and operations research, the ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. Artificial Ants stand for multi-agent methods inspired by the behavior of real ants. The pheromone-based communication of biological ants is often the predominant paradigm used.[96] Combinations of Artificial Ants and local search algorithms have become a method of choice for numerous optimization tasks involving some sort of graph, e.g., vehicle routing and internet routing. The burgeoning activity in this field has led to conferences dedicated solely to Artificial Ants, and to numerous commercial applications by specialized companies such as AntOptima.

2.6.4 Artificial Bee Colony Optimization

In computer science and operations research, the artificial bee colony algorithm (ABC) is an optimization algorithm based on the intelligent foraging behaviour of honey bee swarm, proposed by Derviş Karaboğa (Erciyes University) in 2005.[97]
In the ABC model, the colony consists of three groups of bees: employed bees, onlookers and scouts. It is assumed that there is only one artificial employed bee for each food source. In other words, the number of employed bees in the colony is equal to the number of food sources around the hive. Employed bees go to their food source and come back to hive and dance on this area. The employed bee whose food source has been abandoned becomes a scout and starts to search for finding a new food source. Onlookers watch the dances of employed bees and choose food sources depending on dances.[98]

2.7 Proposed k-NN Classification System

In pattern recognition, the k-nearest neighbors algorithm (k-NN)(k-means clustering.) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression:[99]

- In k-NN classification, the output is a class membership. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

- In k-NN regression, the output is the property value for the object. This value is the average of the values of k nearest neighbors.

k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification.
Both for classification and regression, a useful technique can be to assign weights to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor.
The neighbors are taken from a set of objects for which the class (for k-NN classification) or the object property value (for k-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

NM Khoa, DT Viet, NH Hieu proposed “Classification of power quality disturbances using wavelet transform and K-nearest neighbor classifier” in 2013.[100]

2.8 Summary

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

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

Methodology is the precise, hypothetical examination of the strategies applied to a field of study. It involves the hypothetical investigation of the assemblage of strategies and standards related with a part of information. Commonly, it envelops ideas, for example, ideal models (In science and reasoning, a worldview is a particular arrangement of ideas or thought designs, including speculations, investigate strategies, hypothesizes, and benchmarks for what establishes authentic commitments to a field.), hypothetical model, stages, and quantitative or subjective methods.

3.2 Proposed k-NN Algorithm

Definition: A k-nearest-neighbor is a data classification algorithm that attempts to determine what group a data point is in by looking at the data points around it.

Why we use: KNN is a non-parametric, apathetic learning calculation. Its motivation is to utilize a database where the information focuses are isolated into a few classes to foresee the order of another example point. Only for reference, this is "the place" KNN is situated in the calculation rundown of soul learn.

When we say a technique is non-parametric , it means that it does not make any assumptions on the underlying data distribution. In other words, the model structure is determined from the data. If you think about it, it's pretty useful, because in the "real world", most of the data does not obey the typical theoretical assumptions made (as in linear regression models, for example). Therefore, KNN could and probably should be one of the first choices for a classification study when there is little or no prior knowledge about the distribution data.

How works: KNN works by finding the distances between a query and all the examples in the data, selecting the specified number examples (K) closest to the query, then votes for the most frequent label (in the case of classification) or averages the labels (in the case of regression).

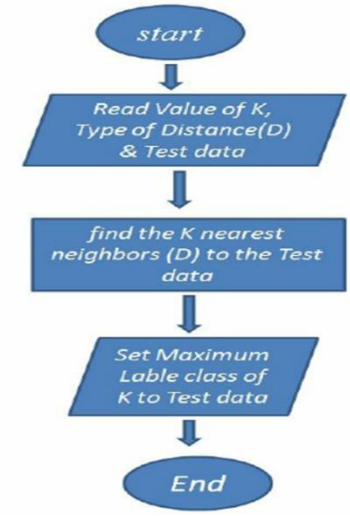


Figure: 3.1 Procedure flow chart of k-NN

KNN algorithm is one of the simplest classification algorithm and it is one of the most used learning algorithms. KNN is a non-parametric, lazy learning algorithm. Its purpose is to use a database in which the data points are separated into several classes to predict the classification of a new sample point.
KNN is also a lazy algorithm (as opposed to an eager algorithm). Does that mean that KNN does nothing. What this means is that it does not use the training data points to do any generalization. In other words, there is no explicit training phase or it is very minimal. This also means that the training phase is pretty fast . Lack of generalization means that KNN keeps all the training data. To be more exact, all (or most) the training data is needed during the testing phase.
KNN Algorithm is based on feature similarity: How closely out-of-sample features resemble our training set determines how we classify a given data point.
Example of k-NN classification. The test sample (inside circle) should be classified either to the first class of blue squares or to the second class of red triangles. If k = 3 (outside circle) it is assigned to the second class because there are 2 triangles and only 1 square inside the inner circle. If, for example k = 5 it is assigned to the first class (3 squares vs. 2 triangles outside the outer circle).

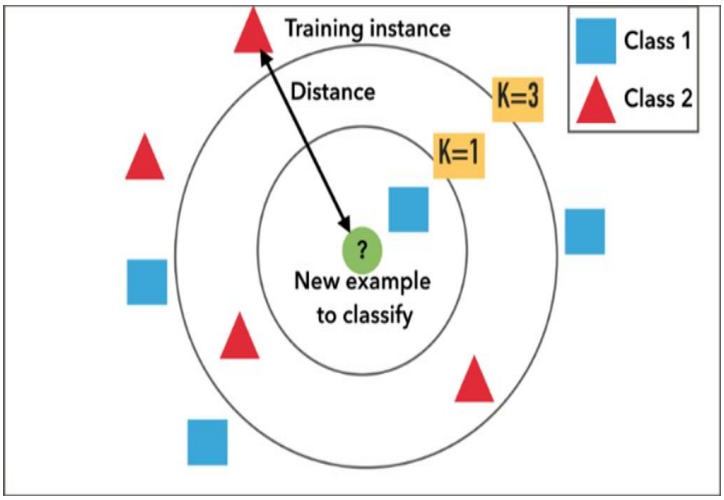


Figure: 3.2 Example of k-NN classification

KNN can be used for classification — the output is a class membership (predicts a class — a discrete value). An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors. It can also be used for regression — output is the value for the object (predicts continuous values). This value is the average (or median) of the values of its k nearest neighbors.

The algorithm can be summarized as:

- A positive integer k is specified, along with a new sample.
- We select the k entries in our database which are closest to the new sample.
- We find the most common classification of these entries.
- This is the classification we give to the new sample.

