MULTIPLE POWER QUALITY EVENTS ANALYSIS

Thesis Submitted to the Delhi Technological University
for the Award of Degree of

Doctor of Philosophy

In

Electronics and Communication Engineering

by

Rahul

(Enrollment No.: 2K13/Ph.D/EC/03)

Under the Supervision of

Prof. Rajiv Kapoor
&
Prof. M M Tripathi

Department of Electronics & Communication Engineering
Delhi Technological University (Formerly DCE)
Bawana Road, Delhi-110042, India.

February 2020

Delhi Technological University

Formerly Delhi College of Engineering

Shahbad Daulatpur, Bawana Road, Delhi-110042

CERTIFICATE

This is to certify that the thesis entitled "**Multiple Power Quality Events Analysis**" submitted by **Rahul** (2K13/PHD/EC/03) to the Department of Electronics and Communication Engineering, Delhi Technological University for the award of the degree of Doctor of Philosophy is based on the original research work carried out by him under our guidance and supervision. In our opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree. It is further certified that the work presented in this thesis is not submitted to any other university or institution for the award of any degree or diploma.

Prof. Rajiv Kapoor

Supervisor,
Department of ECE
Delhi Technological University
Delhi-110042, India

Prof. M M Tripathi

Supervisor,
Department of EE
Delhi Technological University
Delhi-110042, India

CANDIDATE'S DECLARATION

I hereby certify that the research work, which is being presented in the thesis, titled, "**Multiple Power Quality Events Analysis**" in fulfillment of requirements of the award of the degree of Doctor of Philosophy is an authentic record of my research work carried under the supervision of Prof. Rajiv Kapoor and Prof. M M Tripathi. The matter presented in this thesis has not been submitted elsewhere in part or fully to any other University or Institute for the award of any degree.

Rahul

(2K13/Ph.D/EC/03)

ACKNOWLEDGMENTS

First and foremost, I would like to thank GOD Almighty for giving me the strength, knowledge, ability and opportunity to undertake this research study and to persevere and complete it satisfactorily. Without his blessings, this achievement would not have been possible.

The support and expert advice of my supervisors, Prof. Rajiv Kapoor and Prof. M M Tripathi Department of Electronics and Communication Engineering and Department of Electrical Engineering, Delhi Technological University (DTU), are greatly acknowledged with gratitude. I always availed of their priceless supervision, continuous motivation and ever-unforgettable humanitarian considerations.

I am also grateful to Prof. Yogesh Singh, Vice-Chancellor, DTU, Delhi, for providing the research environment in the institute.

And finally, I take this opportunity to sincerely acknowledge the patience of my parents, wife and other family members who experienced all of the ups and downs of my research. I owe my deepest gratitude towards my grandfather late Shri Amar Singh Verma(A Great Academician) for his eternal support and affection. This is the blessings of all the well-wishers that encouraged me to stand firm and continue this journey.

Rahul

ABSTRACT

PQ events have become a serious concern for the power system operations. Literature in this thesis revolves around different signal processing and classification techniques for recognition of PQ events. Volterra series based techniques are the most suitable choice for non-linear and non-stationary signal leaving behind all other techniques based on basis functions like Fourier transform, STFT, S-transform and Wavelet transform etc. Therefore, this work revolves around Volterra analysis of PQ events in the power system. Then features are extracted which act as input to the interval type-2 fuzzy based classifier and finally the results are compared with other methods which show high accuracy of proposed novel technique for detection and classification of power quality events.

A novel technique of adaptive finite element method based on sparse features based approach explored for analysis of power quality events. The role of adaptive finite element method is to generate a unique feature set and type-2 fuzzy system for the purpose of classification of power quality disturbances with minimum error. The concept of stiffness matrix is applied on power quality events. The type-2 fuzzy system utilizes the concept of membership functions to classify the single and multiple power quality events and then the proposed method is compared with other methods and finally with traditional type-I fuzzy logic approach for classification of power quality events. The results revealed that the novel methodology of adaptive FEM can reduce the computation time significantly with high accuracy.

In today's time, maintaining the power quality (PQ) in the electrical system is a major issue between the end user and the utilities due to increase in demand of sensitive microprocessor based controllers, heavy non-linear loads and solid state equipment attached to the grid. To deal with this issue an intelligent system is designed based on Long Short-Term Memory (LSTM)-Convolution Neural Network Based Hybrid Deep Learning approach for Power Quality events monitoring. LSTM is a part of deep learning, proficiency of training data and computational power makes deep learning efficient on complex pattern recognition and power-quality disturbances analysis. Therefore, one section in this thesis is devoted to detection and classification of PQ issues by using LSTM.

This work has tailored an initial layer of CNN; the next stage is max pooling which performs the task of finding low level dependencies in layers. To develop a concise feature map, the features extracted in the first stage are applied as input to subsequent layers of CNN and max pooling layers. The event information is extracted through a two stage feature extraction process to bring out a high dimensional feature set to achieve correct classification of PQ events with less complexity and minimal time using convolution neural networks.

Thus, this work addresses the detection and classification issues of single and multiple PQ events in power systems. The three main issues addressed in this thesis, first detection and classification of multiple power quality events under noisy and noiseless conditions and another is to develop adaptive intelligent systems which will change the mesh size of finite element methods so that memory size for monitoring can be optimized. Then finally the work explored the possibility to join two methods and to develop new techniques which have good features of both the techniques.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVATIONS

PQ	Power Quality
FT	Fourier Transform
STFT	Short Time Fourier Transform
WT	Wavelet Transform
TT	Time-Time
HT	Hilbert Transform
HHT	Hilbert-Huang Transform
ANN	Artificial Neural Network
DTFT	Discrete-Time Fourier Transform
GT	Gabor Transform
DWT	Discrete Wavelet Transform
HST	Hyperbolic S-Transform
HMM	Hidden Markov Model
PQD	Power Quality Disturbance
PNN-ABC	Probabilistic Neural Network-Artificial Bee Colony
PSO	Particle Swarm Optimization
ELM	Extreme Learning Machine
SVM	Support Vector Machine
NN	Neural Network
GA	Genetic Algorithm
SVD	Singular Value Decomposition
AI	Artificial Intelligence
EMD	Empirical Mode Decomposition
THD	Total Harmonic Distortion
PNN	Probabilistic Neural Network
IMF	Intrinsic Mode Function
LQR	Linear Quadratic Regulator
MRA	Multiresolution Analysis

PCA Principal Component Analysis

ICA Independent Component Analysis

LDA Linear Discriminant Analysis

FPGA Field Programmable Gate Array

FL Fuzzy Logic

IT2FLS Interval Type-2 Fuzzy Logic

DL Deep Learning

LSTM Long Short Term Memory

CNN Convolution Neural Networks

MLPNN Multi-Layer Perceptron Neural Network

DNN Deep Neural Network

SA Simulated Annealing

MUSIC Multiple Signal Classification

BGA Breeder Genetic Algorithm

ANFIS Adaptive Neuro-Fuzzy Inference System

LVQ Learning Vector Quantization

Chapter 1

Introduction

1.1 Background

Electrical Power has now become the life line of this digital world. It is considered as a main indicator of the stage of development in a country. The overall development of power resources in terms of quantitative and qualitative plays an important role for the power utility. In the competitive power market, consumer demand of quality in power is a prime concern. Electrical Power quality is any change in the nominal value of the voltage and current. The issue of disturbances in power signal effects both transmission and distribution of power. From a customer point of view, power disturbances are defined as any change in voltage, current and phase that results in disoperation of appliances. Power quality is of prime concern in the present scenario; as most of the solid state devices and non-linear loads are sensitive to the quality of supplied power. Industrial loads and home utility appliances are severely affected with power quality disturbances such as sag, swell, harmonics, transients and interruption.

The power quality disturbance sag is considered as most disastrous one for the industrial loads. The cause of voltage sag or dip is overload and short circuit which results in reduction of rms voltage between 10 to 90 percent of normal voltage. The duration of voltage sag may be half cycle to a seconds and long duration sag is called as sustained sag. When voltage sag occurred with a duration less than 100 ms and dip of 75 percent of normal voltage then material loss of thousands of US dollar happened in semiconductor industry [1]. Voltage Swell disturbance creates over heating effects and severely affects motor drives in industrial setup. The swell is totally opposite to sag, cause of swell is switching off heavy load which results in momentary increase in voltage. Harmonic disturbance badly affects electronic equipment as control function of equipment, as depends on peak value and crossing of the power signal, which is distorted to due to harmonics. The higher order harmonics cause heating effect in the conductor and misfiring can also occur in speed drives, so limiting of higher order harmonics is the main issue of power quality. Interruption is also a decrease in voltage of power supply up to 90 percent of normal voltage with duration of few seconds, the cause of interruption is closing and opening of circuit breakers with short delay.

The duration of interruption depends on functioning of protective device that is how fast closing of circuit breaker occurs when interruption faults comes into picture, limiting of interruption up to 30 cycles can easily be done with high quality circuit breaker. When heavy loads are periodically turned on or off into the system then flicker disturbance may occur in power supply. The voltage fluctuations appear in power supply when short circuit network in the distribution system is not working properly. Voltage flicker appears when heavy loads are regularly turned on and off in a weak distribution system. When heavy loads such as large motor starts then power supply voltage decreases, this affects the lighting circuit connected to same supply voltage in the form of fluctuations in the light. Mostly the area near to industry is severely affected with flickering or blinking in light. Most of the electronic equipment is very sensitive to flickers because it distorts the stability of voltage which affects functioning of these devices. This is main reason why flicker is of prime concern for computerized system. The transient disturbance appears in the form of spikes for a very short duration which may be in the form of voltage, current and energy spike. The effect of this disturbance is to abrupt rise in current for a very short duration which results in malfunction of appliances operation. For analysis of these PQ events and losses that occur in appliances/instruments, monitoring of single and multiple power disturbances has now become prime area of research. Literature of PQ disturbances has two main steps-first is recognition of power quality events and then second step that is classification. In literature, research work has been mainly carried out for the detection and classification. Various techniques based on renowned transforms, machine learning, neural networks and other techniques have been utilized in earlier work.

1.2 Motivation

The utility of quality in power has dramatically increased due to increasing use of programmable logic devices, non-linear loads and solid state devices. Furthermore, demand of electric power is increasing sharply every year; with this growth, focus on the quality of power is also a main goal. Additionally, the technological advancement, new innovations in other fields also require disturbance free power for efficient operation and long life span of components. Industry is facing huge loss due to power quality disturbances that come randomly within every short duration and even long duration disturbances also cause losses but relatively less, so the main focus is on the short duration disturbances because they are severe in terms of maloperation or malfunctioning of devices. Therefore, PQ urgently needs to be analyzed within appropriate time with accuracy so that corrective measure should be decided quickly for further action within short duration.

Finding a fast and accurate system for recognition and classification of power quality disturbances is the major objective of this work. The analysis system should be capable enough for whatever the disturbances, i.e., single and multiple; come into the system can be easily handled quickly. It should lead to a system that ensure disturbance free clean power. Providing accurate analysis of disturbances and isolating these disturbances from the main grid has to be dealt with intelligent system.

1.3 Literature Survey

In most of the earlier state-of-art literature, the common steps of detection and classification comprise of pre-processing of input power signal, then feature extraction, and after that selection of unique features and finally feeding these features as an input to the classifier which takes decision for final output on basis of algorithm applied. First, the synthetic or real time disturbances are pre-processed, then unique and novel features are extracted and then efficient features are chosen and fed to classifiers for accurate classification. The basic block diagram of PQ analysis system is shown in fig. 1.1. The input power signal is applied to pre-processing block where normalization and segmentation is done followed by feature extraction stage. Feature extraction block includes numerous PQ detection techniques based on different methodology. Feature selection and optimization are also a part of this block which reduces the dimension of feature space that helps in improving the accuracy of classification. The selected features act as input to Classifiers and then final decision is totally based on algorithm explored in classifier.

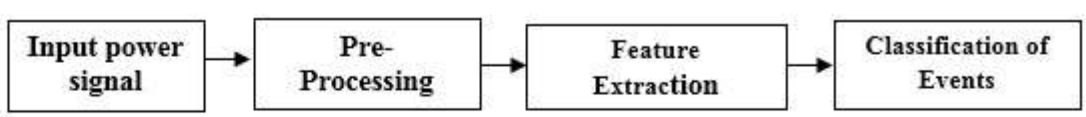


Figure 1.1: Overview of Power Quality Analysis System.

Monitoring of PQ events starts from pre-processing in form of normalization and segmentation followed by feature set extraction by applying some signal processing tools such as Fourier Transform (FT), Short Time Fourier Transform (STFT), Wavelet Transform (WT), Hilbert Transform(HT) and S-transform and finally the classifiers such as Neural Networks(NN), Genetic

Algorithm (GL),Fuzzy Logic (FL) and Support vector machine etc. for the purpose of accurate classification.

Most of the work in the area of power system research covers well-known transform based techniques, separate the unique features, and do the further analysis by choosing any classifier. Some research work is further extended in search of optimization of feature set and tries to explore the effect of optimal features set on classification accuracy. PQ literature provides optimal feature selection method for classification but fails when multiple power quality events come into picture. Detailed analysis of each and every step is done in the subsequent sections.

The pre-processing step covers the input power signals segmentation and then normalization so that redundancy of data can be reduced up to some extent. In the analysis of PQ disturbances, it is useful to divide the input signal into segments. Segmentation is a process in which event information size is reduced and only relevant part of the event is further processed in next stages. In other words, the input power signal is converted into disjoint segments so that the analysis of information becomes effective. Input sequence can be categorized into two part, first transition segment and second is event segment [1]. The event segment is placed between transition segments. The step of normalization converts disturbance parameters into scale function, this is to be done by dividing power signal by RMS value of parameter under consideration, i.e., in the form of per unit (p.u) [2]. Pre-processing is the main step to reduce the memory space requirement, as only pre and post cycle of disturbance are only considered for analysis, while others are irreverent, as disturbance duration is very short in the most of cases. It minimizes the processing time requirement of system. In real PQ data set, addition of noise is important otherwise it will difficult to generate actual power signal disturbance scenario [3, 4, 5, 6]. But this kind of noise severely affects the performance of classifiers, as misjudgment can be happen in noisy environment. Now the role of filters comes into picture to mitigate the effect of noise.

Power setup has three main step, i.e., generation, transmission and distribution to provide electricity to home utility. From PQ point of view, discussion of disturbances in transmission and distribution system is important because environmental (lightening strokes) and load conditions strongly affect these two. The analysis of PQ disturbances starts from pre-processing in form of normalization and segmentation followed by feature extraction by applying some transformation such as FT [7], STFT [8], WT [9, 10, 11], HT [12] and S-transform [13].

Figure 1.2: Feature extraction by various signal processing method.

The fig. 1.2 shows numerous signals processing methods whose mathematical representations are shown in table 1.1. Each and every event has slightly different feature set which act as a base for detection of disturbances. Therefore, the task of feature extraction in earlier state-of-art literature has been done by various transforms. FT is commonly used technique for the frequency domain analysis of the signal, it segments the disturbances into a number of sinusoids with different frequencies. FT is suitable for analysis of voltage sag and swell, but in case of transients and harmonics, it is unable to give correct information about fluctuations. The variations in power signal are often aperiodic and time-varying so, FT is not adequate choice for these non-stationary signals. STFT has fixed window size and can deal with non-stationary signals. The size of window in STFT is much smaller than fluctuation rate of the signal. STFT and other techniques are used for extraction of spectral information of a signal [14] but fixed window size is drawback of this transform [15]. The time windowed technique such as Windowed-FFT, can set the width of window as the size of disturbance under consideration [16]. Voltage disturbances are analyzed with DTFT and STFT respectively [17, 18]. DTFT only has frequency information which is not sufficient for the accurate detection and classification of power quality events.

Table 1.1: Mathematical Representation of different transforms.

S.No	Transform	Mathematical Representation	Description
1	FT	$F(w) = \int_{-\infty}^{\infty} m(t)e^{-jwt}\,dt$	m(t)= input
2	STFT	$STFTm(t,w) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} m(t)w(t-\tau)e^{-jw\tau}dt$	$w(\tau)$ is the window function
3	WT	$WTm(p,q) = \frac{1}{\sqrt{\lvert p\rvert}}\int_{-\infty}^{\infty} m(t)\,\Psi\left(\frac{t-q}{p}\right)dt$	p= scaling function, q =translation function,$\Psi\left(\frac{t-q}{p}\right)$ =mother wavelet
4	HT	$HT[m(t)] = \frac{1}{\pi}P\int_{-\infty}^{\infty}\frac{m(\tau)}{t-\tau}d\tau$ P is the Cauchy principal value	HT convolutes a monotone signal m(t) with (1/πt) & shifts each frequency component of m(t) by ±90 degree
5	ST	$STm(\tau,f) = \frac{\lvert f\rvert}{\sqrt{2\pi}}\int_{-\infty}^{\infty} m(t)e^{\frac{(t-\tau)^2f^2}{2}}e^{-2jft}dt$	f= frequency, t, τ = time, e^{-2jft}= oscillatory exponential kernel
6	GT	$GTm(\tau,f) = \int_{-\infty}^{\infty} m(t)e^{-\pi(t-\tau)^2}e^{-2jf\pi t}dt$	$e^{-\pi(t-\tau)^2}$= Gaussian function as a window

Wavelet transform has mostly been used in earlier state-of-art literature as time-frequency analysis tool to extract spectral features of power quality events [19]. But, WT has drawback that it is sensitive to noise, so to avoid this drawback, selection of mother wavelet and number of decomposition levels are the main parameters to efficiently utilize the power of WT. The family of WT is developed on the basis of properties such as compact support properties, vanishing moments, regularity and orthogonality. Daubechies wavelet is generally used in earlier state-of-art literature due to high energy compaction ratio and low computational overhead in comparison of Morlet, Haar, and Coiflets. The various properties of wavelets are represented in tabular form in table 1.2. The major drawback of WT is that there is no specific criterion for selection for mother wavelets which affects the final accuracy of feature selection and to increase accuracy, if number of levels increases, computational overhead will increase up to large extent. Application of wavelet to analyze power quality events has been explored with comparison to research works employing wavelet transform for analysis of PQ events [20].