A few other features of KNN:

- KNN stores the entire training dataset which it uses as its representation.
- KNN does not learn any model.
- KNN makes predictions just-in-time by calculating the similarity between an input sample and each training instance.

3.3 Power Quality Data Generation

3.3.1 Mathematical Models of PQ Disturbances

Power Quality signals such as sag, swell, interruption, harmonics, transients, flicker, noise have their basic parameters related to the amplitude and frequency as defined by standards i.e. 220V and 50HZ signal. Deviation of amplitude and frequency from their normal value leads to disturbances in the power signal. Frequency variation in power signal leads harmonics and variation in amplitude introduces sag, swell, interruption, transients.

Voltage sag: sudden decrease in rms voltage. The decreased value is between 0.9 p.u. and 1 p.u. and duration between 10ms and 1min.

Voltage swells: sudden increase in rms voltage. The increased value is between 1.1 p.u. and 1.8 p.u. with maximum duration of several milliseconds.

Transients: sudden change in voltage amplitude with very small duration.

Flicker: intensity of nuisance caused by flicker.

Harmonics: sinusoidal voltage with a frequency which is a multiple of fundamental frequency and caused by nonlinear loads.

3.3.2 MATLAB based Simulation of Power Quality Disturbances

Analysis of PQ disturbances requires software reference model of these signals and these signals are generated through the software program written in software called MATLAB. Mathematical equations are used to generate artificial signals. These artificial signals need to have all properties as that of real-time signals so that, the exhibition of the signals can be acknowledged as real-time investigation done. The development of software programs to generate PQ disturbances are created by mathematical equations are given in table 1:

PQ disturbances	**Model**	**Parameters**

Normal Wave	sinewave=sin(ω*t)	t = line-space(0,1024,ns);
		f=50;
		ω=2*pi*f;

Sag Wave	sag=(1-A*(u(t-t1)-u(t-t2))).*sinewave	A = Alpha u = inline('t >= 0') A=0.7 t1=100; t2=200
Swell Wave	swell=(1 + A*(u(t-t1)-u(t-t2))).*sinewave	u = inline('t >= 0') T = time period sinewave=sin(ω*t)

PQ disturbances	Model	Parameters

Oscillatory Transient Wave	osci_trans =sin(ω*t)+ (alpha * temp_o.* ((u(t - t1) - u(t - t2)).* sin(2*pi*fn*t)))	ω=2*pi*f;
		alpha= 0.8;
		fn= 350;
		Tow = 10e-3;
		temp_o= exp(-(t - t1)*Tow)
		pi=3.1416

Sag with Harmonics Wave	sag_harmonics = (temp_sh).*(alpha1_sh*sin(ω *t) + alpha3_sh*sin(3* ω *t) + alpha5_sh*sin(5* ω *t))	alpha_sh=0.6;
		alpha1_sh=0.05;
		alpha3_sh= 0.015;
		alpha5_sh= 0.01;
		temp_sh=(1 - alpha_sh* (u(t - t1) - u(t - t2)))

Swell with Harmonics Wave	swell_harmonics = (temp_swh).*(alpha1_swh*sin(ω *t) + alpha3_swh*sin(3* ω *t) + alpha5_swh*sin(5* ω *t))	alpha_swh=0.6;
		alpha1_swh=0.05;
		alpha3_swh= 0.015;
		alpha5_swh= 0.01;
		temp_swh=(1 + alpha_swh*(u(t - t1) - u(t - t2)))

Flicker Wave	flicker= (temp_f).* sin(ω *t)	alpha_f=.1;
		beta_f=5;
		temp_f=(1 + alpha_f * sin(2*pi*beta_f*t))

TABLE: 1 Mathematical Models of PQ Signals

3.4 Feature Extraction

3.4.1 K Nearest Neighbor

K nearest neighbor algorithm is very simple. It works based on minimum distance from the query instance to the training samples to determine the K-nearest neighbors. The data for KNN algorithm consist of several multivariate attributes name that will be used to classify .

3.4.2 Selection of k-Nearest Neighbor Algorithm

The k-NN algorithm, as other example-based algorithms, is ordinary from a grouping point of view in its absence of express model preparing. While a preparation dataset is required, it is utilized exclusively to populate an example of the hunt space with occasions whose class is known. No real model or learning is performed during this stage; therefore, these algorithms are otherwise called languid learning algorithms. Distinctive separation measurements can be utilized, contingent upon the idea of the information. Euclidean separation is run of the mill for ceaseless factors, yet different measurements can be utilized for clear-cut information. Particular measurements are frequently helpful for explicit issues, for example, content order. At the point when an example whose class is obscure is exhibited for assessment, the algorithm figures its k-nearest neighbors, and the class is allocated by casting a ballot among those neighbors. To forestall ties, one normally utilizes an odd decision of k for double characterization. For various classes, one can utilize the majority casting a ballot or the greater part casts a ballot. The last can now and

again bring about no class being allocated to a case, while the previous can bring about characterizations being made with exceptionally low help from the area. One can likewise weight each neighbor by an opposite capacity of its separation to the example being characterized. The main advantages of k-NN for classification are:

- ✓ Very simple implementation.
- ✓ Robust with regard to the search space; for instance, classes don't have to be linearly separable.
- ✓ Classifier can be updated online at very little cost as new instances with known classes are presented.
- ✓ Few parameters to tune: distance metric and k.

The main disadvantages of the algorithm are:

- ✓ Costly testing of each example, as we have to process its separation to every known occurrence. Particular algorithms and heuristics exist for explicit issues and separation capacities, which can moderate this issue. This is risky for datasets with an enormous number of characteristics. At the point when the quantity of cases is a lot bigger than the quantity of qualities, a R-tree or a kd-tree can be utilized to store examples, taking into consideration quick careful neighbor recognizable proof. Sensitiveness to noisy or irrelevant attributes, which can result in less meaningful distance numbers. Scaling and/or feature selection are typically used in combination with k-NN to mitigate this issue.
- ✓ Sensitiveness to very unbalanced datasets, where most entities belong to one or a few classes, and infrequent classes are therefore often dominated in most neighborhoods. This can be alleviated through balanced sampling of the more popular classes in the training stage, possibly coupled with ensembles.

3.4.3 Multi-Resolution Analysis

The Signal Multiresolution Analyzer app is an interactive tool for visualizing multilevel wavelet and empirical mode decompositions of real-valued 1-D signals and comparing results. With the app, we can:

- Access all the signals in the MATLAB workspace.
- Adjust default parameters and generate multiple decompositions using DT, SVM and k-NN methods.
- Choose decomposition levels to include in the signal reconstruction.
- Visualize and compare results.
- Obtain frequency ranges of the decomposition levels.
- Determine the relative energy of the signal across levels.

- Export reconstructed signals and decompositions to your workspace.
- Recreate the decomposition in your workspace by generating a MATLAB script.

3.4.4 k-NN based Noising

Electrical noise is high frequency interference caused by a number of factors, including arc welding or the operation of some electric motors. If left unnoticed, it may result in processing errors, burned circuit boards, degraded electrical insulations, and equipment damage.

3.4.5 Statistical Features

3.4.5.1 Energy

Vitality in material science, the limit with respect to doing work. It might exist in potential, motor, warm, electrical, substance, atomic, or different structures. There are, in addition, warmth and work—i.e., vitality during the time spent exchange starting with one body then onto the next. After it has been moved, vitality is constantly assigned by its inclination. Henceforth, heat moved may become warm vitality, while work done may show itself as mechanical vitality.

All types of vitality are related with movement. For instance, some random body has motor vitality on the off chance that it is moving. A strain gadget, for example, a bow or spring, however very still, has the potential for making movement; it contains potential vitality due to its setup. Also, atomic vitality is the potential vitality since it results from the arrangement of subatomic particles in the core of an iota.

Vitality can be neither made nor obliterated however just changed starting with one structure then onto the next. This rule is known as the preservation of vitality or the primary law of thermodynamics. For instance, when a container slides down a slope, the potential vitality that the crate has from being found high up on the slant is changed over to active vitality, vitality of the movement. As the crate eases back to a stop through rubbing, the dynamic vitality from the case's movement is changed over to warm vitality that warm the case and the incline. Vitality can be changed over, starting with one structure then onto the next in different manners. Usable mechanical or electrical vitality is, for example, created by numerous sorts of gadgets, including fuel-consuming warmth motors, generators, batteries, power devices, and magneto-hydrodynamic frameworks.

In the Worldwide Arrangement of Units (SI), vitality is estimated in joules. One joule is equivalent to the work done by a one-newton power acting over a one-meter separation.

Vitality is treated in various articles. For the improvement of the idea of vitality and the rule of vitality protection, see standards of physical science; mechanics; thermodynamics; , and preservation of vitality. For the significant wellsprings of vitality and the systems by which the change of vitality starting with one structure then onto the next happens see coal; sunlight-based vitality; wind power; atomic splitting; oil shale; oil; electromagnetism; , and vitality transformation.

3.4.5.2 Entropy

Entropy is the measure of the disorder of a system. It is an extensive property of a thermodynamic system, which means its value changes depending on the amount of matter that is present. In equations, entropy is usually denoted by the letter S and has units of joules per kelvin ($J \cdot K^{-1}$) or $kg \cdot m2 \cdot s^{-2} \cdot K^{-1}$. A highly ordered system has low entropy.

Entropy Equation and Calculation:

There are multiple ways to calculate entropy, but the two most common equations are for reversible thermodynamic processes and isothermal (constant temperature) processes.

Entropy of a Reversible Process

Certain assumptions are made when calculating the entropy of a reversible process. Probably the most important assumption is that each configuration within the process is equally probable (which it may not actually be). Given equal probability of outcomes, entropy equals Boltzmann's constant (kB) multiplied by the natural logarithm of the number of possible states (W):

$S = kB \ln W$

Boltzmann's constant is 1.38065×10^{-23} J/K.

Entropy of an Isothermal Process

Calculus may be used to find the integral of dQ/T from the initial state to final state, where Q is heat and T is the absolute (Kelvin) temperature of a system.

Another way to state this is that the change in entropy (ΔS) equals the change in heat (ΔQ) divided by the absolute temperature (T).

$\Delta S = \Delta Q / T$

Entropy and Internal Energy

In physical chemistry and thermodynamics, one of the most useful equations relates entropy to the internal energy (U) of a system:

$dU = T\,dS - p\,dV$

Here, the change in internal energy dU equals absolute temperature T multiplied by the change in entropy minus external pressure p and the change in volume V.

3.4.5.3 Standard Deviation

The standard deviation is a statistic that measures the dispersion of a dataset relative to its mean and is calculated as the square root of the variance. It is calculated as the square root of variance by determining the variation between each data point relative to the mean. If the data points are further from the mean, there is a higher deviation within the data set; thus, the more spread out the data, the higher the standard deviation.

Standard deviation is a statistical measurement in finance that, when applied to the annual rate of return of an investment, sheds light on the historical volatility of that investment. The greater the standard deviation of securities, the greater the variance between each price and the mean, which shows a larger price range. For example, a volatile stock has a high standard deviation, while the deviation of a stable blue-chip stock is usually rather low.

Standard deviation is calculated as:

1. The mean value is calculated by adding all the data points and dividing by the number of data points.
2. The variance for each data point is calculated, first by subtracting the value of the data point from the mean. Each of those resulting values is then squared and the results summed. The result is then divided by the number of data points less one.
3. The square root of the variance—result from no. 2—is then taken to find the standard deviation.

Key Takeaways:

- Standard deviation measures the dispersion of a dataset relative to its mean.
- A volatile stock has a high standard deviation, while the deviation of a stable blue-chip stock is usually rather low.
- As a downside, it calculates all uncertainty as risk, even when it's in the investor's favor—such as above average returns.

3.4.5.4 Mean

The Arithmetic Mean is the average of the numbers: a calculated "central" value of a set of numbers.
To calculate it:
• add up all the numbers,
• then divide by how many numbers there are.
Example: what is the mean of 2, 7 and 9?
Add the numbers: 2 + 7 + 9 = 18
Divide by how many numbers (i.e. we added 3 numbers): 18 ÷ 3 = 6
So the mean is 6

3.4.5.5 Kurtosis

Kurtosis is a statistical measure that defines how heavily the tails of a distribution differ from the tails of a normal distribution. In other words, kurtosis identifies whether the tails of a given distribution contain extreme values.
Along with skewness, kurtosis is an important descriptive statistic of data distribution. However, the two concepts must not be confused with each other. Skewness essentially measures the symmetry of the distribution, while kurtosis determines the heaviness of the distribution tails.

3.4.5.6 Skewness

In probability theory and statistics, skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. The skewness value can be positive or negative, or undefined.
For a unimodal distribution, negative skew commonly indicates that the tail is on the left side of the distribution, and positive skew indicates that the tail is on the right. In cases where one tail is long but the other tail is fat, skewness does not obey a simple rule. For example, a zero value means that the tails on both sides of the mean balance out overall; this is the case for a symmetric distribution, but can also be true for an asymmetric distribution where one tail is long and thin, and the other is short but fat.