Table 1.2: Wavelet transforms and their properties

Property	**Coiflets**	**Symlets**	**Daubechies**	**Morlet**	**Haar**	**Mexican Hat**
Compactly supported orthogonal	Yes	Yes	Yes	No	No	No
Symmetry	No	No	No	Yes	Yes	Yes
Arbitrary regularity	Yes	Yes	Yes	No	No	No
Infinitely regular	No	No	No	Yes	No	Yes
Crude	No	No	No	Yes	No	Yes
Arbitrary number of vanishing moments	Yes	Yes	Yes	No	No	No
Asymmetry	No	No	Yes	No	No	No
Near Symmetry	Yes	Yes	No	No	No	No
Biorthogonal analysis	Yes	Yes	Yes	No	Yes	No
Existence of scaling function	Yes	Yes	Yes	No	Yes	No
Orthogonal analysis	Yes	Yes	Yes	No	Yes	No
Exact reconstruction	Yes	Yes	Yes	No	Yes	Yes
Vanishing moments for scaling function	Yes	No	No	No	No	No
Explicit expression	No	No	No	Yes	Yes	Yes
Fast algorithm	Yes	Yes	Yes	No	Yes	No
FIR filters	Yes	Yes	Yes	No	Yes	No
Discrete transform	Yes	Yes	Yes	No	Yes	No
Continuous transform	Yes	Yes	Yes	Yes	Yes	Yes

WT breaks signal in terms of scaled and translated form and then Multi resolution analysis (MRA) technique is explored [21]. In MRA technique, PQ signal is segmented in the form of low frequency and high frequency components by using low and high-pass filters respectively, and the process is repeated until desired information is extracted with high accuracy. On every iteration, amount of information is reduced up to large extent [22, 23]. The band pass filter extracts high frequency information with the disturbances such as transients and spikes and other sudden switching disturbances are detected, on the other hand low frequency components, the disturbance like harmonics can easily be detected.

In [24], DWT and ANN are used for recognition and further the classification of disturbances and comparison of results with other wavelets were also done. WT is also utilized in three phase system for analysis of voltage dip [25]. Furthermore, Multiwavelet transform applied for extraction of unique features and then Dempster-Shafer algorithm explored for classification purpose [26].

Hybrid approach of DWT with FFT and HST is explored in [27, 28]. The time-frequency domain analysis WT is applied for localization and recognition of power quality disturbances [29, 30]. Classification of power quality events with rule based method hybrid with wavelet packet based HMM and Dempster-Shafer algorithm is explored [31, 32, 33]. Various features are extracted using WT and then optimization is applied to achieve minimum feature set [34, 35, 36]. In [37], under noisy conditions WT is applied and by self-learning approach classification is done. Automatic analysis of PQ events is proposed in real time condition using 2D representation of wavelet components [38, 39].

The concept of de-noising is also proposed in WT to increase the efficiency of recognition of PQ events [40]. To further extend the concept of de-noising in WT, the intra-and inter- scale dependencies using least mean square method is proposed with two set of layer, i.e., sub network and adaptive probabilistic layer [41, 42]. The capacitor switching based specific PQ events detection is also proposed with DWT technique and self-organizing mapping network for detection and classification of PQ events [43]. Various wavelets such as semi orthogonal, orthogonal and bi-orthogonal are proposed for PQ events detection and classification purpose in [44] and concept of multiwavelet transform is also suggested for PQ events analysis[45, 46], other authors also proposed hybrid concept and multiwavelet and Dampster-Shafer technique[47,48]. The PQ events have been simulated by using parametric equations then applied to DWT, as a feature extractor and probabilistic neural network as a classifier is proposed. A comparison is proposed between STFT and WT, experimental results declared WT as a superior technique for analysis of power disturbances [49,50]. ELM technique with DWT is utilized for recognition of power quality events [51]. A classification method for different types of disturbances in a high power transmission line is presented with help of WT [52]. The features such as WT energy entropy and weights are utilized for classification of events with NN method. In [53], WT based technique is developed which is event specific can be identify and classify harmonics and transients. The application specific voltage dips are considered by authors to avoid false alarms in electrical networks [54]. In [55], PQ events detection based on WT and Principle Components Analysis (PCA) is proposed, but proposed technique has limitation of invariant scale, which causes misinterpretation in decision making.

S-transform (ST) is a generalized form of variable windowed STFT or an extension to WT or a mixed form of WT and STFT [56]. This is based on time-frequency analysis of signal, commonly used in geosciences and power system engineering [57]. A frequency dependent resolution is provided in ST by decreasing the width of analysis window with frequency. ST and WT are similar except the phase correction as well as amplitude and phase spectrum. In [58], S-transform is applied for localization of PQ events. For the detection of complex PQ events, S-transform with decision tree based classifier is used. But in case the non-stationary power signal accompanied with transient, then accuracy of S-transform is severely affected. The S-transform is used for feature extraction from distorted PQ signals [59-62]. In [63], S-transform and ELM are used for detection and classification of PQ events. Eristi et al. [31] apply S-transform and ELM technique to automatically recognize the causes of PQ disturbance. In [64], S-transform which extracts instantaneous frequency of PQ events then Parseval's theorem is utilized for classification purpose. S-transform with modified Gaussian window technique is utilized for localization and for classification of PQ disturbances is done with decision-tree based classifier [65] and adaptive particle swarm optimization technique with fuzzy c-means is also utilized for analysis of PQ disturbances in [66]. A fast adaptive discrete generalized S-transform algorithm based on frequency scaling, window cropping and adaptive window frame estimation of the time varying PQ indices is described [67].

In [68], HST, MM technique hybrid with TT-transform is applied to enhance the accuracy of detection of PQ disturbance and SVM is utilized for classification. The concept of WT is applied for phase correction and then S-transform combined with extended Kalman filter for short-duration power network disturbances. Multiresolution S-transform with a variable window width that changes with frequency by user defined function is used for detection of PQ events [69]. A fast S-transform is proposed by the authors, which gives low computation time [70]. Another variant of S-transform, i.e., HST is used in pattern recognition scheme for PQ disturbances [71, 72] and for classification and localization of faults with radial basis function NN [73]. PQD and islanding detection in hybrid DG system (PV, fuel cell, wind) is presented in [74]; features are extracted using WT and S-transform and a comparative analysis is presented between these two. S-transform is used in feature extraction for islanding and PQD in a grid connected DG system [75]. A Nordic 32 bus model is used for wind and PV system based DG. HST is applied for feature extraction; SVM and decision tree are used as classifiers [76]. Hardware is implemented to generate event patterns for a 400 V, two linear loads and one non-linear load electrical system. A voltage sensor is used for capturing the voltage waveform and a dSPACE 1104 kit is used for digital conversion and for interfacing with computer to extract features of multiple power quality events using S-transform and classification with decision tree algorithm [77].For the detection of phase fault and islanding, the concept of TT transform and pattern recognition is applied in [78]. The main advantage of S-transform is MRA which have capacity to detect exact phase of all frequency components present in the PQ events. However, for some other disturbances such as harmonics, it gives inaccurate results. In some of the earlier state-of-art literature the concept of Hilbert Transform (HT) is also explored for detection of power quality events, where HT work as linear operator to find analytic form of signal under consideration[79].

Other techniques are also explored by researchers for detection and classification of power quality events such as Prony analysis method is used for the analysis of signal and extraction of its model information like frequency, phase shift, damping and magnitude. Prony based optimal Bayes fault classification technique is presented by Faiz et al. [80]. Prony analysis and recursive algorithm are proposed [81-84]. Higher order cumulants technique used for feature extraction is given in [85, 86]. Feature extraction in time-frequency domain using parallel computing is explained in [87]. Another multi-core algorithm for WT/WPT is proposed for harmonic analysis and compression. The parallel processing of the algorithm reduces the computation time [88].The authors present HT and Clarke’s transformation [89]. In [90], authors suggested a method which combines Gabor transform and kernel based type-2 fuzzy-SVM technique for analysis of PQ disturbances. Kalman filters [91-95], GT [96], digital filters [97], Time-Time transform [98], curve fitting [99], EMDRA method [100], hybrid HT and WT with frequency shifting [101], fractal based method [102], covariance analysis, HOS [103, 104], change point approach [105] and ADALINE method [106] have been proposed in the last decade. Slanted transform with FPGA hardware containing analog to digital converter AD976A, Xilinx Virtex-E XCV600E FPGA chip and digital to analog converter AD669AN is used for PQ disturbance detection [107].

The PQ disturbance (such as voltage sag and swell) analysis is based on HOS features. Any change in the parameter value shows presence of a disturbance [108]. In [109], a methodology is presented for voltage sag studies in Brazil. Here, authors make a cluster of different distribution substations and apply PCA to find the similar characteristics among the clustered substations. Goswami et al. [110] propose an analytical expression based method for voltage sag analysis. Balanced and unbalanced faults are taken into consideration and proposed analytical method is compared with method of critical distance.

Table 1.3: Comparison of various feature extraction techniques

S. No	Technique	Pros	Cons	References
1	**STFT**	Easy to implement for stationary signals	Inaccurate for non-stationary signals	[15, 16, 17, 18]
2	**WT**	Resolution of time and frequency components is high	Not suitable under noise	[21, 22,25, 29]
3	**S-Transform**	High accuracy in case of time localization	Not suitable for harmonics	[56, 59, 60, 62]
4	**HT**	Good for instant phase and frequency calculation of signal	suitable for short disturbances only	[79]
5	**Kalman Filter**	High signal to noise ratio	Both time-frequency localization is absent	[91-95]
6	**GT**	Resolution of time and frequency components is high	Not suitable for high frequency disturbances	[96]
7	**Filter bank**	Complexity is less	Inaccurate for harmonics	[106]
8	**TT Transform**	Highly accurate for non-stationary signal	High computation	[98]
9	**HOSA**	Highly accurate for transient detection	Low resolution	[103, 104]

The disturbance (like voltage sag) detection method by dq transformation and mathematical morphological technique presented in [111]. Three-phase voltage is converted to dq axis and is passed through MM filter to find other parameters such as phase angle change and distortion in magnitude. A method to detect voltage sag is presented by the authors [112]. By using the envelope of the system voltage, voltage dips are calculated and simultaneously phase shift is calculated to find the type of the voltage sag. In [113], authors presented a novel detection and classification technique based on voltage sag types, characteristics and zero sequence components of the voltage signal. Two indices, i.e., phase-to-phase voltage index and phase-to-neutral voltage index are proposed for characterizing the event. Various techniques of feature extraction are compared in table 1.3.

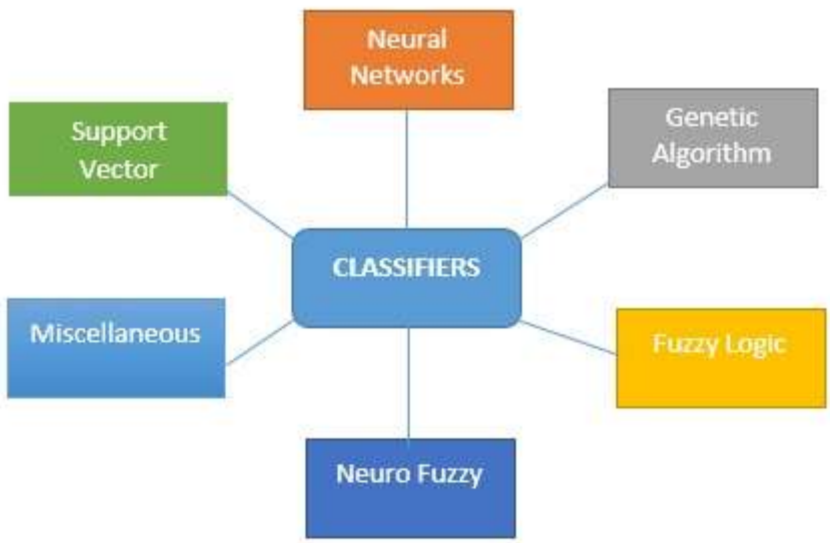


Figure 1.3: Classification techniques of PQ disturbances

Artificial Intelligence (AI) or the knowledge based techniques are adopted as the substitute to the classical techniques for PQ event classification [114]. AI techniques are used to solve complex problems, decision making and classification. AI is the capability of the machines to take intelligent decisions like a human being. AI includes reasoning, knowledge, planning, learning, natural language processing (communication) and perception. The techniques like Support Vector Machine (SVM), rule-based systems, Artificial Neural Network (ANN), fuzzy models, Genetic Algorithm (GA) and swarm intelligence etc. as shown in fig. 1.3, lie under AI.

Neural Networks (NN) works the same way as human brain neurons works, it is just a learning tool utilized as a classifier work as information transfer system form one point to another. In [115-117], authors propose the automatic detection and recognition of single PQDs using WT and NN classifier [118, 119]. S-transform based PNN [120] is compared with feed forward multilayer NN.

LVQ based NN is employed for classification of PQD [121]. A feed forward neural network classifier is used for detection of PQ events using demodulation [122]. Talaat et al. suggest subtractive cluster feature based ANN for PQ classification; this method considers data point as a cluster center and calculates likelihood of each data point [123]. Transient level detection by using HOS and competitive layer based NN is presented [124].

Enhanced wavelet probabilistic network is proposed [125]. Self-adapting ANN is presented [126] and dynamic structural NN approach is described in for detection and classification of PQD [127]. Manke and Tembhurne [128] presented NN with feed forward structure and modified Fisher's discriminant ratio kernel. A chaos synchronization based detector for detection of PQD in power system is proposed by the authors. Here, dynamic error equations are used to extract features and PNN classifier is used for classification [129]. In [130], PNN classifier is used for classification of voltage such under three different real time scenarios. In DG, ANN is used as a classifier for detection of islanding event in non-detection zone [131]. Flicker recognition technique is presented for wind turbines; WT and S-transform are used for feature extraction; relief feature selection method with PSO for optimization and PNN is used for classification [132]. Total PQ index is presented by the authors for PQ deviations analysis on a specific site. MLPNN is used for the classification purpose and input signal is selected through expert system questionnaires [133]. SVM is having advantages over above said ANN because of its learning strategies. SVM is a binary classifier utilized to separate two different classes of data, i.e. used as a statistical tool. In [134], authors propose SVM classifier for PQ disturbance identification by using SVMs for identification of PQ disturbances. In [135-138], SVM is explored for efficient classification of power disturbances. Authors presented application of SVM in PQ disturbance analysis based on HOS by using geometrical pattern establishment for automatic classification [139]. Automatic recognition of PQD with kernel based SVM clustering is proposed where a modified immune optimization algorithm is used for improvement in compactness of clusters and in classification accuracy by refining the center of SVM clusters [140]. Different multiclass SVM algorithms such as k-SVM, fuzzy SVM and directed acyclic graph SVM are compared [141]. Authors present islanding and PQD classification in grid connected power network in DG [142] while [143] classifies transients due to power transformer and PSO is used for tuning SVM parameters. In [144], SVM classifier is explored for recognition of power quality events. A hybrid method of priori algorithm with least square SVM is explored for feature section and identification of PQ disturbances [145]. Gunal et al. use an experimental setup for detection of PQ events. They emphasize on the optimal feature set by comparing seven feature selection techniques and classification performance is compared with Bayes and SVM classifier [146]. In paper [147], SVM is used for PQ disturbance classification after being optimized with GA and SA.In [148], islanding and identification of PQ events in real grid system is explored with MPNN and SVM. Firstly, S-transform is used in feature extraction and then MPNN and SVM are trained separately followed by the classification of disturbances. Wind energy and PV based DG system are presented [149]. Here, PQ disturbance due to effect of load changing as well as change in solar insolation and wind speed is discussed. MPNN, SVM and LS-SVM classifiers are used for PQ disturbance classification. The training of SVM affects its accuracy due to dependency on training data. There is no need of training in the fuzzy systems. Fuzzy logic is based on degree of truth instead of true and false and depends on multivalued logic. It provides a rough estimate just like human thinking or the hypothesis.

The concept of Genetic algorithm is based on search engine with natural selection. It is mostly used in classification and optimization problems. Multi-objective GA and decision tree for PQD's pattern recognition are presented [150]. GA is used to find feature set with minimum classification error and minimum size of tree. Application of LVQ-NN combined with GA is proposed [151]. In [152], concept of pattern recognition is explored with NN and GA based technique for detection and classification purpose. BGA method is used by Yusran for optimum placement of distributed generation in power system network [153]. Wang and Tseng present a WT and extended GA based method for PQ analysis [154]. Optimum location and number of PQ monitors required for PQ analysis are given [155, 156]. For PQ disturbance classification in a wind and PV based DG system, HST is applied for feature extraction, SVM and decision tree are used as classifiers [157]. For an optimum feature selection, GA is used and effect of noise is also considered for checking the robustness of the proposed system.

The technique of fuzzy logic is multi-valued logic that gives approximations and its truth value ranges in between 0 and 1. Zhu et al. [158] present wavelet based fuzzy reasoning approach in which features are extracted by wavelet and on the basis of these features, rule base is generated to draw inference for final decision of classification. The fuzzy logic technique is explored for classification of power quality events [159, 160]. The technique of Kalman filter and fuzzy logic is combined to enhance the accuracy of classification of PQ events. In [161], fuzzy clustering based on chemo-tactic differential evolution and bacterial forging optimization is explored for fast and accurate classification of power quality events. In [162, 163], fuzzy C-means algorithm and data mining techniques are used by the authors respectively and PSO is used for optimization of parameters and performance. The PSO technique is also explored with fuzzy for automatic classification of power quality events [164]. R. Kapoor and M. Saini [165], presented hybrid technique of WT and fuzzy for classification of PQ events. In [166], analysis of PQ events on the basis of fuzzy logic is proposed. For the analysis of voltage sag and current harmonics, fuzzy logic controller is used in unified PQ conditioner. FL controlled unified PQ conditioner effectively mitigates the voltage sag and bounds harmonics in an acceptable limit in grid connected wind power system [167]. The data set of fuzzy system is fixed, so, it is not useful for detection of new problems and fuzzy logic rules also are not robust. Hence, for analysis of combined PQ problems, it is advantageous to use neuro-fuzzy systems.

Neuro-fuzzy systems are the combinations of ANN and FL. These are primarily based on fuzzy systems; the learning algorithm to train these systems uses NN theory. The DG system based PQ disturbances are detected and classified with adaptive neuro-fuzzy and modified ADALINE is explored for feature extraction [168]. In [169], PQD detection and classification is proposed; voltage is converted in three-dimensional (3D) space, then PCA is used for feature extraction from eigenvalues of each disturbance and after that neuro-fuzzy classifier is used for automatic classification of PQDs. ANFIS based representative quality power factor is presented [170]. Displacement power factor, transmission efficiency power factor and oscillation power factor are considered for linear, non-linear, sinusoidal and non-sinusoidal cases with lagging and leading power factors. Ref. [171] presents automatic disturbance recognition based on neuro-fuzzy system. In [172], noised affected PQ disturbances are classified with neuro fuzzy based approach. Data compression techniques are discussed with adaptive neuro-fuzzy technique [173]. Islanding detection for grid connected inverter based distributed generation is presented [174]. Authors describe a two way technique, i.e., recognition of disturbances at distribution level and stability at generating stage [175]. Non-linear transients' identification is proposed by [176] in a pilot refrigerator plant. In [177], authors propose a probabilistic wavelet fuzzy NN controller. This controller works in dual mode for active and reactive power control in three-phase grid connected PV system at the time of grid faults. The main advantage of neuro-fuzzy system is that the combination of these two overcomes the drawbacks of individual techniques. In [178], faults are classified by applying WT and expert base rule. The expert rules classify four types of fault events on the basis of magnitude of the waveform. The concept of filter bank is explored for detection of power quality events with based ruled based approach for classification [179].An expert system is proposed which contains optimized NN combined with DWT and FL for PQ events classification. DWT, NN and FL are used for feature extraction, processing and post processing respectively [180]. For classification of voltage dip events and their causes, i.e., fault induced, transformer energization and induction motor starting and transients (due to fault or non-fault), an expert system is proposed [181].