Consider the two distributions in the figure just below. Within each graph, the values on the right side of the distribution taper differently from the values on the left side. These tapering sides are called tails, and they provide a visual means to determine which of the two kinds of skewness a distribution has:

- negative skew: The left tail is longer; the mass of the distribution is concentrated on the right of the figure. The distribution is said to be left-skewed, left-tailed, or skewed to the left, despite the fact that the curve itself appears to be skewed or leaning to the right; left instead refers to the left tail being drawn out and, often, the mean being skewed to the left of a typical center of the data. A left-skewed distribution usually appears as a right-leaning curve.

- positive skew: The right tail is longer; the mass of the distribution is concentrated on the left of the figure. The distribution is said to be right-skewed, right-tailed, or skewed to the right, despite the fact that the curve itself appears to be skewed or leaning to the left; right instead refers to the right tail being drawn out and, often, the mean being skewed to the right of a typical center of the data. A right-skewed distribution usually appears as a left-leaning curve.

3.4.5.7 Root Mean Square Value

The RMS value is defined as the square root of the mean value of the squared function. This is often used as the effective d.c. voltage (or current) of an a.c. voltage (or current). This value can then be used in the calculation of the average power of an AC waveform

If we consider the waveform defined in the previous section. $v(t) = V_m \sin \omega_0 t$. The RMS can then be calculated using the following formula:

$$V_{rms} = \sqrt{(\frac{1}{T} \int_{\frac{-T}{2}}^{\frac{T}{2}} (V_0^2 \sin^2 \omega_0 t) dt)}$$

Where **T** is the period of the waveform. The mean value of the squared function is given by the integral of the squared function divided by the period of the integration. The RMS value is then the square root of this.

The above then gives a value of: $V_{rms} = \frac{V_0}{\sqrt{2}}$

This then demonstrated that the RMS value can be used as the effective d.c. voltage of an a.c. voltage.

3.4.5.8 Range

The difference between the lowest and highest values.
In {4, 6, 9, 3, 7} the lowest value is 3, and the highest is 9, so the range is 9 − 3 = 6.
Range can also mean all the output values of a function.

3.5 Feature Selection

The training phase for k-NN consists of simply storing all known instances and their class labels. A tabular representation can be used, or a specialized structure such as decision-tree. If we want to tune the value of 'k' and/or perform feature selection, n-fold cross-validation can be used on the training dataset. The testing phase for a new instance 't', given a known set 'I' is as follows:

1. Compute the distance between 't' and each instance in 'I'
2. Sort the distances in increasing numerical order and pick the first 'k' elements
3. Compute and return the most frequent class in the 'k' nearest neighbors, optionally weighting each instance's class by the inverse of its distance to 't'

3.6 Classification Stage

3.6.1 Decision Tree Algorithm

Definition: Decision tree is one of the predictive modelling approaches used in statistics , data mining and machine learning . Decision trees are constructed via an algorithmic approach that identifies ways to split a data set based on different conditions.

Why use: Decision Trees are a non-parametric supervised learning method used for both classification and regression tasks. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.

Introduction: A decision tree is a tree-like graph with nodes representing the place where we pick an attribute and ask a question; edges represent the answers to the question; and the leaves represent the actual output or class label. They are used in non-linear decision making with simple linear decision surface.

Decision trees classify the examples by sorting them down the tree from the root to some leaf node, with the leaf node providing the classification to the example. Each node in the tree acts as a test case for some attribute, and each edge descending from that node corresponds to one of the possible answers to the test case. This process is recursive in nature and is repeated for every subtree rooted at the new nodes.

Let's illustrate this with help of an example. Let's assume we want to play badminton on a particular day — say Saturday — how will you decide whether to play or not. Let's say you go out and check if it's hot or cold, check the speed of the wind and humidity, how the weather is, i.e. is it sunny, cloudy, or rainy. You take all these factors into account to decide if you want to play or not.

So, you calculate all these factors for the last ten days and form a lookup table like the one below.

Day	Weather	Temperature	Humidity	Wind	Play?
1	Sunny	Hot	High	Weak	No
2	Cloudy	Hot	High	Weak	Yes
3	Sunny	Mild	Normal	Strong	Yes
4	Cloudy	Mild	High	Strong	Yes
5	Rainy	Mild	High	Strong	No
6	Rainy	Cool	Normal	Strong	No
7	Rainy	Mild	High	Weak	Yes
8	Sunny	Hot	High	Strong	No
9	Cloudy	Hot	Normal	Weak	Yes
10	Rainy	Mild	High	Strong	No

Table 2. Observations of the last ten days.

Now, you may use this table to decide whether to play or not. But, what if the weather pattern on Saturday does not match with any of rows in the table? This may be a problem. A decision tree would be a great way to represent data like this because it takes into account all the possible paths that can lead to the final decision by following a tree-like structure.

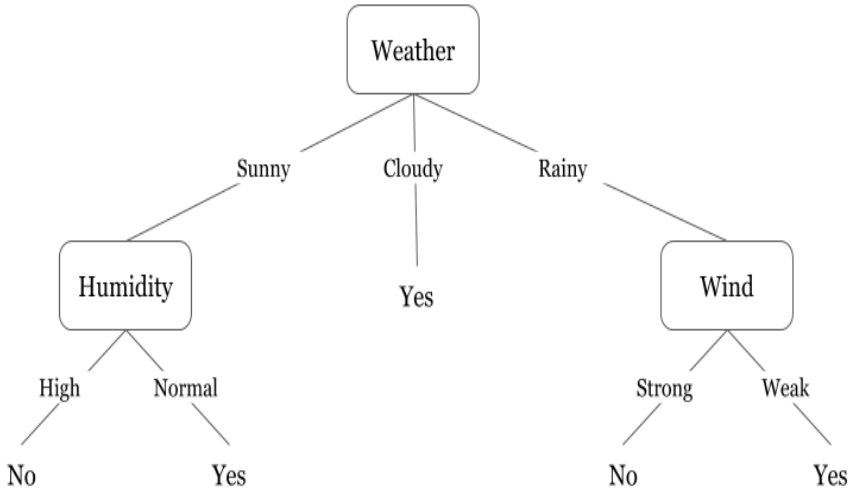


Figure:3.3 A decision tree for the concept Play Badminton

Fig:3.3 illustrates a learned decision tree. We can see that each node represents an attribute or feature and the branch from each node represents the outcome of that node. Finally, its the leaves of the tree where the final decision is made. If features are continuous, internal nodes can test the value of a feature against a threshold (see Fig. 3.4).

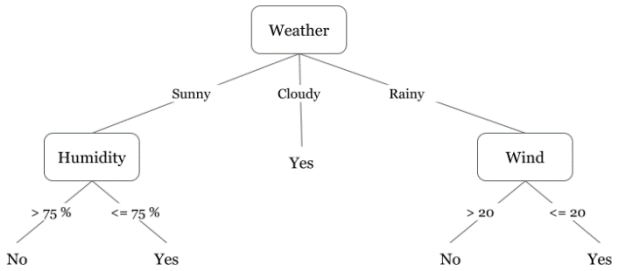


Figure:3.4 decision tree for the concept Play Badminton (when attributes are continuous)

A general algorithm for a decision tree can be described as follows:

1. Pick the best attribute/feature. The best attribute is one which best splits or separates the data.
2. Ask the relevant question.
3. Follow the answer path.
4. Go to step 1 until you arrive to the answer.

3.6.2 Support-Vector Machines Algorithm(SVM)

In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on the side of the gap on which they fall.

More formally, a support-vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks like outliers detection. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin, the lower the generalization error of the classifier.

Whereas the original problem may be stated in a finite-dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by SVM schemes are designed to ensure that dot products of pairs of input data vectors may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function $k(x, y)$ selected to suit the problem. The hyperplanes in the higher-dimensional space are defined as the set of points whose dot product with a vector in that space is constant, where such a set of vectors is an orthogonal (and thus minimal) set of vectors that defines a hyperplane. The vectors defining the hyperplanes can be chosen to be linear combinations with parameters α_i of images of feature vectors x_i that occur in the data base. With this choice of a hyperplane, the points x in the feature space that are mapped into the hyperplane are defined by the relation $\sum_i \alpha_i k(x_i, x) = \text{constant}$. Note that if $k(x, y)$ becomes small as y grows further away from x, each term in the sum measures the degree of closeness of the test point x to the corresponding data base point x_i. In this way, the sum of kernels above can be used to measure the relative nearness of each test point to the data points originating in one or the other of the sets to be discriminated. Note the fact that the set of points x mapped into any hyperplane can be quite convoluted as a result, allowing much more complex discrimination between sets that are not convex at all in the original space.

3.7 Summary

PQ disturbance signals are the most important signal which is analyzed for the diagnosis of any abnormal situation. Since conventional analysis is found inadequate to describe the characteristics of a non-stationary signal, in this chapter, we propose to transform the PQ disturbance signals by algorithms. The feature vector is fed to SVM, DT and k Nearest Neighbor classifier in order to classify PQ disturbance of six different types along with normal pure PQ signal. A number of simulations are carried out using model equations of each events. It is shown that the proposed method based on HOS is capable of producing greater efficiency in comparison to that obtained by using some methods of PQ disturbance classification using the same classifiers and the data set.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

Performance evaluation of the proposed method for classifying six types of PQ disturbances is an important task. For this purpose the evaluation criteria taken into account in this Chapter are confusion matrix, overall efficiency calculation, overall efficiency with increased training and testing data set and required CPU time. Decision-tree and Support-Vector Machines (SVM)based methods are used for performance comparison with the proposed method.

4.2 Data set and Simulation Conditions

In the proposed method, PQ disturbance signals are generated using MATLAB based on the equations in Table:1 with a sampling frequency of 2 kHz. Six types of PQ disturbance signals are levels as:

1. C0- Sag,
2. C1- Swell,
3. C2 - Oscillatory Transient,
4. C3- Sag with Harmonics,
5. C4 - Swell with Harmonics and
6. C5- Flicker

4.3 Comparison Methods

For the purpose of comparison, we use DT and SVM based classification methods. We have implemented the DT and SVM based classification methods independently using the parameters specified there in.

Extracted features based classifier on DT according to are:

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

In the SVM classifier is employed for classification of the various PQ disturbance signals.
Combining SVM and DT, k-NN is suggested in. The DT is applied to first. The feature vector set is formed by considering –

- Energy of the elements corresponding to magnitude sample.

- Standard deviation of the amplitude contour.
- Standard deviation of phase contour.

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

4.4 Performance Evaluation Criteria

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

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

Confusion Matrix:
Confusion matrix is a form of representing the result from a classification exercise. The rows in the matrix stand for the actual classes to be tested and columns provide the class classified by a method. In particular, any [row, column] entry in the confusion matrix indicates the number of cases from the test database that belongs to the class corresponding to the row but classified as the class corresponding to the column. In Fig. 4.1, a general confusion matrix for a two class problem (C1 and C2) is shown, where TP, FP, FN and TN are represented for class C1.
In general, TP_{C1}, true positive for any class C1, denotes the number of testing cases, which are correctly classified as class C1.
FP_{C1}, false positive for any class C1, measures the number of testing cases, which are incorrectly classified as class C1.
FN_{C1}, false negative for any class C1, measures the number of testing cases, which are incorrectly classified as other than class C1.
TN_{C1}, true negative for any class C1, denotes the number of testing cases, which are correctly classified as other than class C1.

		Actual Class	
		C1	C2
Detected Class	C1	TP_{C1}	FP_{C1}
	C2	FN_{C1}	TN_{C1}

Table 3: Confusion Matrix for two class with respect to C1

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

$$Efficiencyc1 = \frac{TPc1}{TPc1+FPc1} \quad \text{..... 3.1}$$

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

$$Overall\ Efficiency = \frac{Numberofeventsclassifiedcorrectly}{Totalnumberofevents} \quad \ldots\ldots\ldots\ldots\ldots \quad 3.2$$

Increased training and testing dataset:
The performance of a classification method in classifying different PQ disturbance signals can be evaluated in terms overall efficiency with the random selection of increased training and testing dataset.
Required CPU time:
CPU time is an important factor that should be considered for the evaluation of performance of a method. Method which is faster than the other method, can be considered as an efficient one.

4.5 Performance Evaluation

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

4.5.1 Performance Comparison using Confusion Matrix Analysis

The confusion matrix inferred for the technique utilizing DT classifier is spoken to in figure: 4.1. In this Figure: 4.1, the diagonal entries stand for the number of cases when a particular class of PQ disturbance signal is correctly classified. It can be seen from the diagonal entries of the confusion matrix in Figure: 4.1 that DT algorithm based method is unable to distinguish among PQ disturbance signals and misclassification occurs in case of sag(C0), swell (C1), oscillatory transient(C2), sag with harmonics(C3) and flicker (C5).
Figure: 4.2 represents the confusion matrix derived for SVM based method classifier. It is provide from Figure: 4.2 that SVM based method misclassifies some interruption and sag with harmonics (C3) signals. It also misclassifies a small number of swell(C1) data.
Figure: 4.3 shows the confusion matrix derived for the proposed method using k-NN Classifier. It is demonstrated from Figure: 4.3 that HOS based features of the proposed method are able to classify all of the PQ disturbance signals almost perfectly.