Table 1.4: Comparison of PQ classifiers

S. No	Technique	Pros	Cons	Reference
1	SVM	Best suited for quadratic optimization and fast learning	Accuracy affect with large training data set	[140, 134, 139, 138]
2	GA	Suitable for dynamic systems	Slow computation	[150, 152, 151, 153]
3	FL	Best for complex systems	Classify only on the basis of training data set.	[162,159, 247, 160]
4	ANN	Suitable for real systems	Noise affect the performance	[202-207]
5	ES	Performance is independent of data set size	slow and costly	[181,182]

An event specific method is developed by hybrid approach of Fourier linear combiner for feature selection and fuzzy expert system for classification [182]. Adaptive boosting algorithm is proposed in the multi-machine distribution system for the detection of islanding event [183]. Decision tree is used for classification of single and complex PQ problems with noisy signals [184]. MM and HHT are used for PQD detection, where MM is also used for noise suppression [185]. Digital filters are used for decomposition and classification of disturbances [186]. HMM based on WT, WPT and vector quantization is presented [187-189]. A recursive implementation of MUSIC algorithm is presented for mitigation of power disturbances occurring due to arc furnace in noisy and noiseless conditions [190]. The implementation is based on experimental setup which consists of DSP board TI-320LF2407, a voltage source converter, hysteresis current controller, programmable AC power source and a current transducer. An experimental setup is used for transmission line fault classification using systematic fuzzy rule base [191]. A transmission line of

100 km length, voltage sensor and dSPACE 1104 kit with computer are used for practical model. A hybrid approach is developed with PNN and SVM to analyze PQ events in DG system.

Table 1.5: Comparison of various methods of PQ detection and classification

S.No	Reference	Detection method	Classification method	Power Signal	Accuracy
1	Eristi and Demir [04]	WT	SVM	Simulated and noise less/noisy	With noise 95.81 and without 99.71
2	Reaz et al. [180]	WT	NN+Fuzzy	Real without noise	98.19
3	Masoum et al.[05]	WT	NN	Real noisy	98.18
4	Meher and Pradhan[197]	WT	Fuzzy	Simulated and noise less/noisy	With noise 96.87 and without 98.95
5	Alshahrani et al.[213]	WT	ANN	Simulated and noiseless	90
6	Jayasree et al. [214]	HT	RBF	Simulated and noise less/noisy	With noise 94 and without 97
7	Salem et al.[200]	ST	ES	Real without noise	99.44
8	Behera et al.[199]	ST	ES	Simulated and noisy	99
9	Uyer et al. [210]`	ST	NN	Simulated and noisy	99.56
10	Parez et al.[108]	HOS	-	Real without noise	83
11	Huang et al.[195]	WT	FSCL+LVQ	Real without noise	93.76
12	Zhu et al.[158]	WT	Fuzzy	Real with noise	95.31
13	Hu et al[193]	WT	SVM	Simulated and noiseless	98.5
14	Abdoos et al.[203]	ST+WT	PNN	Simulated and noise less/noisy	With noise 97.44 and without 99.22
15	Biswal et al.[215]	WPT	LVQ	Simulated and noiseless	99.14
16	Lee and Sheen [216]	ST+TT transform	MLP	Simulated and noise less/noisy	With noise 97.20 and without 98.10
17	Zhang et al. [207]	Modified ST	ELM	Simulated and noise less/noisy	With noise 96.85 and without 99.99
18	Khokhar et al.[114]	DWT	MPNN	Simulated and noise less/noisy	With noise 88.75 and without 97.68
19	Hajian et al.[72]	DWT+HST	SVM+NN	Simulated noiseless	99.38
20	Ferreira et al.[103]	HOS	NN	Simulated noiseless	100

Two 9kVA alternators and a 5kW load are used for demonstration of wind energy conversion connected to grid. Tran et al. [192] propose an application of transient current in induction motor fault diagnosis which is based on Fourier-Bessel expansion. Data set is generated using an induction motor, pulleys, shaft and fan with changeable blade pitch angle. Table 1.4 represents the pros and cons of PQ classifiers explored in earlier state-of-art. In table 1.5 various methods of detection and classification are compared. For improving performance and execution time, various feature selection methods or optimization techniques is utilized by the authors. The results claimed by authors are based on selected PQ events and the classification performance is significantly high. A lot of research works rely upon WT for excellent time-frequency domain analysis of PQ signals [193-198]. WT facilitates effective feature extraction from PQ signals using a variety of wavelet functions depending upon PQ signal. Another customarily used signal processing technique is S-transform which gives signal representation in time-frequency domain and accurately localizes the occurrence of PQ disturbances [199-201]. In the classification domain, ANN rules the field of PQ in one or another form. There are many variants of ANN like ELM, of feature space and complexity of the system; consequently, computation time is also reduced [202-207]. Hybrid methods for the feature extraction and classification give comparatively better results than individual techniques. Many algorithms are formulated by various authors to attain fast response and to get rid of noise effects. Many researchers have proved the robustness of their proposed techniques by using the noisy PQ signals [209-212]. In the earlier state-of-art most of techniques are developed for single PQ events, so there is need to develop a technique that can easily analyze multiple power quality events.

1.4 Research Gaps

Based on the literature survey, following research gaps were identified:

1. Limited multiple power quality events detection techniques are available, and there is scope to develop new techniques for multiple power quality events detection & classification.
2. Most of detection and classification techniques are events specific, so this opens a scope to identify new strategies for real time monitoring for power quality.
3. Classification techniques may be explored for further improvement in accuracy.

4. All types of detection techniques may be worked upon to detect disturbances with low SNR value.

1.5 Objective of Research

The objective of this research is to investigate the most harmful multiple power quality disturbances. Most of the power disturbance aspects, such as: recognition, characterization and classification issues have been addressed.

1. To efficiently recognize and classify multiple power quality events.
2. To classify disturbances even in heavy noise and low SNR conditions.
3. To develop an intelligent system for power quality events analysis for real time applications.
4. To design and develop a hybrid technique for fast and automatic detection and classification of power quality events.

1.6 Thesis Overview

The thesis proposes fast detection and classification of multiple power quality events with high accuracy and low computation complexity. In chapter 1, the concept of PQ disturbance is briefly explained and then literature survey is conducted to find research gaps and then research objectives were decided on this basis of research gaps. Rest of thesis is organized as follows:

Chapter 2: This chapter introduce the detection and classification of power quality events, which includes extraction of relevant features of PQ events such as kurtosis and spectral entropy and then these features acts as input to classifier, which is Interval type-2 fuzzy logic system (IT2FLS) and comparative analysis of results under three different SNR condition, and finally discussion of results is done.

Chapter 3: The objective of this chapter is to develop an intelligent system for power quality events analysis for real time applications based on sparse feature based Adaptive Finite Element Method (FEM). They key ingredients in this chapter cover comprehensive study of sparse features with adaptive discretized triangular mesh used for calculation of stiffness matrix. Results, discussion and comparison with earlier state-of-art works are also presented.

Chapter 4: The objective of this chapter is to design and develop a hybrid technique based on Long Short Term Memory-Convolution Neural Network (LSTM-CNN) for fast and automatic detection and classification of power quality events. The key ingredients in this chapter include the comprehensive study of hybrid approach for analysis of power quality events, results, discussion and comparative analysis of results with non-hybrid approach is done.

Chapter 5: This chapter sheds light on conclusions drawn from this study on the basis of work reported either experimentally or theoretically and covers the future research scope in the field of power quality disturbances.

Chapter 2

Volterra Series based Power Quality Disturbance Analysis

This chapter introduces the detection and classification of power quality events, which includes extraction of relevant features of PQ events such as kurtosis and spectral entropy and then these features act as input to classifier, which is Interval type-2 fuzzy logic system (IT2FLS). Comparative analysis of results under three different SNR conditions, and finally discussion of results is done.

2.1 Introduction

The study of power quality disturbances has become crucial from last few decades due to increase in use of non-linear solid state devices. The competitiveness and open access power market insists for better quality of servicing. The power quality disturbances include voltage sag, swell, harmonics, transient, interruption and flickers, Some of these disturbances act in combination. The main causes of disturbances are heavy inductive loads, capacitor switching, Ac motor drives, unbalanced loads and poor power factor. To address these issues, detection, localization and classification of disturbances is the main task so that necessary corrective action can be taken in appropriate time limit. The objective of this chapter is to present a new approach for multiple power quality events analysis i.e., Volterra series for feature extraction and interval type-2 fuzzy logic system (IT2FLS) for classification of PQ events. The Volterra series is represented in the form of infinite power series with memory which provides convenient and strong platform for representation of input-output relationship for non-linear systems. IT2FLS uses the concept of membership functions to perform classification of multiple PQ events. When supply power is distorted by additive noise where SNR is low and uncertain, IT2FLS has shown improved performance over SVM, neural networks, probabilistic neural network and type-1 fuzzy logic system classifiers, which makes an interval type-2 fuzzy logic system favorable for real time applications. Therefore, the concept of type-2 fuzzy logic is utilized here for the purpose of classification of single and multiple power disturbances so that whatever the disturbances come into system, these can be analyzed easily.

2.2 Proposed Methodology

Power quality events taken as input and data base is formed for detection for classification of power quality events then Volterra series methodology is applied for detection and extraction of features of power quality events then IT2FLS is trained based on features extracted from Volterra series, i.e., spectral entropy and kurtosis. The next step is rule based fuzzification to classify power quality events then classified events are obtained based on rule designed with the help of extracted features as shown in fig 2.1.

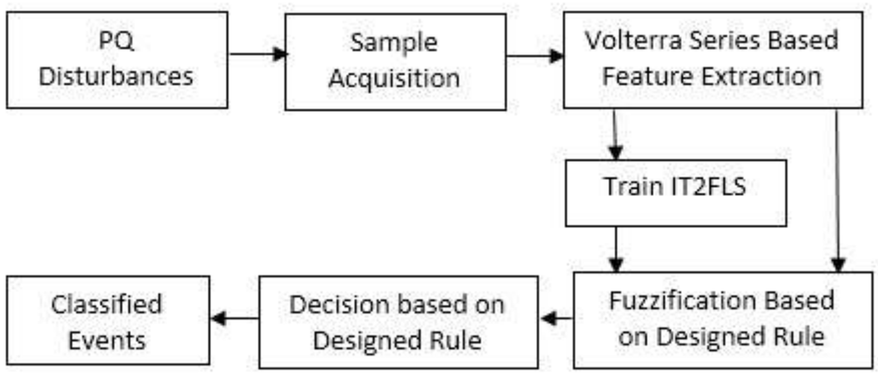


Figure 2.1: Workflow diagram of proposed framework.

The planned state-of-art uses limiting methodology to handle the lengthy calculations of IT2FLS. The results obtained based on the above mentioned methodology are discussed in the subsequent sections.

2.3 Volterra Series Basics

A discrete-time and causal nonlinear system with input signal x[n] and output signal y[n]. The Volterra series representation of x[n] is given by:

$$y(n) = h_0 + \sum_{a_1=0}^{\infty} h_1[a_1]x[n-a_1] + \sum_{a_1=0}^{\infty}\sum_{a_2=0}^{\infty} h_2[a_1,a_2]x[n-a_1]x[n-a_2] + \ldots \tag{2.1}$$

In (2.1), h_b[a1, a2,..., ab] is known as the b-th order Volterra kernel of the system; without any loss of generality, the kernels can be assumed to be symmetric. In general any kernel h_b [a1, a2,..., ab] can be replaced by symmetric one by simple setting.

$$\left[h_b^{sym}[a_{1,}a_2,\cdots a_b] = \frac{1}{n!}\sum_{(a_{i_1},a_{i_2}\cdots a_{i_b})\varepsilon_s} h_b[a_{i_1},a_{i_2}\cdots a_{i_b}]\right] \quad (2.2)$$

Where s is set of all permutations of a_1, a_2,...,.a_b. The Volterra series is a power series with memory. This can be checked by changing the input by a gain factor d so that the new input is dx(t). By using (2.2), the new output is

$$\begin{aligned} y(n) = h_0 + f^a[\textstyle\sum_{a=0}^{\infty} h_1[a_1]x[n-a_1] + \\ \textstyle\sum_{a_1=0}^{\infty}\sum_{a_2=0}^{\infty} h_2[a_1, a_2]x[n-a_1]x[n-a_2] + ...] \end{aligned} \quad (2.3)$$

This equation 2.3 is a power series with amplitude factor f. The integrals are convolutions it shows that series having memory [217]. As an effect of its power series features, it can detect signal in very less computational overhead and doesn't require so many samples for training. The trained samples of PQ events are implemented as input in kernel of Volterra series in the next section.

2.3.1 Exponential Method for Kernel Estimation (Volterra Series)

The various methods are available to resolve the kernels or the associated transfer functions of Volterra series. In between, the method of exponential inputs precisely picked for calculating Volterra kernel in this work. Let's consider the Volterra series expansion of a nonlinear system of the form

$$y(t) = \sum_{b=1}^{\infty}\int_0^{t_1}\cdots\int_0^{t_b} h_b(a_{1,}a_2,\cdots a_b)x(t-a_1)\cdots x(t-a_b)d\,a_1\cdots\cdots d\,a_b \quad (2.4)$$

Let the input x(t) be a sum of exponentials

$$x(t) = \exp^{S_1 t} + \exp^{S_2 t} + \cdots\cdots \exp^{S_g t}$$

Where $s_1, s_2, \ldots s_g$ rationally independent. This means that there are no rational numbers $\gamma_1, \gamma_2, \ldots . \gamma_g$ such that the sum $\gamma_1 s_1 + \gamma_2 s_2 + \cdots \gamma_g s_g$ is rational. Then (2.4) becomes

$$y(t) = \sum_{b=1}^{\infty} [\sum_{g_1}^{g} \cdots \sum_{g_b=1}^{g} H_b(s_{g_1} \cdots s_{g_a}) e^{(s_{g_1} + \cdots s_{g_a})t}] \quad (2.5)$$

If each s_i occurs $s_{g_1 \ldots\ldots} s_{g_a}$, v_i times, then the ratio becomes

$$\frac{b!}{v_1!\, v_2! \ldots \ldots v!}$$

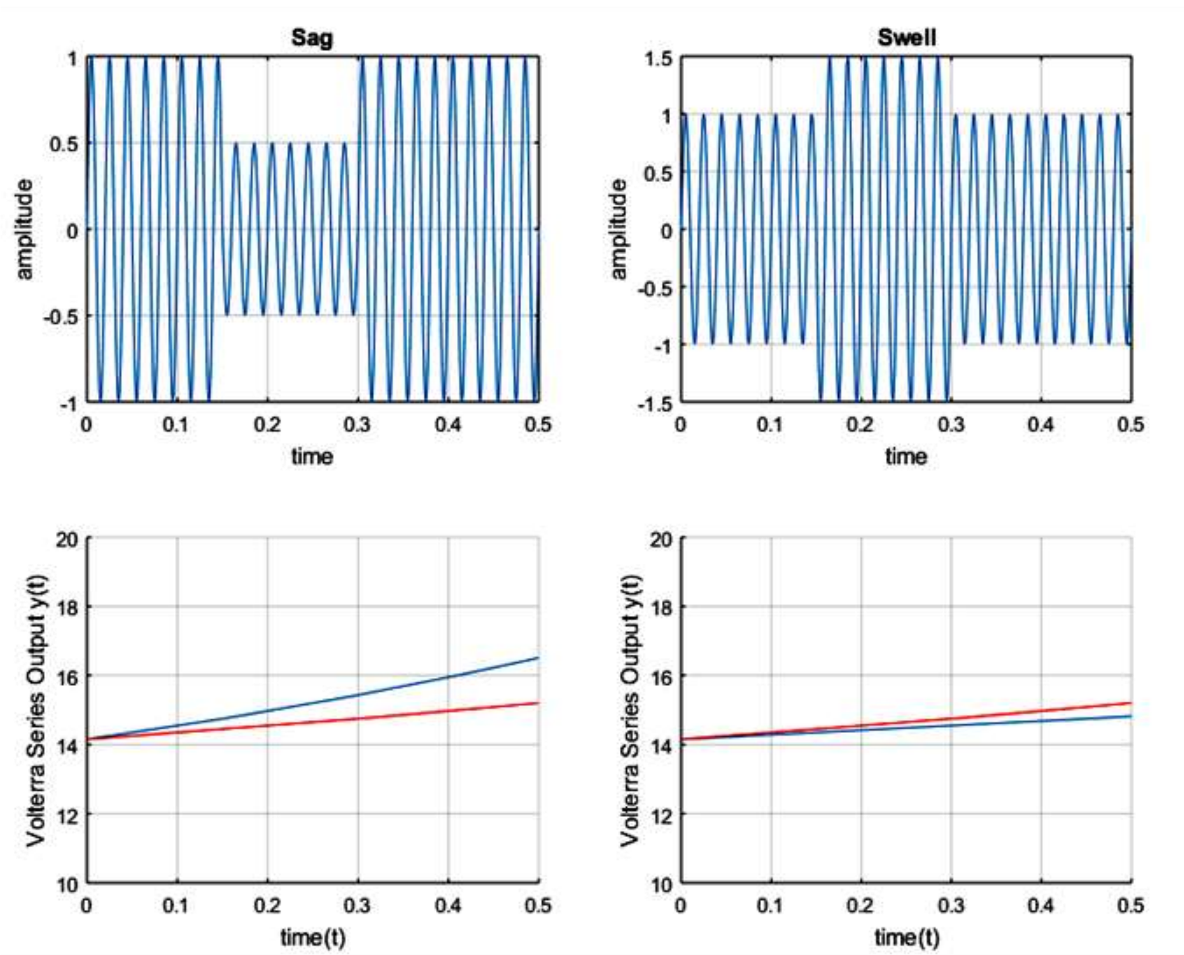
Then (2.4) can be written in the form

$$y(t) = \sum_{b=1}^{\infty} \sum_{v} \frac{b!}{v_1! v_2! \cdots v_g!} H_b(s_{g_1} \cdots s_a) e^{(s_{g_1} + \cdots s_{g_a})t}] \quad (2.6)$$

In equation 2.5, v under the summation sign indicates that the sum includes all the distinct vectors$(v_1, v_2, \ldots . v_g)$ such that $\sum_{i=1}^{g} v_i = b$. If $v_1 = v_2 = \cdots = v_g = 1$ then the amplitude associated with the exponential term $\exp^{(s_{g_1} + \cdots s_{g_a})t}$ is $g!\, H_g(s_1, \ldots . s_g)$. Now, calculation of Volterra series kernel is possible, just calculating the transfer function of the system [218]. Volterra series find application in numerous fields of engineering and physics and essentially classified into two different categories, within the first classification, a model of an observed dynamical phenomenon is framed using Volterra series and the estimation of Volterra frequency response function requires experimental and numerically generated data. On the other hand, second classification includes the analysis of dynamical systems that are already represented by an analytical model, such as differential equation in mathematics. The harmonically stimulated nonlinear systems behavior is explored more suitably using Volterra series representation.