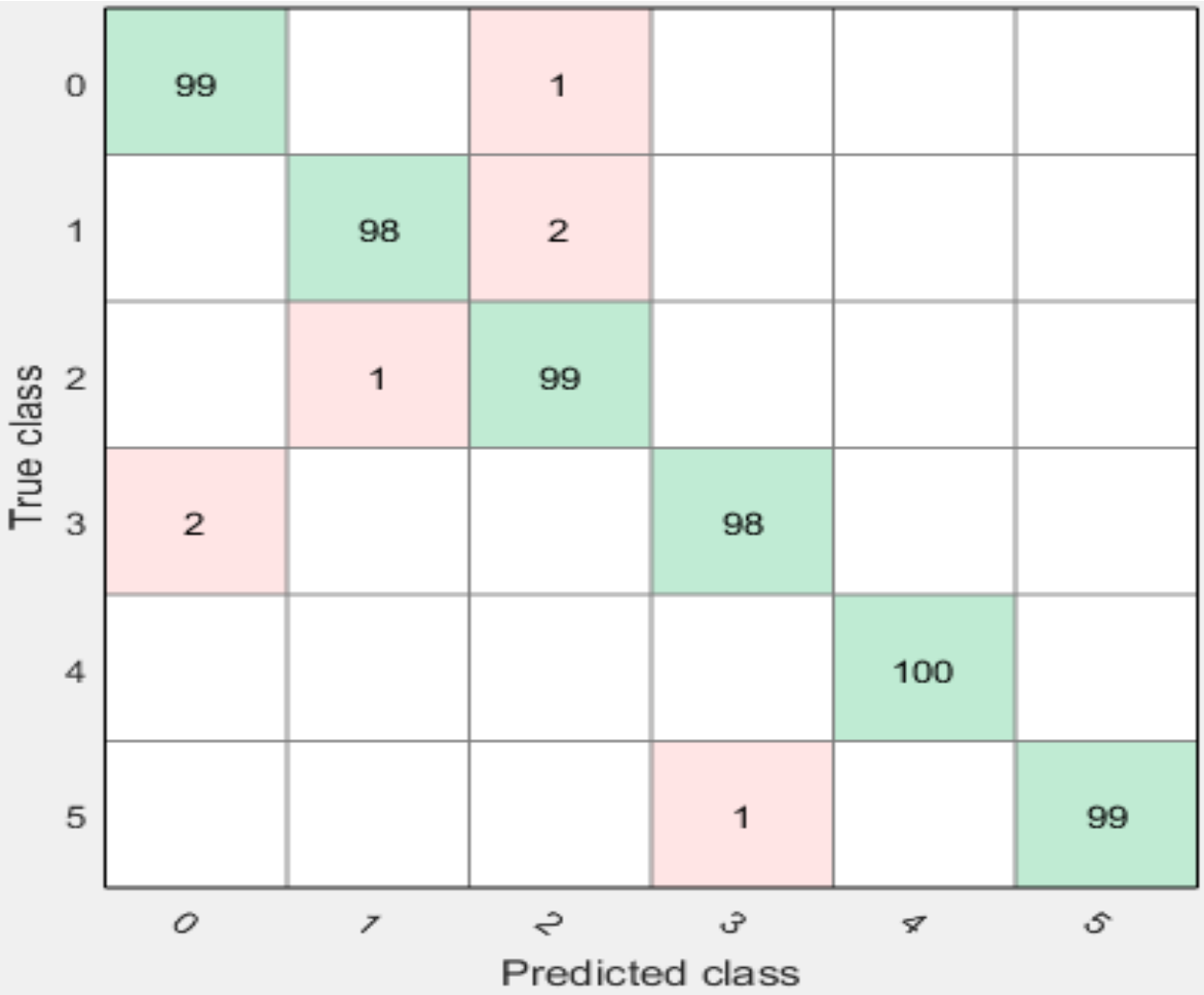


Figure: 4.1 Representation of DT classifier. (Using MATLAB)