2.4 Volterra Series Based Feature Extraction

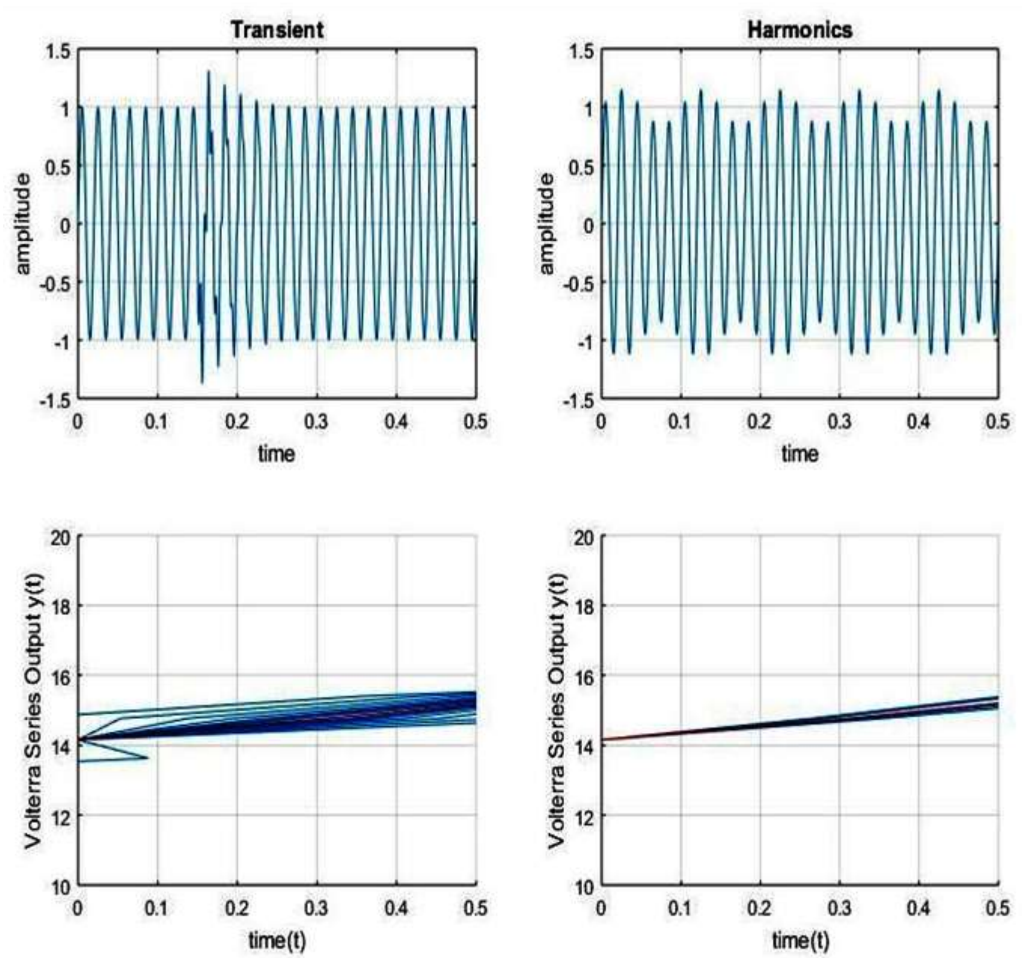
The single and multiple power quality events have been taken into consideration and corresponding results are obtained. The detection of power quality events involves exploiting Volterra series response on non-stationary PQ events represents deviation in output in contrast to pure power signal. Generally a stationary process is a stochastic process whose joint probability distribution does not change when shifted in time. The parameters such as mean and variance, if they are present, also change over the time in case of non-stationarity. Although stationarity is an assumption underlying many statistical procedures used in time series analysis, non-stationary data is often transformed to become stationary. The most common cause of violation of stationarity are trends in mean, which can be due to either the presence of a unity root or of a deterministic trend.



(a) (b)

Figure 2.2: Volterra series output for (a) Sag (b) Swell

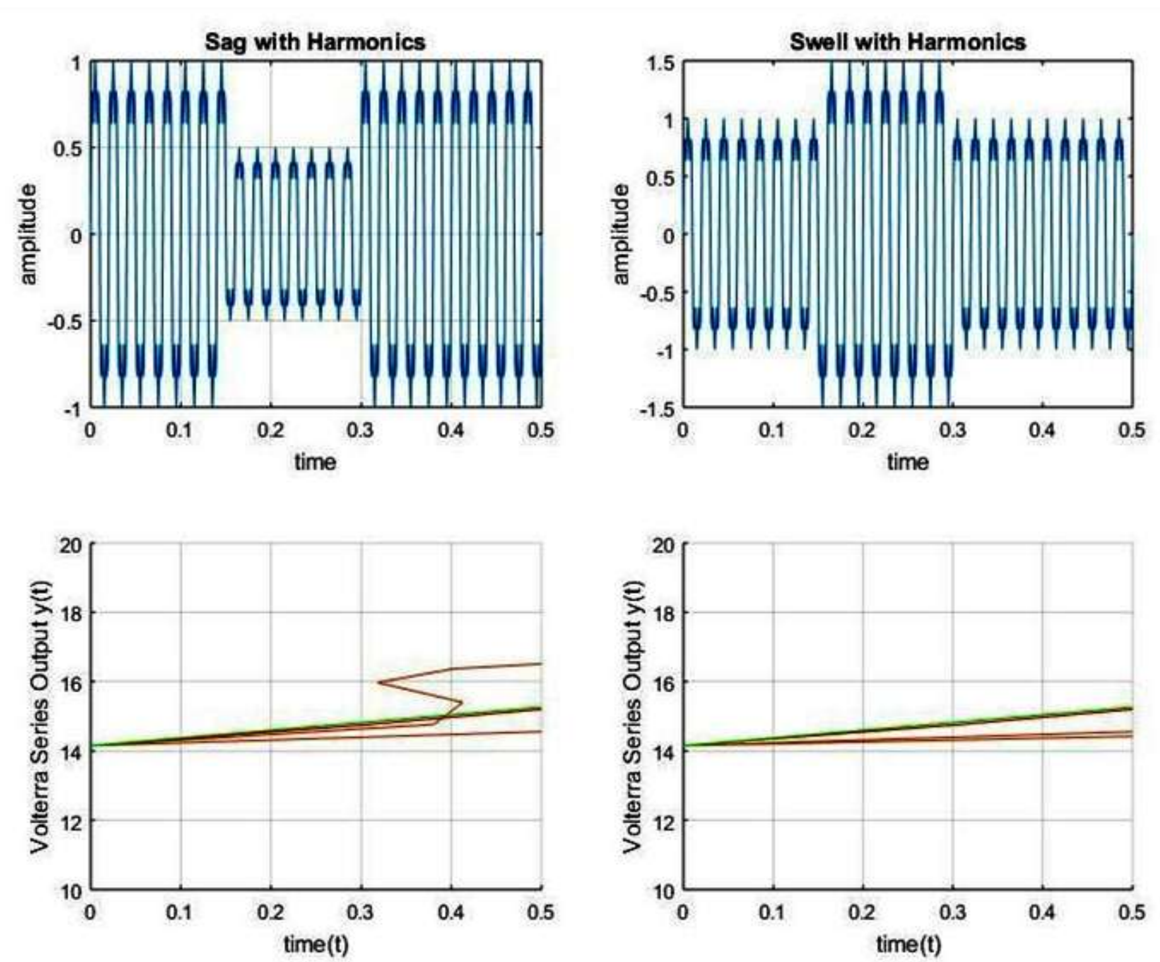
The event sag refers to decrease in rms voltage or current to between 0.1 and 0.9 pu at the power frequency for durations of half cycles to one minute. Swell causes an increase in rms voltage and current to between 1.1 pu and 1.8 pu at the power frequency durations from half cycle to one minute. At the time of starting electric motors draw heavy current, starting an electric motor can be a major cause of voltage sag. Harmonics in an electric power system are due to non-linear electric loads. Harmonic frequencies in the power grid are a frequent cause of power quality problems. Although the effects of sag are more prominent but the effects of a voltage swell are often more destructive. It may cause burning of components on the power supplies of the equipment, though the effect may be a gradual and aggregating. While during the no disturbance response of Volterra Series is approximately linearly vary with time, but in condition of sag it is totally different as shown in fig 2.2.



(a) (b)

Figure 2.3: Volterra series output for (a) Transient (b) Harmonics

During swell PQ event, Volterra series output lies over the pure sine wave output and in actual case when swell overs then sag events comes, therefore the output of Volterra series for sag event lies below the pure sine wave output of Volterra series. In fig 2.3, when transient event arises by cause of switching action in power system, at that instant the Volterra series output shows inconsistency in output due to disturbance. Usual solution of transient is to adopt controlled switches in the setup. The PQ event harmonics that cause voltage waveform distortion can change the amplitude of signal 0-20 percent from its actual value. The output response of Volterra series is completely different for harmonics, having multiple curves in response which represents the presence of multiple frequencies in the power signal..

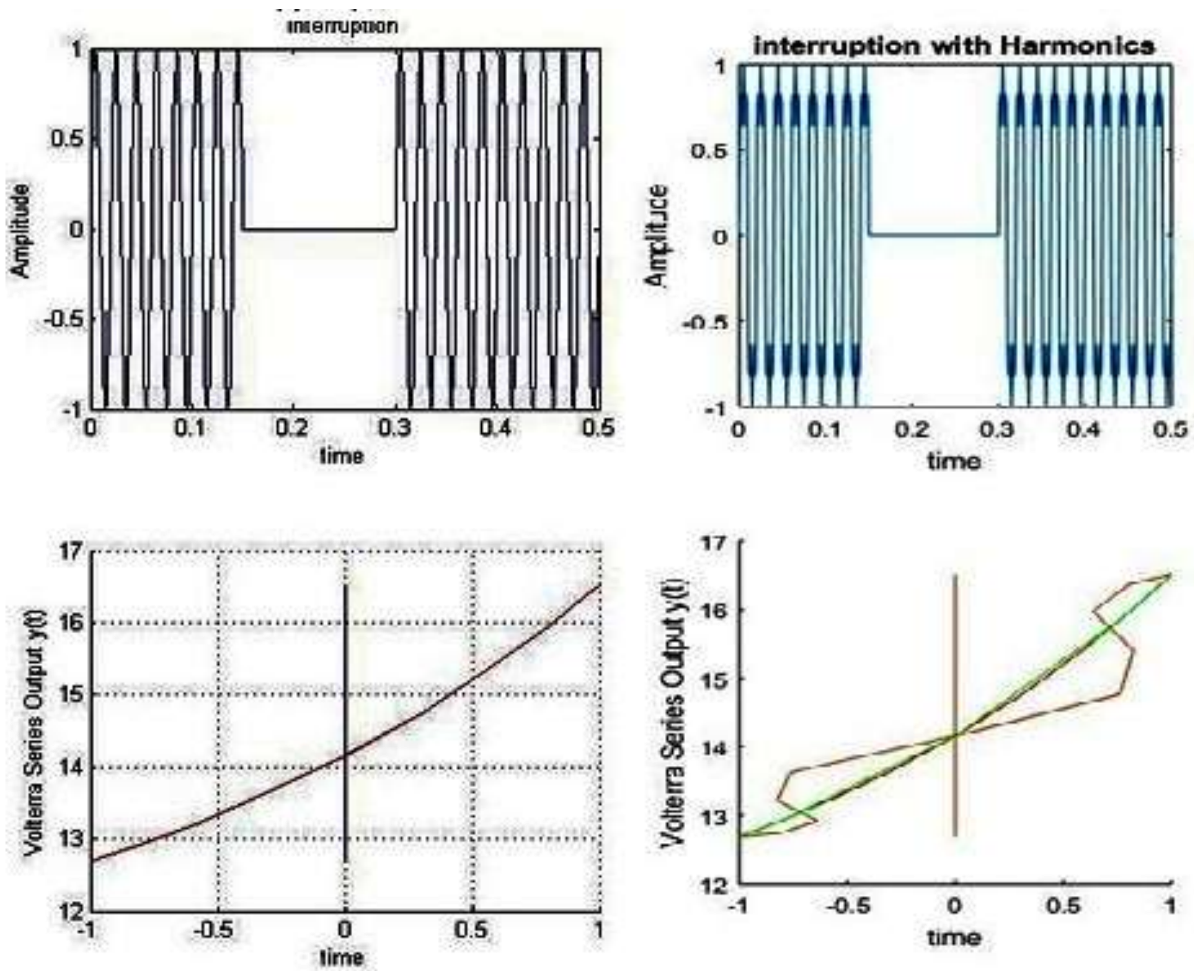


(a) (b)

Figure 2.4: Volterra series output for (a) Harmonics (b) Swell with Harmonics

In fig 2.4, when sag with harmonics arises as a disturbance within the system, then Volterra series output clearly find the harmonics with totally different curve for various harmonics. Just in case of swell with harmonics, the event swell and harmonics each detected with different curves within the Volterra series output plot. When momentary interruption event comes due to Very short planned or accidental power loss duration of milliseconds to second in the power line then the Volterra series output a vertical line appears as shown in the fig 2.5, represents the detection of interruption event in the power signal. The multiple events interruption + harmonics comes due to

Switching operations attempting to isolate an electrical problem then in the Volterra series output a vertical line with multiple irregular plots which shows the harmonics event with interruption appears as shown in the fig 2.5. These results are used for feature extraction that helps in classification of PQ events. In this study, features extraction phase is different from that inspected in literature, attributable to the fact that two features, namely spectral entropy (SE) and kurtosis requires less process overhead.



(a) (b)

Figure 2.5: Volterra series output for (a)interruption (b)Interruption + Harmonics

The spectral entropy (SE), i.e., frequency domain feature and time domain feature, kurtosis are selected to classify events; these specifically extracted features are used for classification using Interval type-2 fuzzy logic system. The spectral entropy analyzes complexity and inconsistency in spectrum and also a measure used to characterize signal spectrum flatness. The estimation of SE needs the spectrum $\beta(w_i)$ of PQ events. Now calculation of the power spectral density ($\alpha(w_i)$) is done by squaring its amplitude and normalizing the power spectral density between (0, 1), in order that it can be treated as a probability density function p_i. The calculation of SE is possible using common formula for entropy.

$$\alpha(w_i) = \frac{1}{N}\left|\beta(w_i)\right|^2 \tag{2.7}$$

$$p_i = \frac{\alpha(w_i)}{\sum_i \alpha(w_i)} \tag{2.8}$$

$$SE = -\sum_{i=1}^{n} p_i \ln p_i \tag{2.9}$$

In this work, SE is implemented for the purpose of feature extraction of PQ events for classification of PQ events. The SE is calculated for each and every event. This SE based information is employed as input in interval type-2 fuzzy logic system for classification of power quality disturbance. In fig 2.6, Spectral entropy values for numerous PQ events are plotted, for every event the value of SE is totally different.

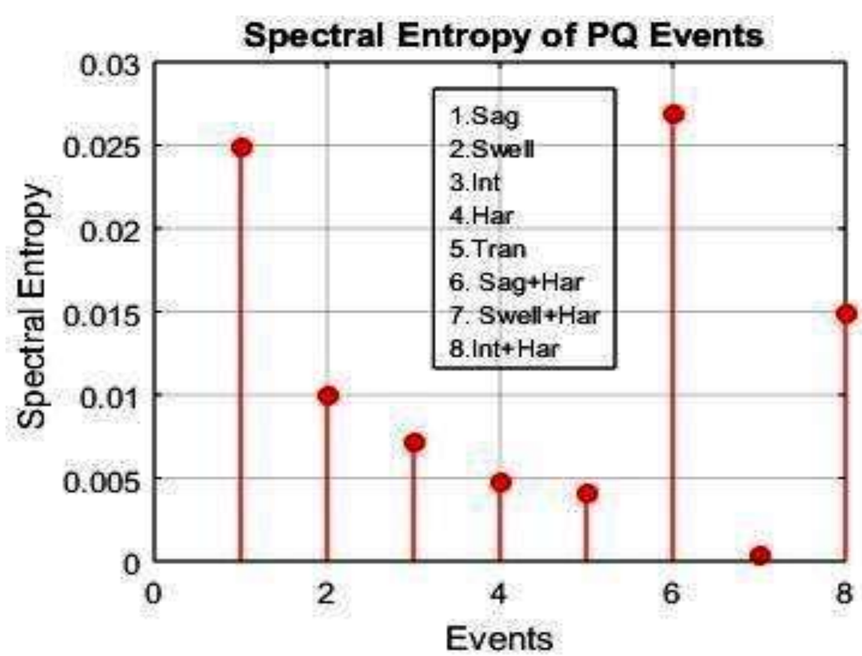


Figure 2.6: Spectral Entropy of PQ events.

Kurtosis has ability to outline the pattern of random variable's probability distribution. It can measure peakedness or flatness of samples into consideration. There are various methods of computing it for an analytical distribution and corresponding steps of evaluating it for the data samples from a population, wholly depends on individual measure of kurtosis. There are three sorts of kurtosis, mesokurtic, platykurtic and leptokurtic. For the calculation of kurtosis, standard normal distribution taken as a reference. The standard normal distribution encompasses a kurtosis value three. If the data samples have kurtosis value near to three, then the graph is about to be normal and said to be mesokurtic. When the kurtosis value is under three, then the distribution said to be platykurtic, also referred to negative kurtosis. If the kurtosis value comes out to be larger than three, then the distribution is Leptokurtic, which has positive kurtosis. Calculation of kurtosis is done by moments and is given by (2.10) in the subsequent formula:

$$K = \frac{\frac{1}{N}\sum_{i=1}^{N}(c_i - mean)^4}{\left[\frac{1}{N}\sum_{i=1}^{N}(c_i - mean)^2\right]^2} \qquad (2.10)$$

Here c_i is random variable and kurtosis that is represented by K may be treated as ratio of fourth moment to the second moment.

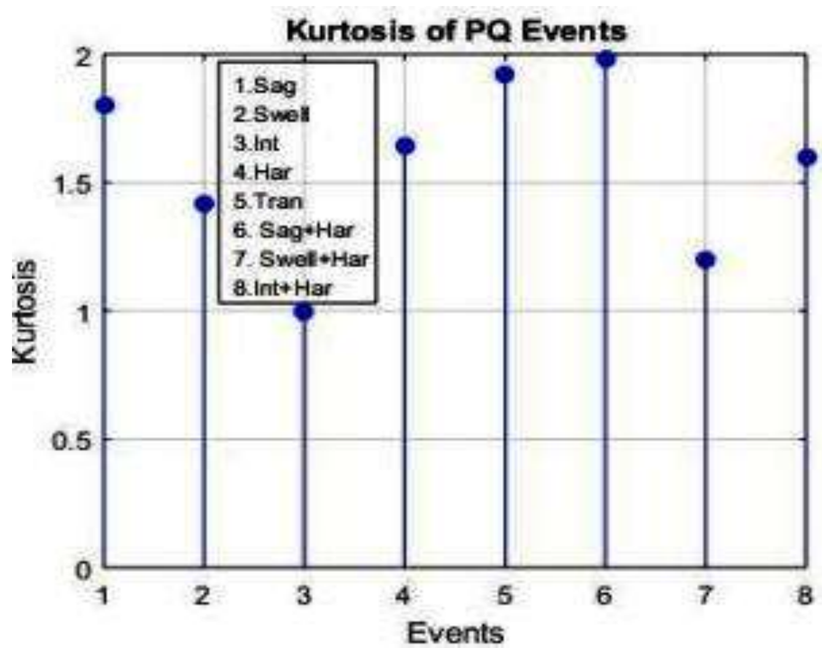


Figure 2.7: Kurtosis value of PQ events

In fig 2.7 kurtosis value for numerous PQ events are plotted, when sag event appears then it has kurtosis value in between 1.5 to 2. The disturbance swell shows decrease in kurtosis value up to 1.3, interruption event takes the kurtosis value 1. Both harmonics and transient events lie in range of 1.5-2 value of kurtosis but having significant difference in kurtosis value, multiple events sag + harmonics, swell + harmonics and interruption + harmonics also have some different value of kurtosis.

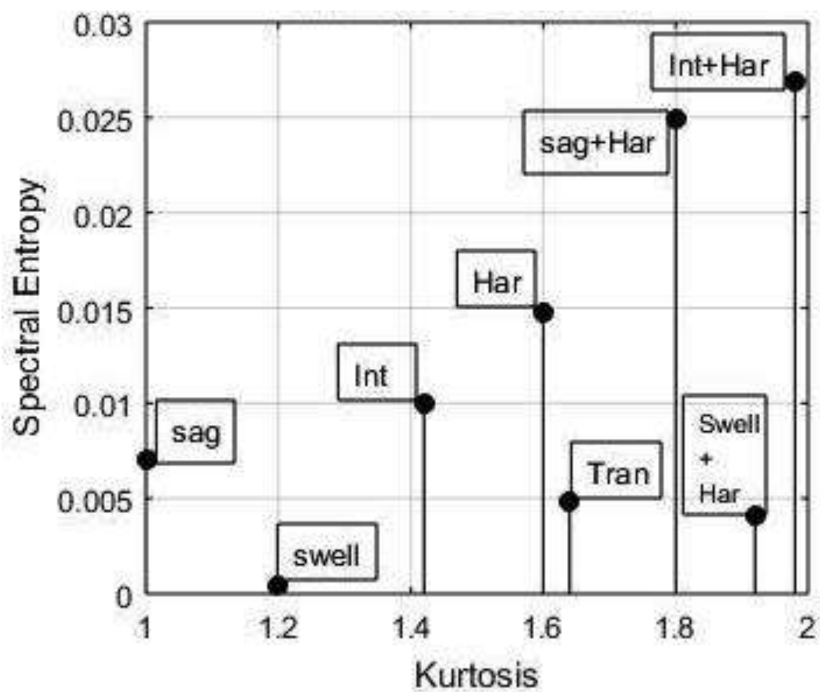


Figure 2.8: Spectral entropy vs kurtosis of PQ events.

In fig. 2.8, once the plotting of SE Vs Kurtosis done then its shows the distinction clearly between the various PQ events on the bases of extracted features from Volterra series output. This analysis notifies that any disturbance in power will simply be detected by Volterra series with straightforward computations. Volterra series takes terribly less time to spot disturbances in power quality signal as compared to other techniques such as S-transform, wavelet transform which consume massive time, large computing overhead and enormous memory. In order to classify the detected single and multiple PQ events, interval type-2 fuzzy logic system approach has been implemented in the next section.

2.5 Interval Type-2 Fuzzy Logic System (IT2FLS)

The role fuzzy logic in several scientific and engineering applications is crucial, particularly in controlling systems. The fuzzy sets were first used by L.A. Zadeh in 1965 to process data and information affected by un-probabilistic uncertainty. The information that is used to formulate the rules in a fuzzy logic system (FLS) is completely uncertain [219]. Antecedent and consequent uncertainties regenerate into uncertain antecedent and consequent membership functions. In type-2 FLSs, antecedent and consequent membership functions are type-2 fuzzy sets, and can simply handle rule uncertainties. The conception of type-2 fuzzy sets was introduced as an extension of the concept of a standard fuzzy set, i.e., a type-1 fuzzy set. The grades of membership function in type 2 fuzzy are itself fuzzy. A type-2 membership grade will be any subset in (0, 1) and it's referred to as primary membership [220, 221]. Corresponding to each primary membership, there's a secondary membership (also be in (0, 1)) that defines the chances for the primary membership. A type 2 fuzzy is a special case of type-1 fuzzy that completely represented by membership function as shown in fig. 2.9, with triangular membership function [222, 223]. A type-2 FLS includes fuzzifier, rule base, fuzzy inference engine, and output processor as in type-1 fuzzy [224,225]. The output processor includes defuzzifier and type-reducer, it generates a type-1 fuzzy set output or a crisp number.

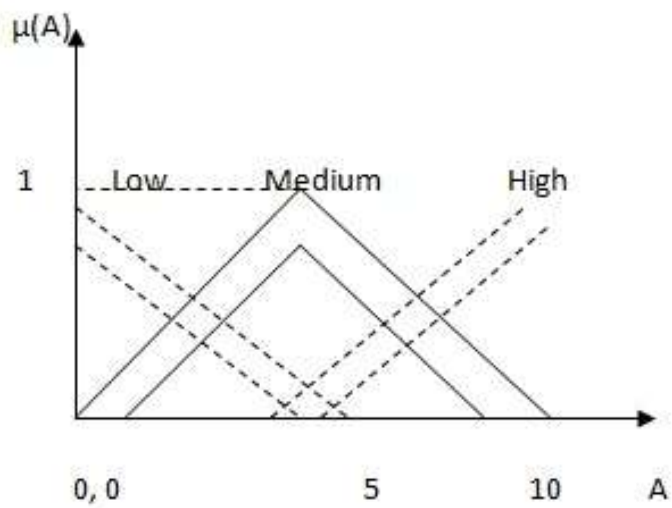


Figure 2.9: Type-2 fuzzy membership function.

Principally If-then rules are used to characterize type 2 fuzzy logic, however its antecedent or consequent sets are now type-2. If membership function in type 2 fuzzy logic represented in the form of interval then type 2 fuzzy logic become "interval type 2 fuzzy logic". Interval type-2 fuzzy set, Ĩ, can be represented as:

$$\tilde{\mathrm{I}} = \{((a,\mu), \mu_{\tilde{\mathrm{I}}}(a,\mu)) \big| \forall_a \in X, \forall_\mu \in J_a \subseteq [0,1]\} \qquad (2.10)$$

In (2.10) $\mu_{\tilde{\mathrm{I}}}(a,u)$ is the IT2FLS membership function, which vary as

$0 \leq \mu_{\tilde{\mathrm{I}}}(a,u) \leq 1$.

$\tilde{I}$, can be calculated as

$$\tilde{\mathrm{I}} = \int_{a \in A} \int_{\mu \in JA} \mu_{\tilde{\mathrm{I}}}(a,\mu)/(a,\mu)\, J_A \subseteq [0,1] \qquad (2.11)$$

In (2.11) $\iint$ represents union over all acceptable a and u. J_a is primary membership of a, For each primary membership value, there's a secondary membership value that explains the chance for primary membership value. The secondary membership function can take values in the interval of (0,1) showing in fig. 2.10. The specification of MFs is one of the foremost tasks in design of type 2 fuzzy logic system. The option of style of MF (Gaussian, triangular etc.), therefore the selection of their certain parameters directly affects the performance. A range of strategies to mitigate this issue are researched for interval type-2 FLSs. These techniques are usually based on the utilization of expert knowledge, genetic algorithms, neural networks etc. However, there is still scope in this area to standardize and abridge the selection of explicit MFs. Interval Type-2 fuzzy logic techniques are applied in varied field of engineering and science, because of additional practicableness within the computations. If the position of membership functions might not make sure accurately, then in such cases, the membership degree cannot be chosen as a selected range in (0, 1), then the utilization of type-2 fuzzy sets is preferred over type-1 fuzzy sets. In fig. 2.9, the membership function doesn't have a unique value for a selected value of A. The values on the intersection of vertical line and also the region of membership function don't want all to be weighted same. The three-dimensional membership function of type-2 fuzzy logic that indicates the features of a type-2 fuzzy set is generated if all a ∈ A have attributed to its own distribution. The union of all primary memberships is alleged to be the finite region that expresses the uncertainty in the incipient memberships of a type-2 fuzzy set termed as footprint of uncertainty (FOU)[22]. Each higher membership function and a lower membership function may be taken as two type-1 membership functions that are the constrained for the footprint of uncertainty of a type-2 fuzzy set.

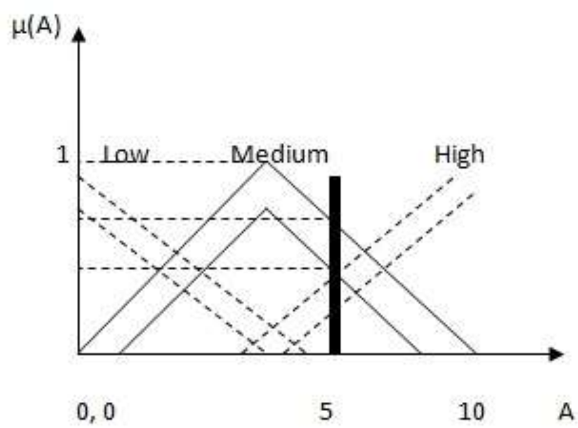


Figure 2.10: Membership function showing grading

During proposed analysis, interval type -2 fuzzy logic system (IT2FLS) is implemented for classification of multiple power quality disturbances. It will handle higher degrees of uncertainty as compared to type-1 fuzzy logic. One extra dimension in type-2 fuzzy logic systems give a lot of degrees of freedom for better analysis of uncertainty compared to type-1 fuzzy sets. IT2FLS is helpful in circumstances wherever it's tough to see the precise membership function for a fuzzy set. Interval type-2 FLS provides the potential of handling a higher level of uncertainty and provides variety of missing elements that have held back successful deployment of fuzzy systems in human decision making [227]. The IT2FLS has various steps for classification, the main steps are fuzzification and rule evaluation discussed in the next section.

2.6 Classification Results and Discussion

On the basis of rules designed in below table 2.1, based on analysis done by Volterra series, classification is done simply for instance in fig 2.11. If kurtosis is low and SE is also low then event classified surely be swell, once kurtosis is moderate and SE having higher value during this case event is sag. If kurtosis is high and SE is low then harmonics are the reason behind disturbance. This model provides a systematic approach and helps in speeding the classification process in single event case as shown in fig 2.11(a) and fig. 2.11(b). If type-1 fuzzy logic is used as shown in fig 2.11(a) then some of events of swell are classified as sag but in type-2 fuzzy classification is done clearly without overlapping of events.

Table 2.1. Rule Editor for IT2FLS

Kurtosis/SE	Low	Moderate	High
Low	Swell	Swell+ Harmonics	None
Moderate	Interruption	Transient	Sag
High	Harmonics	Interruption+ Harmonics	Sag+ Harmonics

The rules designed for classification of multiple events like sag plus harmonics and swell plus harmonics are also displayed in table 2.1. During this case if kurtosis is high and SE is also high then multiple events sag plus harmonics occur as disturbance in power quality. In another case when kurtosis is low and SE is moderate then disturbance classified is going to be swell + harmonics. In fig 2.12(a) & fig 2.12(b) classified events shown as surface of type-1 fuzzy and type-

2 for multiple events. If type-1 fuzzy is used then some of transient events classified as sag+ harmonics shown in fig 2.12(a) but this is not the case in type-2 fuzzy classifier. The type- 2 fuzzy logic can simply classify PQ events on the basis of rule design for the fuzzification, this novel technique will classify multiple events without ambiguity.

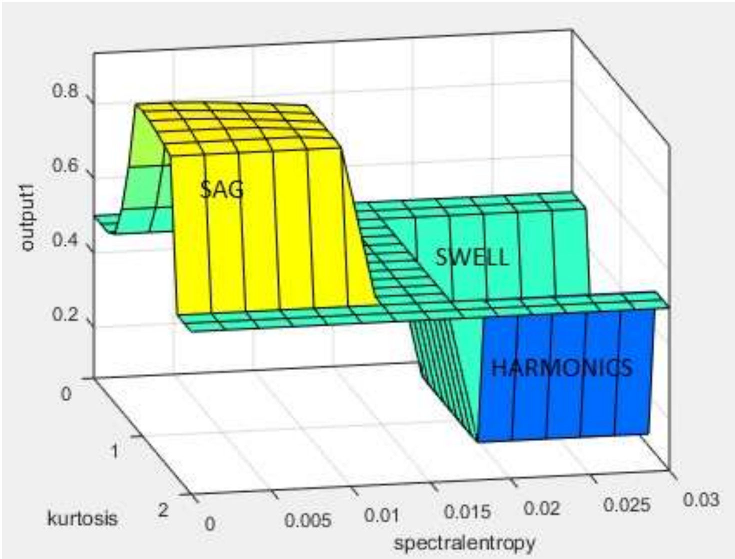


Fig 2.11(a). Classification Results type-1 fuzzy (sag, swell and harmonics)

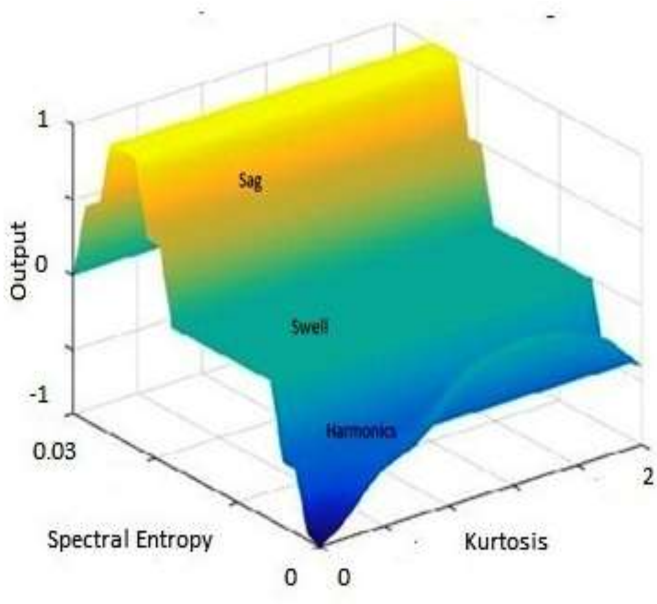


Fig 2.11(b). Classification Results type-2 fuzzy (sag, swell and harmonics)

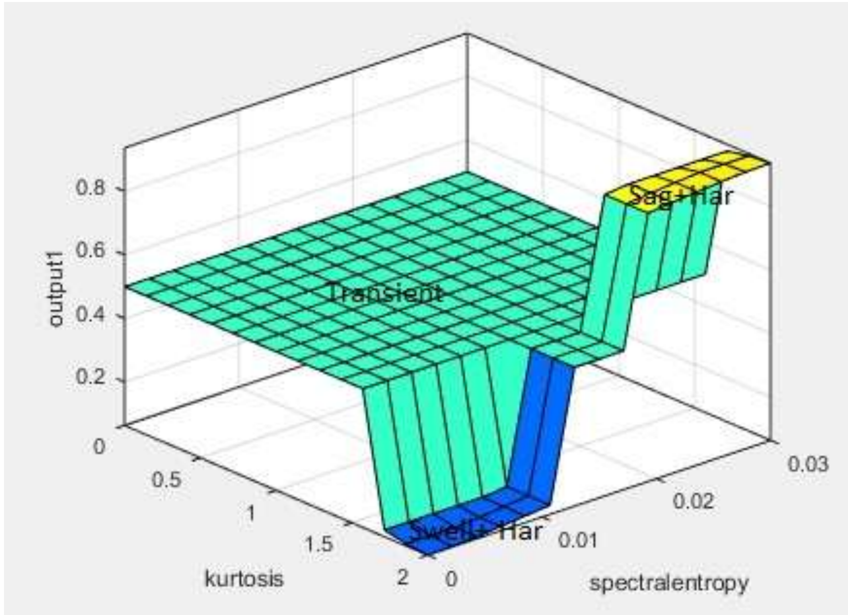


Fig 2.12(a). Classification Results type-1 fuzzy (transients and sag + harmonics)

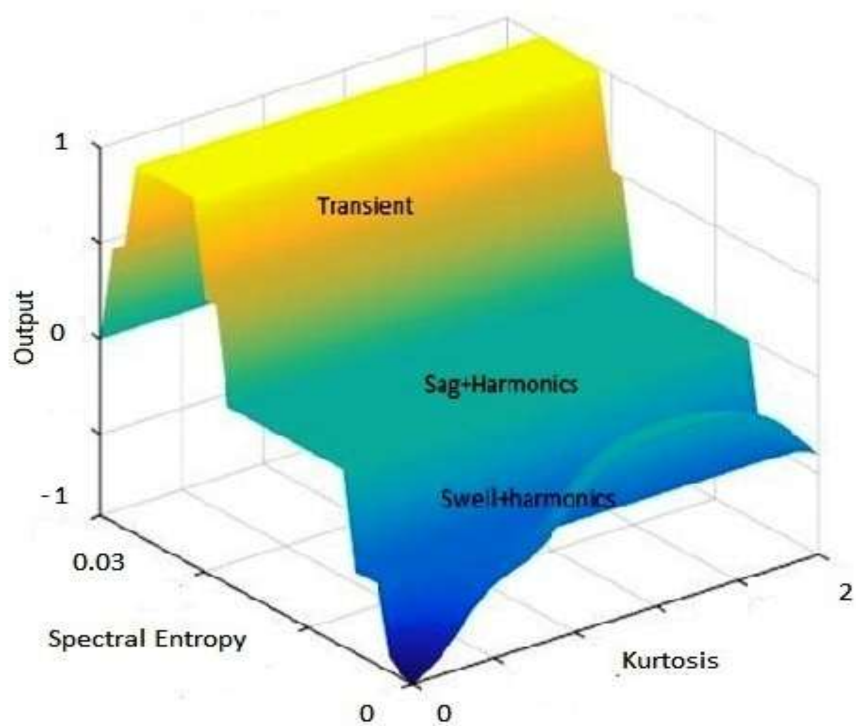


Fig 2.12(b). Classification Results type-2 fuzzy (transients and sag + harmonics)