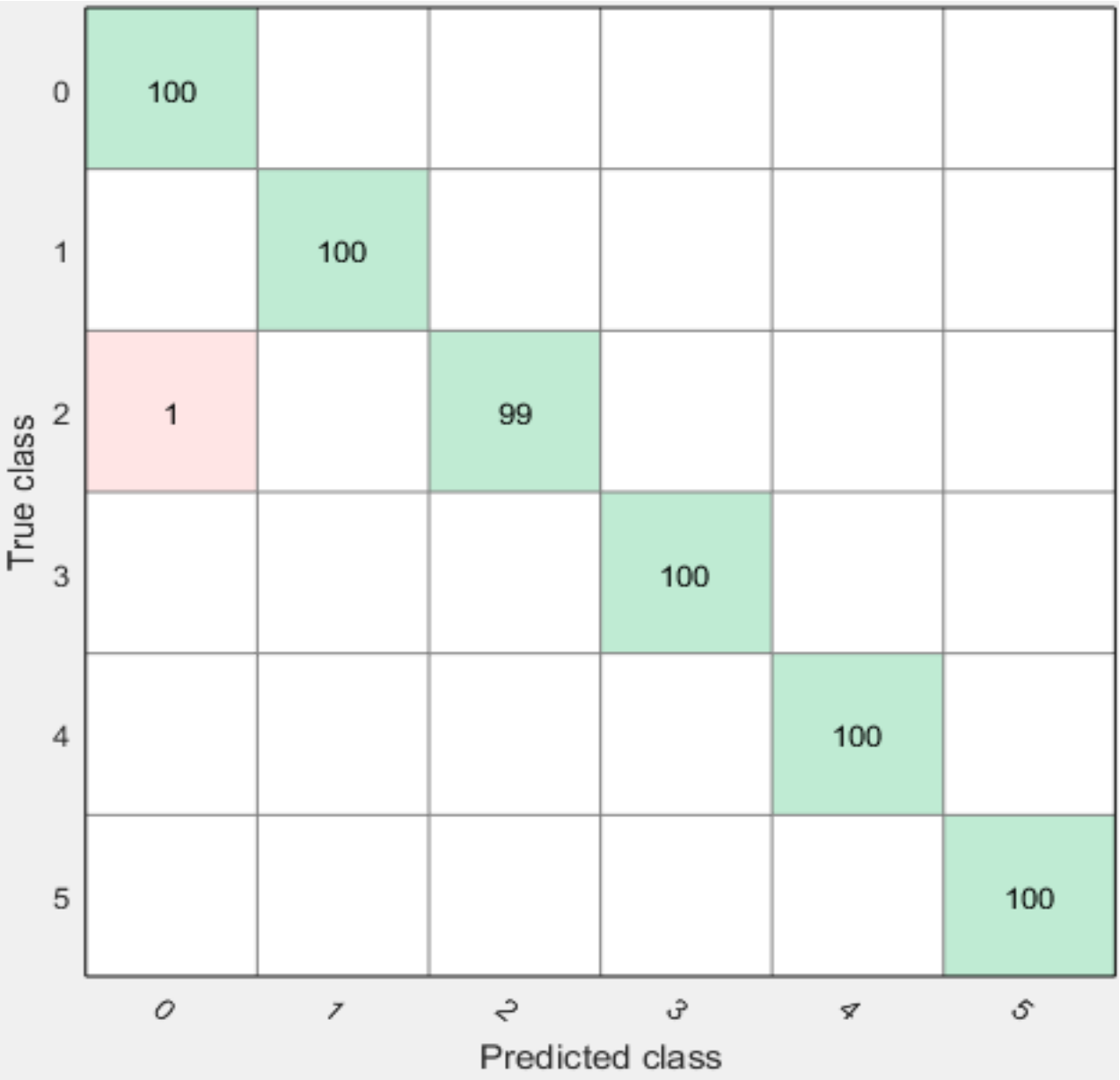


Figure: 4.2 Representation of SVM classifier. (Using MATLAB)

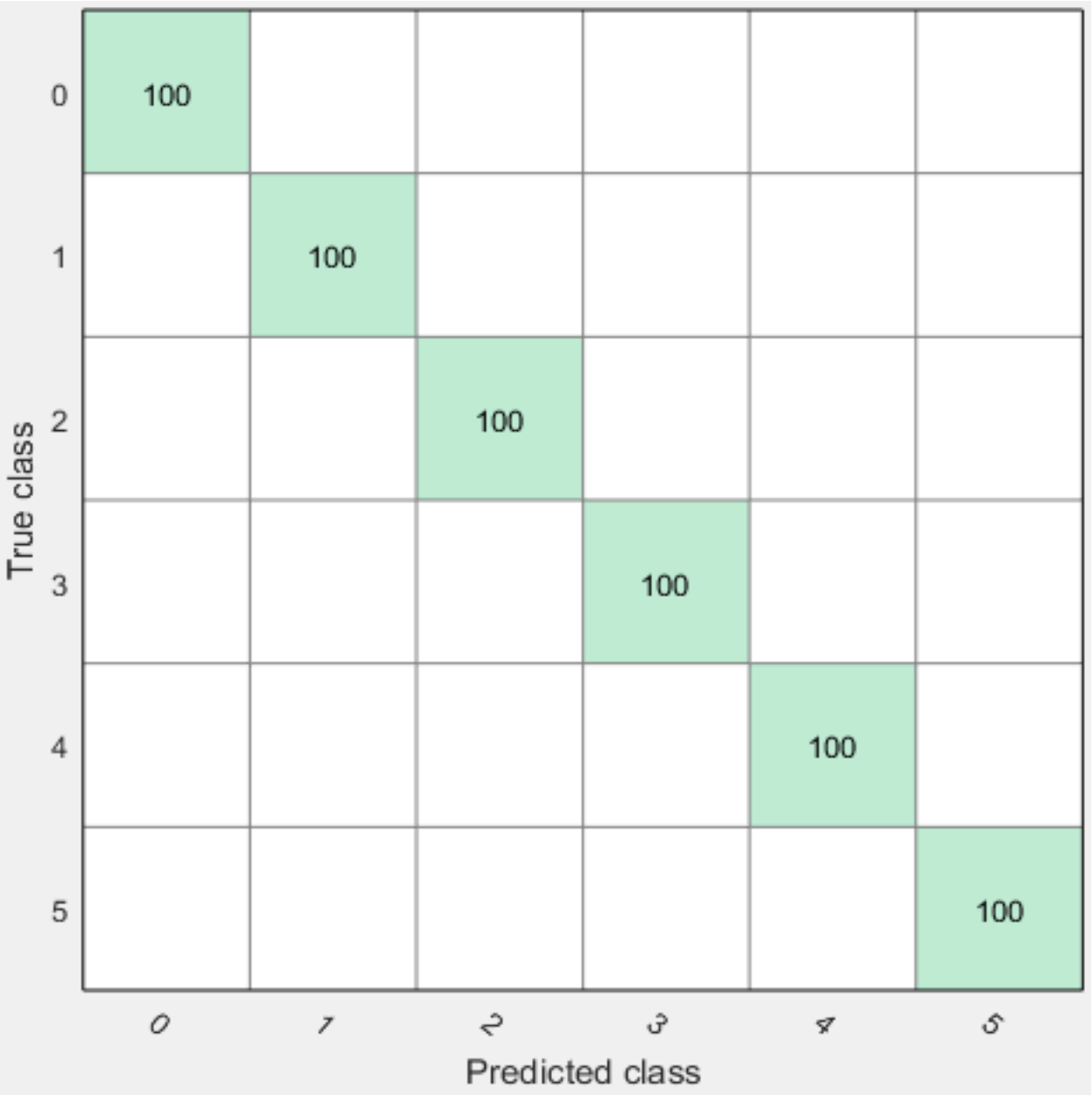


Figure: 4.3 Representation of k-NN classifier. (Using MATLAB)

Serial Number	Algorithm Name	Average accuracy in (%)
01	Decision Tree(DT)	98.8%
02	Support Vector Machine(SVM)	99.8%
03	Clustering Nearest Neighbor (k-NN)	100.0%

Table 4: Classification performance. (Using MATLAB)

Classification performance in terms of overall efficiency (%) resulting from the proposed method and other comparison methods using DT, SVM and k-NN classifiers are calculated over all classes and are presented in Table 4. Compared to the other methods, the proposed method shows higher overall efficiency (%) while using DT and SVM classifier. For each method, overall efficiency (%) increases while using the k-NN classifier instead of the DT and SVM classifier. However, the proposed method is found provide the highest overall efficiency (%) using the k-NN classifier.

4.5.2 Performance Comparison with Increased Training and Testing dataset

Classification accuracy can be further enhanced by using higher number of events in the training and testing dataset. Table 4 shows the testing results in terms of overall efficiency (%) for the proposed method using k-NN classifier when training and testing dataset are made double (200 events of each class for training and 1200 events of each class for testing). By increasing the training and testing dataset, classification performance in terms of overall efficiency (%) resulting from the proposed method and other comparison methods using DT, SVM and k-NN classifiers are calculated over all classes and are presented in Table 4. As expected, it is found from comparing Tables 4 the overall efficiency (%) of each method increases with the increased training and testing dataset using both DT, SVM and k-NN classifiers. It is noticeable from Table 4 the overall efficiency (%) enhances to 100.0% for our proposed method using k-NN classifier in such a condition of training and testing dataset.