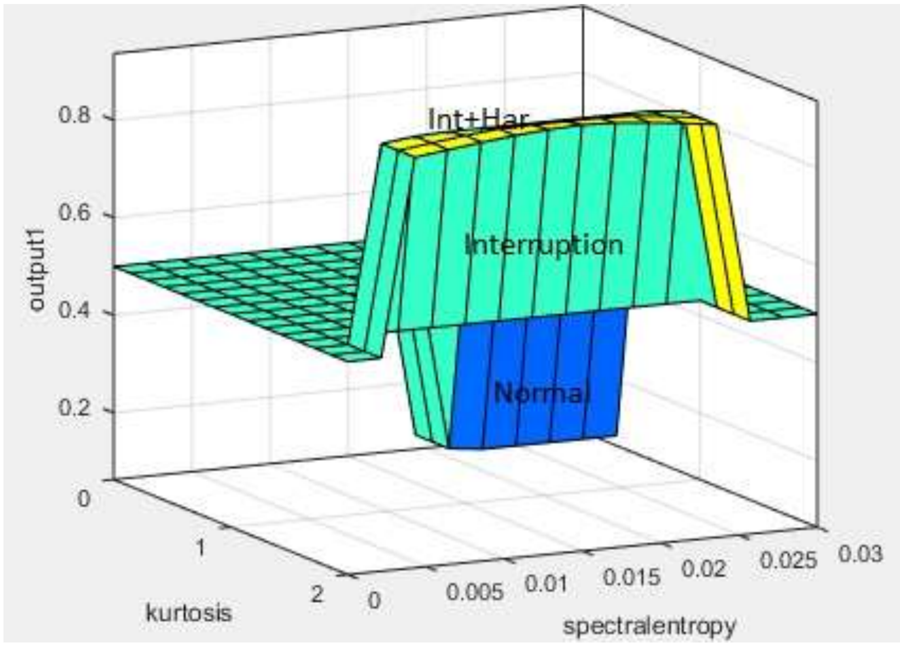


Fig 2.13(a). Classification Results type-1 fuzzy (interruption and interruption+ harmonics)

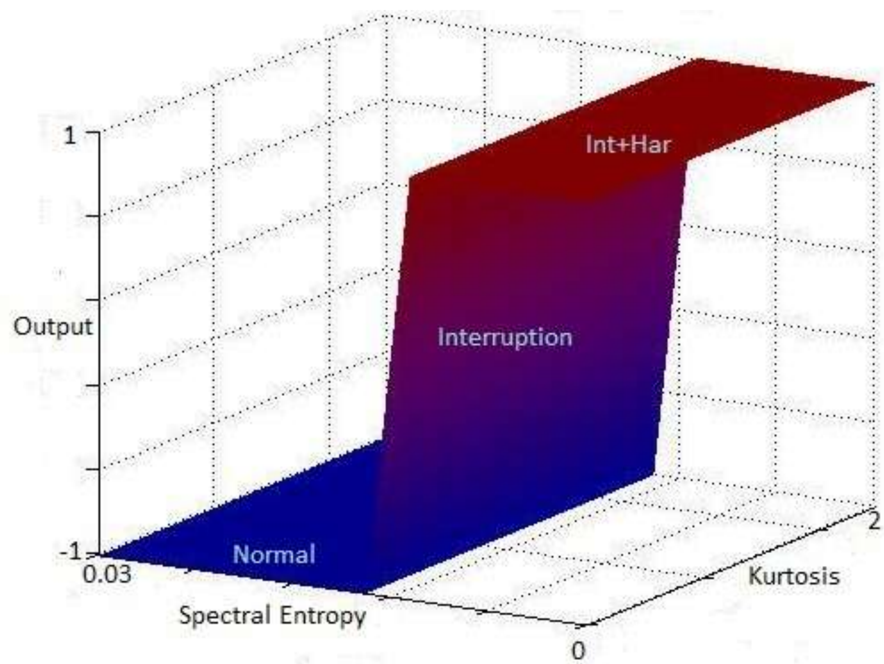


Fig 2.13(b). Classification Results type-2 fuzzy (interruption and interruption+harmonics)

In fig. 2.13(a) and fig 2.13(b) classification surfaces of type-1 and type-2 fuzzy logic have been shown for interruption and interruption+ harmonics. In type-1 fuzzy surface some of interruption events are classified as normal; this creates error in classification as shown in fig 2.13(a) but type-2 fuzzy classifies events without any error. In fig. 2.13(b), if vertical surface shows classification of interruption event and upper horizontal surface shows classification of multiple events i.e. interruption+ harmonics and below surface is for normal power signal. Now these classified events are tested in different conditions. In table 2.2 testing is done for calculation of efficiency based on Volterra series and IT2FLS.

Table 2.2: Classification results type-2 fuzzy (Ideal Condition (Noise free))

Events	Sag	Swell	Harmonics	Transient	Sag + Harmonics	Swell+ Harmonics
Sag	100					
Swell		100				
Harmonics			100			
Transient				100		
Sag+ Harmonics					100	
Swell+ Harmonics						99
Classification efficiency in %	100	100	100	100	100	99
classification error in %	0	0	0	0	0	1
Overall efficiency	**99.83**					

Table 2.3: Classification results for type-1 fuzzy (Ideal (Noise free))

Events	Sag	Swell	Harmonics	Transient	Sag + Harmonics	Swell+ Harmonics
Sag	100					
Swell		100				
Harmonics			100			
Transient				98		
Sag+ Harmonics					91	
Swell+ Harmonics						90
Classification efficiency in %	100	100	100	98	91	90
classification error in %	0	0	0	2	9	10
overall efficiency	**96.57**					

When classification of power quality events is done in ideal condition, i.e., no noise within the system then IT2FLS system classifies most of the single event sag, swell, harmonics, transient events with 100 percent classification efficiency however multiple events sag+ harmonics and swell+ harmonics events having classification efficiency 100 and 99 percent respectively in table 2.2.

Table 2.4. Classification results type-2 fuzzy SNR 30 dB

Events	Sag	Swell	Harmonics	Transient	Sag + Harmonics	Swell+ Harmonics
Sag	100					
Swell		100				
Harmonics			100			
Transient				100		
Sag+ Harmonics					98	
Swell+ Harmonics						96
Classification efficiency in %	100	100	100	100	98	96
classification error in %	0	0	0	0	2	4
overall efficiency	**99**					

Table 2.5. Classification results type-1 fuzzy SNR=20 dB

Events	Sag	Swell	Harmonics	Transient	Sag + Harmonics	Swell+ Harmonics
Sag	100					
Swell		98				
Harmonics			97			
Transient				98		
Sag+ Harmonics					89	
Swell+ Harmonics						91
Classification efficiency in %	100	98	97	98	89	91
classification error in %	0	2	3	2	11	9
overall efficiency	**95.48**					

In case of multiple events such as sag plus harmonics and swell plus harmonics then average efficiency comes out to be 99.5 percent in table 2.2. Overall efficiency in ideal signal condition is 99.83 percent that shows that this system will classify most of events with more than 99 percent efficiency respectively as shown in table 2.2. In table 2.3 classification done with type-1 fuzzy with ideal condition. When classification done under certain noise condition i.e. SNR 30 dB in table 2.4. Then IT2FLS classifies sag, swell, harmonics and transient with 100 percent efficiency, remaining events multiple events like sag plus harmonics and swell plus harmonics having average efficiency 97 percent; as shown in table 2.4, overall efficiency during this case is 99 percent this shows that given classification technique is additionally applicable for real time scenario.

Table 2.6: Classification results for type-2 fuzzy SNR 20 dB

Events	**Sag**	**Swell**	**Harmonics**	**Transient**	**Sag + Harmonics**	**Swell+ Harmonics**
Sag	100					
Swell		100				
Harmonic			99			
Transient				98		
Sag+ Harmonics					98	
Swell+Harmonics						98
Classification efficiency in %	100	100	99	98	98	98
classification error in %	0	0	1	2	2	2
Overall efficiency	**98.83**					

In table 2.5 classification done with type -1 fuzzy with SNR 20dB. Then single events like swell, transient and harmonics also having ambiguity in classification but this is not the case in type -2 fuzzy classification as shown in table 2.6. If classification performed under SNR 20dB then IT2FLS classifies sag, swell harmonics with good efficiency of around 99 percent; remaining events transient and remaining multiple events also have efficiency 98 percent as shown in table 2.6. Overall efficiency in this case is 98.83 percent.

2.7 Comparison of Results

To justify the robustness and practicability of the proposed technique, a comparison of results in forms of PQ events classification efficiency has been presented as given in table 2.7. In the proposed technique, six types of PQ events have been taken into consideration and simulated in broad range. In case of 20dB SNR wavelet transform and S-transform are implemented for feature extraction in ref.[228,229] and classifier utilized in each case is support vector machine(SVM) with classification potency of 96.33 and 98.11 percent respectively.

Table 2.7: Comparison of proposed technique with other methods.

Ref.	Method	Parameter 1	Parameter 2	Efficiency in %	
				Ideal	**SNR 20dB**
[230]	WT + NN	Wavelet entropy	Normal entropy	95.7	89.9
[231]	WT+ PNN	Mean value of WT Coefficient	Energy value of WT coefficients	99.2	97.4
[228]	WT+ SVM	Standard deviation of WT coefficients	Mean value of disturbances energy	98.9	96.3
[229]	ST+ SVM	Energy of the magnitude contour.	Standard deviation of phase contour.	99.7	98.1
3[232]	WT+ FUZZY	Energy of detailed coefficient.	Energy of approximate coefficient.	97	95
[233]	WT+ FUZZY	Average value of WT Coefficients	Maximum of the wavelet coefficients	97.7	92.6
Present work	VS+ IT1FLS	Spectral entropy	Kurtosis	96.6	95.5
Present work	VS+ IT2FLS	Spectral entropy	Kurtosis	99.8	98.3

In Ref. [230,231] wavelet transform [WT] for feature extraction and neural network [NN] and probabilistic neural networks [PNN] are implemented for classification of PQ events which gives out efficiency of 89.92 & 97.44 percent respectively with 20dB SNR. In earlier state-of-art

[232,233] WT for detection of PQ events and type-1 fuzzy logic simulated for classification purpose; in this scenario, efficiency was 95 and 92.56 percent with the noise of 20dB SNR.

2.8 Conclusion

This work proposes a PQ event detection and classification scheme utilizing a Volterra series based feature extractor and a classifier based on interval type-2 fuzzy logic system. The proposed method can reduce the quantity of extracted features of distorted signal without losing its characteristics and thus, requires less memory space and computation time. The performance of classifier is tested under three conditions i.e. ideal, SNR 30 and SNR 20 dB for effective classification of PQ events. It is observed that IT2FLS correctly classifies the PQ event with high accuracy and IT2FLS gives the best performance as compared to neural network based classifier and SVM & type -1 fuzzy logic. Therefore, the proposed method can be used in real time analysis of PQ events. The overall classification efficiency of IT2FLS is 99.27 percent; if we take average of all three condition mention in this chapter. The simulation results show that IT2FLS has higher performance than NN, PNN and support vector machine. The performance of the hybrid approach is successfully verified. The future work includes hardware implementation of hybrid technique of VS+IT2FLS so that this novel hybrid technique may be applied in real time detection and classification of power quality events.

This chapter is based on the following works:

1. Rajiv kapoor, **Rahul**, M M Tripathi "Volterra bound interval type- 2 fuzzy logic based approach for multiple power quality events analysis" **IET Electrical Systems in Transportation**, Volume 8, Issue 3, September 2018, p. 188 – 196, DOI: 10.1049/iet-est.2017.0054 **(Pub.: IET), (Indexing-SCIE) [259]**

2. **Rahul,** Rajiv Kapoor and M M Tripathi "Detection and classification of power signal pattern using volterra series and interval type -2 fuzzy logic system**" protection and control of modern power system,** Volume 2, Issue 1, 2017, DOI 10.1186/s41601-017-0039-z. **(Pub.: SPRINGER), (Indexing-ESCI)** [246]

.

Chapter 3

Sparse Features with Adaptive Discretized Triangular Mesh for Detection of Power Disturbances

The objective of this chapter is to develop an intelligent system for power quality events analysis for real time applications based on sparse feature based Adaptive Finite Element Method (FEM). They key ingredients in this chapter covers comprehensive study of sparse features with adaptive discretized triangular mesh used for calculation of stiffness matrix results discussion and comparison with earlier state of arts.

3.1 Introduction

In this chapter, a novel technique of adaptive finite element method based on sparse features based approach explored for detection and classification of power quality events. The function of adaptive finite element method is to extract features and type-2 fuzzy system for the purpose of classification of power quality disturbances with minimum error. The adaptive finite element method utilized to find stiffness matrix for analysis of power quality events. The type-2 fuzzy system utilizes the concept of membership functions to classify the single and multiple power quality events and then the proposed method is compared with other methods and finally with traditional type-I fuzzy logic approach for classification of power quality events. The results revealed that the proposed method can reduce the computation time significantly with high accuracy.

3.2 Proposed Methodology

The proposed novel methodology utilizes sparse signal decomposition for extraction of disturbed part, i.e. power quality events from input power signal so that desired disturbed part is separated from pure disturbance free power signal part. Then process of discretization is done so that it can easily be deal for further processing, after that novel adaptive finite element method is applied to form triangular mesh to find stiffness matrix based features for the analysis of power quality disturbances then classification of disturbances is done with artificial intelligence based renowned technique of fuzzy logic. The prime utility of FEM is that it has capability to break down large complex equations into smaller parts which can be solve in much easier manner. The solutions from each of the broken parts can then be combined to make a complete and entire solution. With FEM, sag, swell, transient, harmonics and combination of sag, swell with harmonics is analyzed and broken down into a set of smaller regular signals such that when the sub-signals are fitted together, that closely approximate the actual signal.

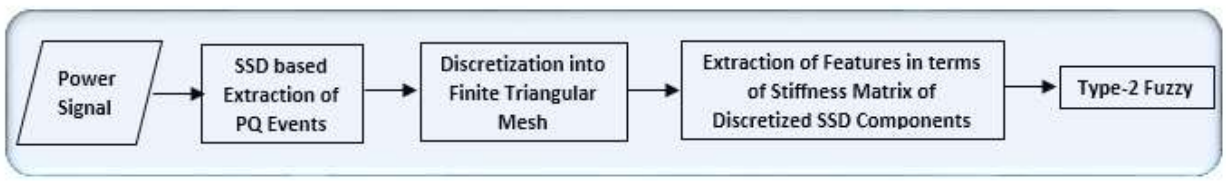


Figure 3.1: Flow diagram of proposed method.

Each of the sub-signals can be treated as a separate signal. Equations can be applied to the sub-signals to approximate how it will respond over time. Once the reaction of one sub-signals is computed in the form of stiffness matrices, then it is possible to compute how it will react with its neighbors. This process is repeated until the entire power signal disturbance has been computed. Various approaches are available to process power quality patterns but Galerkin method is best suited for non-stationary power quality events as this method gives best approximation, i.e. error in the system is minimized.

3.3 Sparse Signal Decomposition (SSD)

The sparse signal decomposition is utilized for extraction of PQ disturbances with over complete hybrid dictionaries (OHDs). The PQ disturbances extracted from both detail and approximation signals are used for extraction of single and multiple PQ disturbances. Let's consider that the power signal p is sparse in an A × B OHD matrix $\varphi \in C^{AXB}$, A> B that contains hybrid elementary waveforms from different analytical functions. For a predefined OHD matrix φ with A > B, B×1 signal p can be expressed as $\boldsymbol{p} = \varphi\beta = \sum_{n=1}^{N} \beta_n \varphi_n$ here $\beta = [\beta_1, \beta_2, \ldots\ldots \beta_n]$ are sparse coefficients calculated with the help of OHD, which is totally different from time-frequency analysis based on single basis matrix. The sparse coefficients calculated with the help of spectral and temporal information of power signal under consideration. When all the coefficients of OHD has been evaluated then it will better represents the complete composite signal whether it is stationary or non-stationary for this role of adaptive nature of OHD is important to set the training samples.

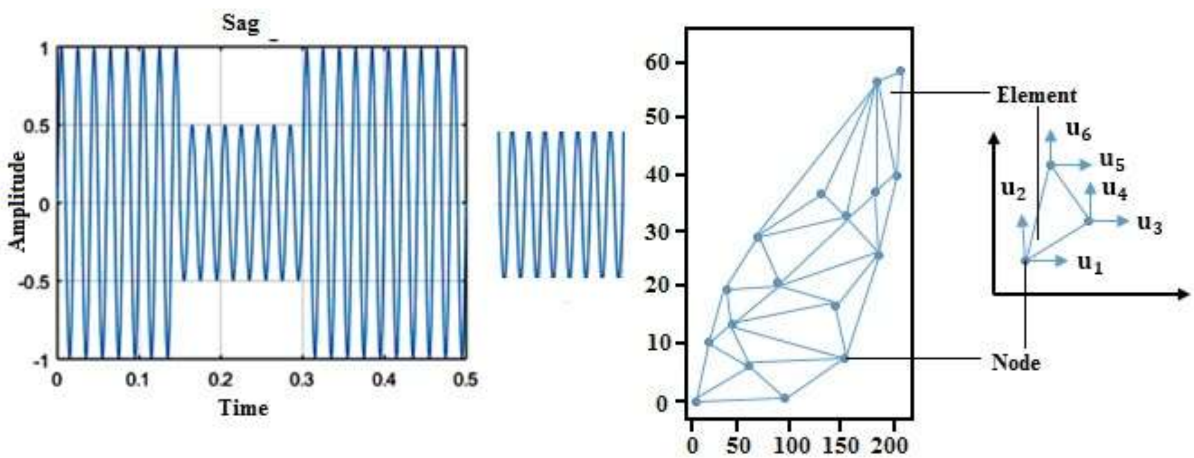


Figure 3.2: Power quality events extraction and discretization

In fig. 3.2, power quality event sag generated with actual industrial data set and elements are selected where disturbances comes with the help of finite element method based novel technique for power quality events detection. After extraction of PQ disturbances with SSD technique then discretization is done with finite element method then further applied Galerkin approach to calculate stiffness matrix.

3.4 Galerkin Approach

While multiple ways to evaluate the values for the finite elements in an FEM problem, the Galerkin Approach has become most common for complex patterns. This approach is exploited here for the single and multiple power quality events. The most important thing that will be shown here is the relations between the different variables and representations of various parts of equations. Various relational equation of Galerkin method is shown below[234].

$$\sum_{\Delta}\int_{\Delta}\wp^{T}Y\wp(\Theta)A\cdot dx-\sum_{\Delta}\int_{\Delta}\Theta^{T}\varpi A\cdot dx \\ -\sum_{\Delta}\int_{\Delta}\Theta^{T}\kappa\cdot dx-\sum_{\Delta}\Theta_{n}G_{n}=0 \qquad (3.1)$$

In (3.1), the $\wp(\Theta)$ represents the strain function of a finite element, Y represents elastic modulus, is the body force and A is area of cross section and G is the axial load. The $\wp$ term is the absolute strain of the finite element. The element is actually a function Θ(x) which represents the virtual displacements function. It approximates the actual displacement of a certain node of the object under analysis. In (3.2) and (3.3) show other forms of Θ(x) and $\wp(\Theta)$

$$\Theta(x) = M \cdot \zeta \tag{3.2}$$

$$\wp(\Theta) = P \cdot \zeta \tag{3.3}$$

The ζ element represents the specific node displacements of the particular element Δ. It can also be describe as $[\zeta_1\zeta_2]^T$. Additionally, ζ represents the overall virtual displacements at the nodes and is written as $[\zeta_1\zeta_2 \ldots \zeta_M]^T$ for M nodes. Further steps make the four separate parts of the Galerkin equation into a convenient form. In (3.4), (3.5), (3.6) and (3.7) it show the corresponding representations of the various parts of the Galerkin relational equation. In (3.4) r is the axial force.

$$\int_\Delta \wp^T Y \wp(\Theta) A \cdot dx = \zeta^T z^\Delta r \tag{3.4}$$

$$\int_\Delta \Theta^T \varpi A \cdot dx = \zeta^T \varpi^\Delta \tag{3.5}$$

$$\int_\Delta \Theta^T \kappa \cdot dx = \zeta^T \kappa^\Delta \tag{3.6}$$

$$\Theta_n G_n = \Psi_n G_n \tag{3.7}$$

Equation 3.8 gives the final altered equation and its simple form in equation 3.9.

$$\sum_\Delta \zeta^T z^\Delta r - \sum_\Delta \zeta^T \varpi^e - \sum_\Delta \zeta^T \kappa^\Delta - \sum_\Delta \Psi_n G_n = 0 \tag{3.8}$$

$$\Psi^T (ZR - \overline{W}) = 0 \qquad (3.9)$$

The three matrices that is of interest in the above equation: z^{Δ}, ϖ^{Δ}, and κ^{Δ} [235,236]. These matrices are explained on every finite element for element Δ. These matrices called stiffness matrix of structure, force and mass of element, when power quality event occurs in the system. Equations 3.10, 3.11 and 3.12 explain each of these matrices [237].

$$z^{\Delta} = \frac{Y_{\Delta} A_{\Delta}}{\gamma_{\Delta}} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \qquad (3.10)$$

$$\varpi^{\Delta} = \frac{A_{\Delta} \gamma_{\Delta} \varpi}{2} \begin{Bmatrix} 1 \\ 1 \end{Bmatrix} \qquad (3.11)$$

$$\kappa^{\Delta} = \frac{\kappa \gamma_{\Delta}}{2} \begin{Bmatrix} 1 \\ 1 \end{Bmatrix} \qquad (3.12)$$

In each and every case, the superscript Δ represents the value of different variables for the finite element indicated by Δ [238,239].From (3.9), we find that four matrices are required for solution of FEM problem. Some of the matrices have already been explained in (3.9): ζ and **R**; the remaining two matrices **Z** and $\overline{W}$ require explaining. These two are called the stiffness matrices of structure and force respectively, (3.13) show the overall structure assemblage (3.14) shows the force. Note that the final **Z** stiffness matrix assumes that $Y_1 = Y_2 = Y_3 = Y_4 = Y$ [240,241].

$$Z = \sum_{\Delta} z^{\Delta}$$

$$= \frac{Y_1 A_1}{\gamma_1} \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} + \frac{Y_2 A_2}{\gamma_2} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad (3.13)$$

$$+ \frac{Y_3 A_3}{\gamma_3} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} + \frac{Y_4 A_4}{\gamma_4} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & -1 & 1 \end{bmatrix}$$

$$
Z = Y\begin{bmatrix}
\frac{A_1}{\gamma_1} & -\frac{A_1}{\gamma_1} & 0 & 0 & 0 \\
-\frac{A_1}{\gamma_1} & \left(\frac{A_1}{\gamma_1}+\frac{A_2}{\gamma_2}\right) & -\frac{A_2}{\gamma_2} & 0 & 0 \\
0 & -\frac{A_2}{\gamma_2} & \left(\frac{A_2}{\gamma_2}+\frac{A_3}{\gamma_3}\right) & -\frac{A_3}{\gamma_3} & 0 \\
0 & 0 & -\frac{A_3}{\gamma_3} & \left(\frac{A_3}{\gamma_3}+\frac{A_4}{\gamma_4}\right) & -\frac{A_4}{\gamma_4} \\
0 & 0 & 0 & -\frac{A_4}{\gamma_4} & \frac{A_4}{\gamma_4}
\end{bmatrix} \qquad (3.14)
$$

The assemblage of the overall force matrix is shown in (3.15) and the final matrix is shown in (3.16).

$$
\overline{W} = \sum_{e} (\varpi^{\Delta} + \kappa^{\Delta}) + G \qquad (3.15)
$$

$$
\overline{W} = \left\{
\begin{matrix}
\frac{A_1\gamma_1\varpi}{2} + \frac{\gamma_1\kappa_1}{2} \\
\left(\frac{A_1\gamma_1\varpi}{2} + \frac{\gamma_1\kappa_1}{2}\right) + \left(\frac{A_2\gamma_2\varpi}{2} + \frac{\gamma_2\kappa_2}{2}\right) \\
\left(\frac{A_2\gamma_2\varpi}{2} + \frac{\gamma_2\kappa_2}{2}\right) + \left(\frac{A_3\gamma_3\varpi}{2} + \frac{\gamma_3\kappa_3}{2}\right) \\
\left(\frac{A_3\gamma_3\varpi}{2} + \frac{\gamma_3\kappa_3}{2}\right) + \left(\frac{A_4\gamma_4\varpi}{2} + \frac{\gamma_4\kappa_4}{2}\right) \\
\left(\frac{A_4\gamma_4\varpi}{2} + \frac{\gamma_4\kappa_4}{2}\right)
\end{matrix}
\right\} + \left\{
\begin{matrix} 0 \\ G_2 \\ 0 \\ G_4 \\ 0 \end{matrix}
\right\} \qquad (3.16)
$$

These matrices are used in analysis of power quality events.

3.4.1 Novel Methodology of Adaptive FEM

Let’s consider a continuous function f which denotes finite element mesh of triangular shape where: σ→ R, interpolating axial displacement u by a constant piecewise function F_N over Ψ_N .

Given σ = (0,1), a partition $\Psi_N = \{p_i\}_{n=0}^{N}$. Consider that $\|f'\|L'(\sigma) = 1$, a non-decreasing function. Let $0 = p_0 < p_1 < \cdots p_n \ldots \ldots < p_N = 1$ here p be a particular sample with total N samples of power quality disturbance.

$$\Theta(p) = \int_0^p |f'(t)|\, dt \tag{3.17}$$

It satisfy Θ(0)=0 and Θ(1)=1. Consider that $\|f'\|L'(\sigma) = 1$ be the subdivision given by

$$\int_{p_{n-1}}^{p_n} |f'(t)|\, dt = \Theta(x_n) - \Theta(x_{n-1}) = \frac{1}{N} \tag{3.18}$$

Now for $p \in [p_{n-1}, p_n]$

$$|f(p) - f(p_{n-1})| = \left|\int_{p_{n-1}}^{p} f'(t)\, dt\right| \leq \int_{p_{n-1}}^{p} |f'(t)|\, dt \leq \int_{p_{n-1}}^{p_n} |f'(t)|\, dt = \frac{1}{N}. \tag{3.19}$$

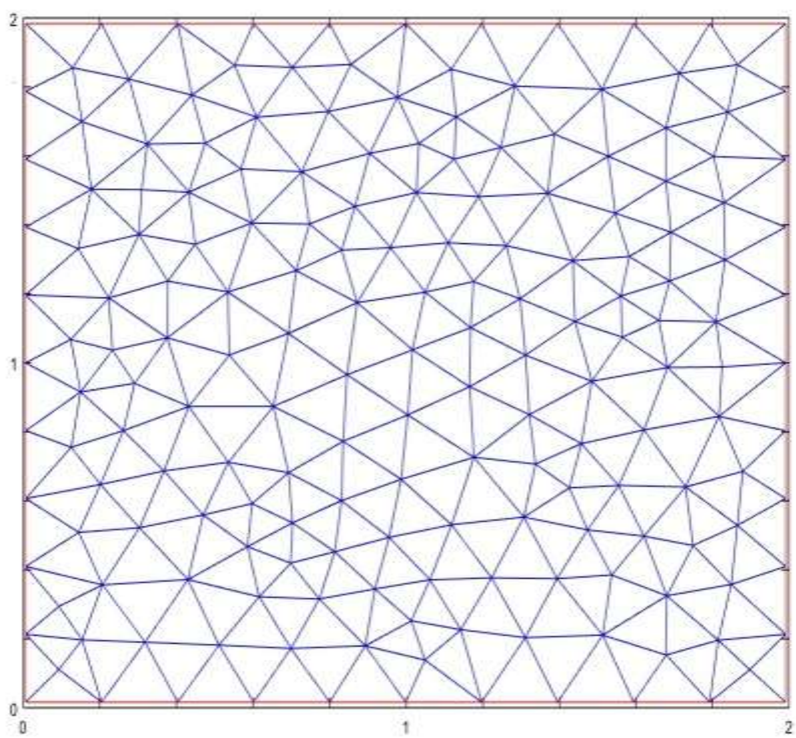


Figure 3.3: Finite element method triangular mesh

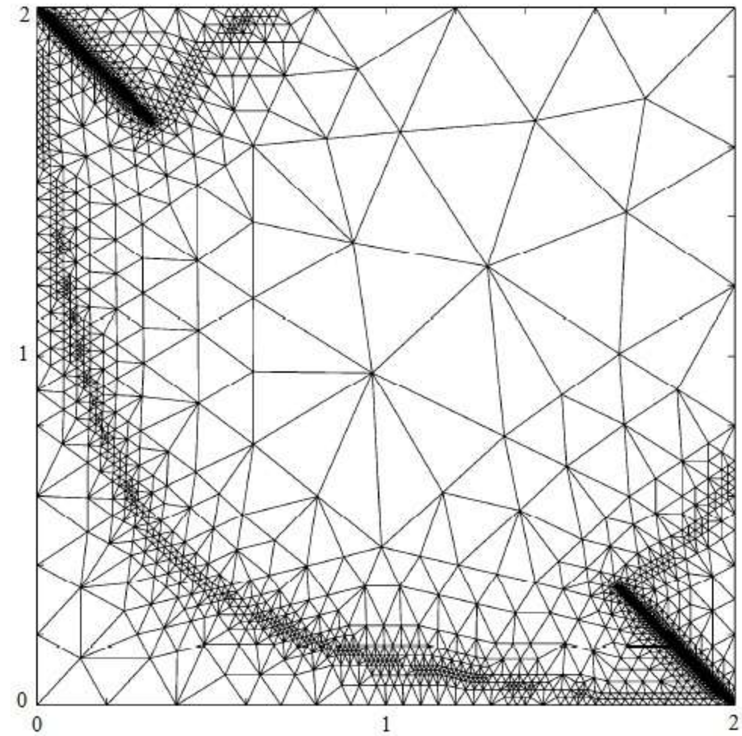


Figure 3.4: Adaptive FEM triangular mesh.

From the above equations, it is find that in case of adaptive FEM rate of convergence of N^(-1) for variable step size of samples is same as normal FEM under the condition ‖f^' ‖ L^' (σ)<∞.Sampling method is mainly explored to simplify complexity in structure by providing a set of random samples from posterior distribution at the desired space under consideration. Suppose that R is the observation of certain parameters at different discrete time instants; the probabilistic information for the prediction of the future responses R at different time instants is contained in the robust predictive PDF which is given by the well-known Total Probability theorem (P(R/D)=P(R/E)P(E/D)d[E]). Total probability theorem depends on the posterior distribution function which cannot be easily solve by analytical method due to the dynamic nature of power quality events as the parameters are regularly updating consequently , sampling techniques, such as Markov chain Monte Carlo method, is employed to predict the updating parameter distribution. Consider a set of N random parameter vector drawn from a pdf P(E/D) the expectation value of any observed function R can be easily estimated. An algorithm is designed for adaptive mesh so that mesh size will change with change in disturbance size. Figure 3.3 and 3.4 shows uniform and adaptive mesh of finite element method.

3.4.2 Adaptive FEM Algorithm

Given a power signal as input then feature vectors can be constructed as follows:

Step 1: Extraction of disturbed part with help of SSD technique from input power signal

Step 2: Extraction of prominent points on the boundary of the disturbed part.

Step 3: Prominent points are given as nodes to the adaptive finite element method.

Step 4: PQ events are discretized into finite triangular elements where nodes act as vertices of the triangle.

Step 5: Each triangular element is represented by three nodes displacement vector (U) of the triangle.

Step 6: Structured stiffness matrix (z) of each triangle is calculated

Step 7: Stiffness matrices of force and mass are calculated for each triangle with the help of displacement function $\Theta(x)$.

Step 8: Complete the Stiffness matrix of the SSD extracted part is created by combining stiffness matrices of all possible triangles of the SSD component.

Step 9: Stiffness matrix is represented as one-dimensional feature vectors

Step 10: Feature vector is calculated for meshes of PQ events under consideration

Step 11: The type-2 fuzzy Classifier is utilized for classification.

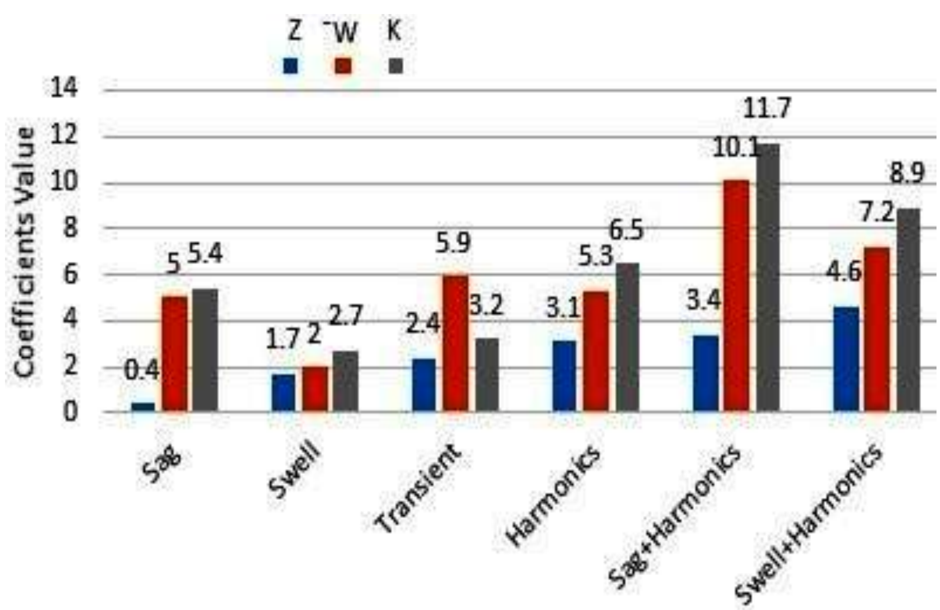


Figure 3.5: Detection of PQ events with Adaptive FEM

Now this adaptive approach is used for analysis of disturbed part of power signal, and further calculation of extraction of features based on stiffness matrix Z, $\overline{W}$ and κ coefficients is done which is given in Fig. 3.5 by using equation 3.13, 3.14, 3.15 and 3.16. These feature values of stiffness matrices Z, $\overline{W}$ and be used for classification purpose of power quality events with the help of type-2 fuzzy logic.

Table 3.1: Comparison of Uniform and Adaptive Mesh

Mesh Details	**Uniform Mesh**	**Adaptive Mesh**
Number of elements	1580	1050
Number of nodes	832	617
Number of sides	4340	2772
Error	3.045905e-03	1.217424e-03

In table 3.1 we find that in case of adaptive mesh as in fig. 3.4 number of elements required is less so that less processing and computation time is requires in adaptive finite element method.

3.5 Classification Results and Discussion

The proposed method of type-2 fuzzy system extends type-1 fuzzy system logic with more capability to handle uncertainty. In type 2 fuzzy the grades are itself fuzzy, subset in set (0, 1) and termed as primary membership .The probability of each primary membership function is defined by secondary membership function. A specialized case of type 1 fuzzy system i.e type-2 fuzzy system that entirely represented with rectangular, triangular membership function, square cubic and Gaussian membership function etc. [242,243]. A type-2 fuzzy system includes fuzzifier, rule base designing, fuzzy inference engine, and output processing system [220]. The output processor incorporate defuzzifier and type-reducer, it generates a type-1 fuzzy system output or a crisp number [244,245]. For the classification purpose with type-2 fuzzy, extracted features of power quality events based on FEM Z, $\overline{W}$ and κ matrix now these extracted features are tested for the optimization purpose. In the next step tested features of power signal disturbances trained for type-2 fuzzy logic for classification as shown in fig. 3.1. Further step comprises of rule design for the objective of fuzzification based classification of events as shown in table 3.2. The type-2 fuzzy classifier do the job of classification with the help of inference engine and output processor and rule designed. When Z is low $\overline{W}$ takes moderate value and κ also lie in moderate range then the classified power disturbance is sag, repeat the process for all the events as in table 3.2.

Table 3.2: Rule Editor for Fuzzy Logic

Events	**Z**	$\overline{\mathbf{W}}$	κ
Sag	Low	Moderate	Moderate
Swell	Moderate	Low	Low
Transient	Moderate	Moderate	Low
Harmonics	High	Moderate	Moderate
Sag + Harmonics	Moderate	High	High
Swell + Harmonics	High	High	Moderate

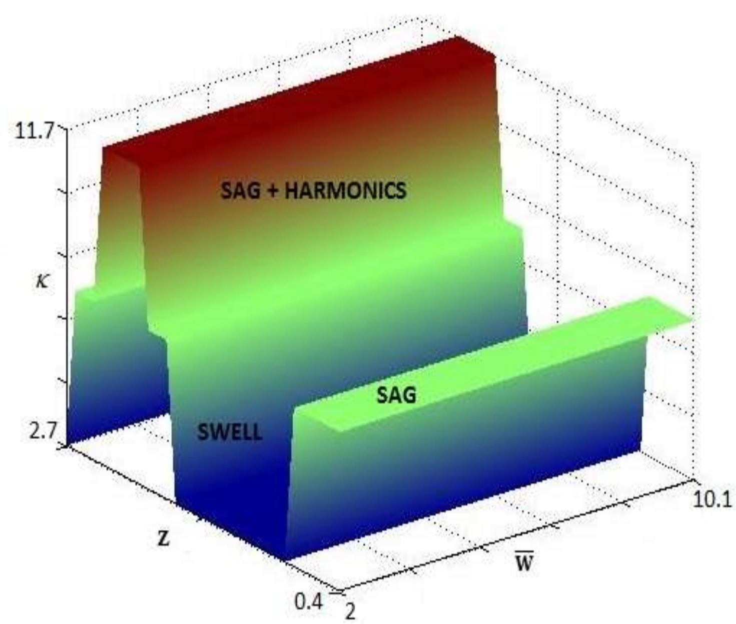


Figure 3.6: Classification of sag, swell and sag + harmonics.