4.5.3 Required CPU time

The required CPU time for the proposed and other comparison methods using DT, SVM and k-NN classifiers. However, compared to the DT and SVM classifiers, it can be seen that proposed method requires much less time to classify a particular input data during testing using all the DT, SVM and k-NN classifiers. Moreover, it is clearly observable that the proposed feature set resulting from the HOS domain when fed to k-NN classifier can effectively classify six kinds of PQ disturbances not only with the highest overall efficiency but also with the least CPU time.

4.6 Summary

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

CHAPTER FIVE

CONCLUSION & FUTURE RECOMMENDATION

5.1 Conclusions

In this thesis, an k-NN based approach using the higher order statistics has been presented to solve the classification problem of different PQ disturbances. In this thesis, the PQ disturbance signals are obtained by using k-NN operation. The feature set thus obtained then fed to the and k Nearest Neighbor (k NN) classifiers for classifying the multi class PQ disturbance signals. For the characterization of PQ disturbance signals, mathematical models of six classes of disturbances are used. In comparison to the other methods using Decision Tree and SVM classifiers, the more effectiveness of the proposed method in classifying multi-class PQ disturbance signals has been shown through simulation results with increased training and testing dataset. Detail simulation results reveal the effectiveness of the proposed method. It is shown that the proposed method outperforms with superior efficacy.

5.2 Significant Contributions of Research

The major contribution of the thesis are:

- Introducing k-NN that decomposes the signals of PQ disturbances. This classified disturbances can be handled more easily for extracting features.
- Appropriateness of HOS in the k-NN domain are shown for feature extraction in case of multiclass PQ disturbances classification problem.
- Among three types of classifier, we confirmed that the k-NN classifier is the most suitable for PQ disturbance classification using the proposed feature set due to its faster processing time and the highest overall efficiency.
- Detail simulations have been carried out in order to investigate the performance of the proposed feature set for the classification of different types of PQ disturbance signals. The performance of our proposed method is compared with Decision Tree and SVM based methods. Simulation results show that the proposed method is able to classify different types of PQ disturbance signals with greater overall efficiency. Moreover, the performance is enhanced with increased training and testing dataset as expected.

5.3 Future Scope of Work

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

- In this research, we used Table 1 which gives us the mathematical models of six class PQ disturbance signals. Our proposed method is needed to be tested for handling data from various practical situations.
- There are many other disturbances to be classify using proposed method.
- In future, online PQ classification can be performed using different databases.
- In an electrical power distribution network, the practical data consists of noise; therefore, the proposed approach will be analyze under noisy condition.

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Appendix

Code:

```
clear
ns = 1024;
t = linspace(0,1024,ns);
f=50;
w=2*pi*f;
sinewave=sin(w*t);
%plot(sinewave)
u = inline('t >= 0');
a=.1;
b=.9;
%A=0.7;
A= (b-a).*rand(100,1)+a;
t1=100;
t2=600;
c=100;
d=400;
e=600;
f1=800;
s=100;
t1_new=t1+(d-c).*rand(s,1);
t2_new=t2+(f1-e).*rand(s,1);

sag_new=[];
for n= 1:100
    sag=(1-A(n)*(u(t-t1_new(n))-
u(t-t2_new(n)))).*sinewave;


ns = 1024;
t = linspace(0,1024,ns);
f=50;
w=2*pi*f;
sinewave=sin(w*t);
alpha= 0.8;
fn= 350;
Tow = 10e-3;
temp_o= exp(-(t - t1)*Tow);
u = inline('t >= 0');
a=.1;
b=.9;
%A=0.7;
A= (b-a).*rand(100,1)+a;
t1=100;
t2=600;
c=100;
d=400;
e=600;
f1=800;
s=100;
t1_new=t1+(d-c).*rand(s,1);
t2_new=t2+(f1-e).*rand(s,1);
    sag_new = [sag_new;sag];
end

swell_new =[];
for n= 1:100
    swell=(1 + A(n)*(u(t-
t1_new(n))-u(t-
t2_new(n)))).*sinewave;
    swell_new = [swell_new;swell];
end
alpha= 0.8;
osci_trans_new =[];
Tow = 10e-3;
temp_o= exp(-(t - t1)*Tow);
fn= 350;
for n= 1:100
    osci_trans =sin(w*t)+ (alpha *
temp_o.* ((u(t - t1_new(n)) - u(t -
t2_new(n))).* sin(2*pi*fn*t)));
    osci_trans_new =
[osci_trans_new;osci_trans];
end

dataset1=[sag_new;swell_new;osci_tr
ans_new];


alpha_sh=0.6;
alpha1_sh=0.05;
alpha3_sh= 0.015;
alpha5_sh= 0.01;

alpha_swh=0.6;
alpha1_swh=0.05;
alpha3_swh= 0.015;
alpha5_swh= 0.01;
temp_sh=(1 - alpha_sh*(u(t - t1) -
u(t - t2))) ;
sag_harmonics_new=[];
for n= 1:100
   sag_harmonics = (1-
A(n)*(temp_sh).*(alpha1_sh*sin(w*t)
+ alpha3_sh*sin(3*w*t) +
alpha5_sh*sin(5*w*t)));
   sag_harmonics_new =
[sag_harmonics_new;sag_harmonics];
end
```

```
temp_swh=(1 + alpha_swh*(u(t - t1)
- u(t - t2))) ;
swell_harmonics_new=[];
for n= 1:100
   swell_harmonics =
(temp_swh).*(alpha1_swh*sin(w*t) +
alpha3_swh*sin(3*w*t) +
alpha5_swh*sin(5*w*t));
   swell_harmonics_new =
[swell_harmonics_new;swell_harmonic
s];
end
alpha_f=.1;
beta_f=5;
```

```
temp_f=(1 + alpha_f *
sin(2*pi*beta_f*t));

flicker_new=[];
for n= 1:100
    flicker=(1-A(n)* (temp_f).*
sin(w*t));
    flicker_new =
[flicker_new;flicker];
end
dataset=[sag_harmonics_new;swell_ha
rmonics_new;flicker_new];
```

Final Data-Set:

```
x=zeros(100,1);
y=ones(100,1);
z=2*ones(100,1);
u=3*ones(100,1);
v=4*ones(100,1);
w=5*ones(100,1);
dataset2=[x;y;z;u;v;w];
fulldataset=[dataset1;dataset];
fulldataset1=[fulldataset,dataset2];
```