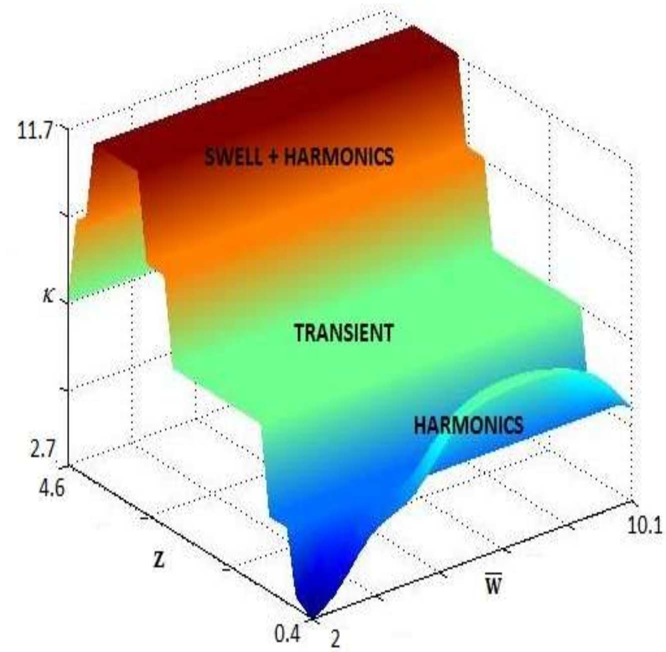


Figure 3.7: Classification Results transient, harmonics and swell+ harmonics

The classification rules for type-2 fuzzy system shown in table 3.2. When Z is moderate, K and $\overline{W}$ both takes high values results in sag in combination with harmonics occur as disturbance in power disturbance. If $\overline{W}$ and Z both are high K takes moderate value then event classified appeared to be swell with harmonics. Classification results shown in shown in fig. 3.6 and 3.7. In table 3.3, investigation is done under ideal condition for performance analysis based on adaptive FEM and type-2 fuzzy system. Now finally classified results examined with two hundred samples under three different conditions first in idealistic condition, second and third conditions having SNR 30 and 20 dB respectively in table 3.3 and 3.4. In idealistic condition with no noise in power system then type -2 fuzzy classify all the single disturbance classified with maximum efficiency of 100 percent and multiple events classified with average efficiency of 99.75 percent. Idealistic scenario having comprehensive efficiency of 99.91 percent so in this case whatever the disturbance comes will be classified with 99.75 percent which is approximately equal to maximum efficiency. In second case of SNR 30 dB condition in table 3.4 overall efficiency is 99.08.When performance analysis with SNR 20 dB shown in table 3.5, got overall accuracy of 98.91 %. To check the reliability of proposed novel hybrid technique, performance is compared with earlier state of art as shown in table 3.6.

Table 3.3: Performance Analysis in Idealistic Condition

Events	Sag	Swell	Harmonics	Transient	Sag+ Harmonics	Swell+ Harmonics
Sag	200					
Swell		200				
Harmonics			200			
Transient				200		
Sag+ Harmonics					200	
Swell+Harmonics						199
Classification efficiency in %	100	100	100	100	100	99.5
classification error in %	0	0	0	0	0	0.5
Overall efficiency				**99.91**		

Table 3.4: Performance analysis with SNR 30 dB

Events	Sag	Swell	Harmonics	Transient	Sag+ Harmonics	Swell+ Harmonics
Sag	200					
Swell		200				
Harmonics			200			
Transient				197		
Sag+ Harmonics					196	
Swell+ Harmonics						196
Classification efficiency in %	100	100	100	98.5	98	98
classification error in %	0	0	0	1.5	2	2
overall efficiency				**99.08**		

Table 3.5: Performance analysis with SNR 20 dB

Events	Sag	Swell	Harmonic	Transient	Sag+ Harmonics	Swell+ Harmonics
Sag	200					
Swell		200				
Harmonic			199			
Transient				197		
Sag+ Harmonics					195	
Swell+ Harmonics						196
Classification efficiency in %	100	100	99.5	98.5	97.5	98
classification error in %	0	0	0.5	1.5	2.5	2
Overall efficiency				**98.91**		

Table 3.6: Performance Comparison with Previous Work

REF.	Approach	Feature (1)	Feature (2)	Accuracy (%)
[246]	Volterra +IT2FLS	Power spectral entropy	Standard deviation	93
[247]	GT+FPNN	Max area of MGT	Energy of MGT	94.56
[233]	WT+Fuzzy	Average value of WT coefficients	Maximum value of WT coefficients	92.56
[248]	DWT+PNN	Detailed coefficients	Approximation coefficients	96.47
[229]	ST+SVM	Energy contained in magnitude contour	Standard deviation of phase contour	98.11
[249]	WT+PNN	Energy of Detailed coefficients	Standard deviation Detailed coefficients	98.64
[232]	WT+Fuzzy	Energy of Detailed coefficients	Energy of Approximation coefficients	95
[250]	WT+RBFNN	Total energy of WT coefficients	Average power of WT coefficients	97.85
[228]	WT+SVM	Standard deviation of WT coefficients	Mean of disturbances energy	96.37
[251]	ST+Decision Tree	Skewness	Kurtosis	98.5
proposed	**AFEM+type-2 fuzzy**	**Sparse signal decomposition**	**Stiffness matrix**	**98.91**

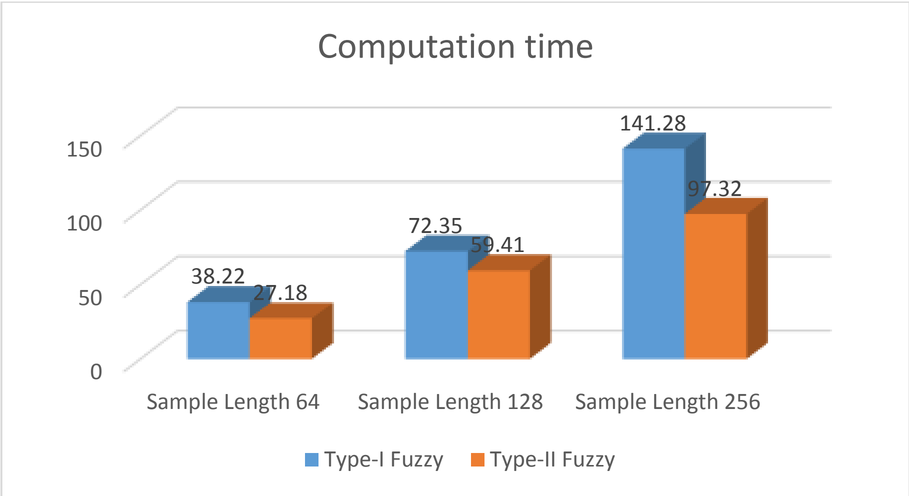


Figure 3.8: Computation time (ms) for Type-I fuzzy Vs Type-II Fuzzy.

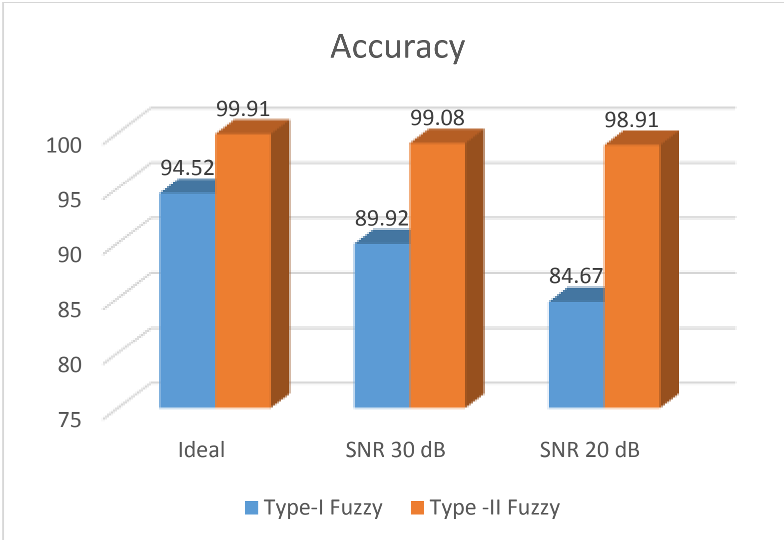


Figure 3.9: Accuracy for Type-I fuzzy Vs Type-II fuzzy.

Based on comparison done in table 3.6, fig. 3.8 and fig. 3.9, proposed methodology shows best results which justify the time efficiency as in comparison of type-I fuzzy the type-II fuzzy with 256 samples takes 97.32 ms and type-I fuzzy takes 141.28 ms and accuracy of type –II fuzzy in case of 20 dB SNR is 98.91 percent and type-I fuzzy in same case having 89.72 percent accuracy in real time scenario of PQ events.

3.6 Conclusions

This work proposes novel methodology of adaptive recognition and classification of power signal disturbances and having advantage of less features for recognition of distorted PQ events results in less memory requirement and time efficient. When performance analysis is done under three different SNR conditions then minimum efficiency is come out to be 98.91 percent and maximum efficiency is 99.91 percent. The performance of proposed method is much better than type-1 fuzzy system, support vector machine and artificial intelligence based classifiers. So, the proposed a novel methodology can be applied in actual real time situation monitoring systems. If we combine all the three condition of SNR i.e. ideal 30 and 20dB then the average accuracy comes out to be 99.30 percent this shows that the proposed method having much better performance than RBFNN, PNN support vector machine and type-1 fuzzy based classifiers.

This chapter is based on following work:

1. Rajiv Kapoor, Rahul, M M Tripathi " Adaptive FEM based Detection and classification of power disturbances" **Communicated in** IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS**.(Under review)**

Chapter 4

Deep Learning Based Automatic Detection and Classification of Power Quality Events

The objective of this chapter is to design and develop a hybrid technique based on long short term memory –convolution neural network for fast and automatic detection and classification of power quality events. The key ingredients in this chapter include the comprehensive study of hybrid approach for analysis of power quality events, results discussion and comparative analysis of results with non-hybrid approach is done.

4.1 Introduction

This chapter presents novel method of deep learning for automatic selection of features and classification of power quality events. The power quality events analysis based on hybrid approach of long short-term memory - convolution neural network is proposed here to ensure reliability, security of supplied power. It is necessary to recognize and classify the power quality events. Power quality disturbance classification methods mostly based on unique feature extraction such as statistical behavior, spatial-temporal information, nonlinear and non-stationary characteristics of power quality disturbances. The concept of presented long short-term memory-convolution neural network is based on deep learning approach. Deep learning (DL), which is a robust classifier in scenario of massive data to train, is applied here for power quality disturbances data analysis. In comparison with earlier state of art proposed methodology takes the advantage of image file based classification in contrast with sampled database analysis techniques, sampled data of the power quality disturbances are not exercised here, but image files of the disturbances are used by utilizing the superiority of deep learning approach on image file based classification. As in PQ disturbances analysis, we are dealing with patterns such as voltage sag, swell, harmonics and flickers etc., DL is competent of analyzing these patterns in separate level of information. Each and every layer utilize previous layer data such as input and output for processing result in a large gain in the form of system’s capability to generalize power quality image data. Hence, the uniqueness of the proposed methodology is that, images of power quality disturbances are classified with high accuracy rather, classifying the sampled data strings of power quality events.

The developed model is novel for feature training and classification of various disturbances. Totally different from the conventional methods such as Support vector machine (SVM), fuzzy logic, probabilistic neural networks (PNN) and artificial neural networks (ANN). The achieved results show that the deep learning based classifier is more efficient than the earlier state of art. In addition, the proposed method can be efficiently used to classify the complex power quality events.

4.2 Architecture of Proposed Methodology

The input power quality events are applied to the first stage which is convolution layer, function of this layer is to overcome the complexity of power quality events image data set, i.e. it will do the job of sharpening and edge detection. Now the filter data is compressed so that it can easily be applied to next layer which is maxpooling layer, which mixes the features extracted from the last layer in the form of edge detection and sharpening of power quality events.

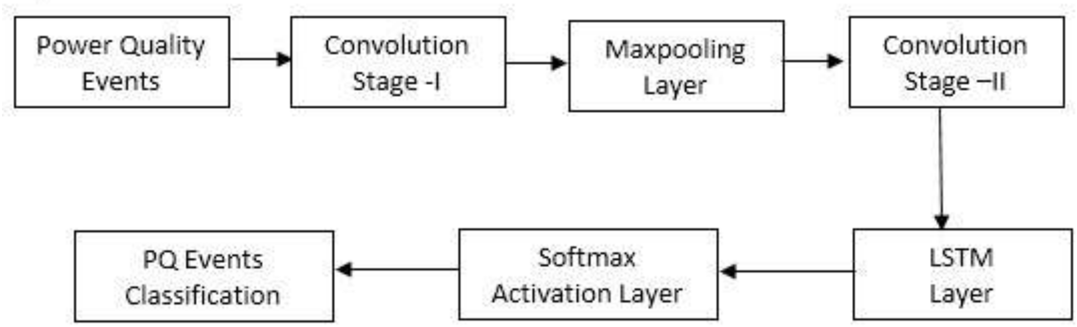


Figure 4.1: Work flow chart of proposed methodology

After the max-pooling layer again convolution is done to filter out irrelevant features so that the size of extracted feature set will be become shorter and further the complexity will reduce. The next layer is LSTM layer which is having memory cells. The LSTM layer finds large temporal dependencies and develops a more concise feature vector. Final layer having non-linear activation module termed as softmax, task is to evaluate the probabilities of accurate classification of power quality events. On the basis of output of this layer decision of classification of power quality events are taken. The classified power quality events are voltage sag, swell, harmonics and flickers.

4.3 Concept of Deep Learning

Deep learning is a robust and time efficient technique in machine learning, artificial intelligence and data processing. Most of the machine learning algorithm works on extracted features, which needs tedious effort to extract the adequate features. Deep learning approaches are data dependent while feature extraction aspect is function specific. In artificial intelligence methods data are continuously generating and a stage will come where automatic extraction of feature is impossible but this is not the case in deep learning techniques. DL process combines training which includes interactive learning of data samples and inference step extracts the output from trained model. In training network, a huge data is decomposed into training and testing sets, and finally a validation module as well. A machine learning algorithm fed the given training set data to review some representation that can be in terms of function approximation of the given feature extraction or in the form of decision sets based on the addition of each feature to others.

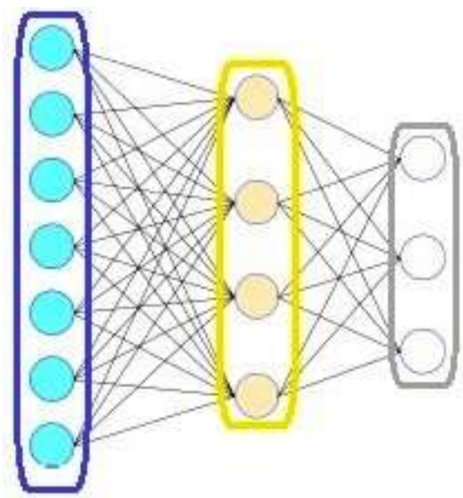


Figure 4.2: Basic deep learning network.

The role of validation comes into picture during training, in terms of method to validate the robustness of the training action, obtained results fed to tune learning module of the algorithm and revamp the concluding efficiency. The final test set then gives unobserved data set to evaluate the last accuracy of the training module, and is broadly the source of the obtained accuracy scores and other potentiality metrics. The role of inference mainly is to feeding a data set into a trained and executed machine learning module and results in inferred output. The initial small data fed into the deep architecture are adequate to train features and to classify. A simple deep learning network has multiple deep layers to extract unique features of power quality disturbance's data. The yield from previous layer is passed as input to next layer, and trains multiple levels of sparse data [252]. For instance, the first layer can extract information about voltage amplitude, and second layer can collect the information how much voltage dip occurred and the third give the information which portion have voltage sag in power signal and the final layer combines all the information from previous layers and takes decision regarding classification of power quality disturbance. A general deep learning model has an input layer, several hidden layers and finally output layers. In fig.4.2 first blue layer is the input layer that takes the input data sets and then forward the information to multiple middle, yellow hidden layers and finally output grey layers classifies the signals on the basis of training data sets and inference system build up in middle hidden layers.

4.4 Long Short-Term Memory (LSTM)-Convolution Neural Network

LSTM is a specific type of recurrent neural network that solves the problem of vanishing gradient [17]. The block diagram of an LSTM module is shown in fig. 4.3. The main concept behind LSTMs is a memory cell network $\mathrm{M_t}$ which is capable to maintain state information for a long time, that can makes gradients to flow over entire sequences. The data set information going in and out of the memory cell network $\mathrm{M_t}$ is controlled by three gates: an input gate $\mathrm{p_t}$, a forget gate $\mathrm{q_t}$ and an output gate $\mathrm{r_t}$. For every clock time instant, the LSTM cell collect input data of the present time $\mathrm{y_t}$ and the hidden information$\mathrm{z_{t-1}}$ from the previous state. The multiplication of input $\mathrm{y_t}$ and hidden information$\mathrm{z_{t-1}}$ is analyzed by passing over a tanh function:

$$\mathrm{d_t = tanh(W_g y_t + U_g z_{t-1} + b_g)} \tag{4.1}$$

Here $\mathrm{W_g}$, $\mathrm{U_g}$ and $\mathrm{b_g}$ represents input weights, recurrent weights and bias, respectively. The role of forget gate $\mathrm{q_t}$is to decide which data should be erased from the memory $\mathrm{M_t}$ over an element-wise sigmoid function:

$$\mathrm{q_t = \sigma(W_q y_t + U_q z_{t-1} + b_q)} \tag{4.2}$$

However, the input gate takes a decision regarding which data will be saved in the memory cell $\mathrm{M_t}$over an element-wise sigmoid function:

$$p_t = \sigma(W_p y_t + U_p z_{t-1} + b_p) \quad (4.3)$$

Further, the information in the memory is refreshed through fractional erasing of data saved in the last memory cell M_{t-1}through the following step:

$$M_t = q_t * M_{t-1} + p_t * d_t \quad (4.4)$$

Here $*$stands for element-wise product operation of two constituent. Now the role of forget gate $q_t$at this stage is to decide the extent to which previous data saved in M_{t-1} will be clean up. The set q_t having value in between 0 and 1. If$q_t \to 0$, the previous state data will be completely clean up and if $q_t \to 1$, the previous data will be stored as it is in the memory. Finally, the output hidden state $h_t$will be refreshed on the basis of evaluated cell state $M_t$as shown:

$$z_t = o_t * \tanh(M_t) \quad (4.5)$$

Here network input weights $W_{\{d,p,q,o\}}$, bias $b_{\{d,p,q,o\}}$and recurrent weights $U_{\{d,p,q,o\}}$ are computed through the training and inference process.

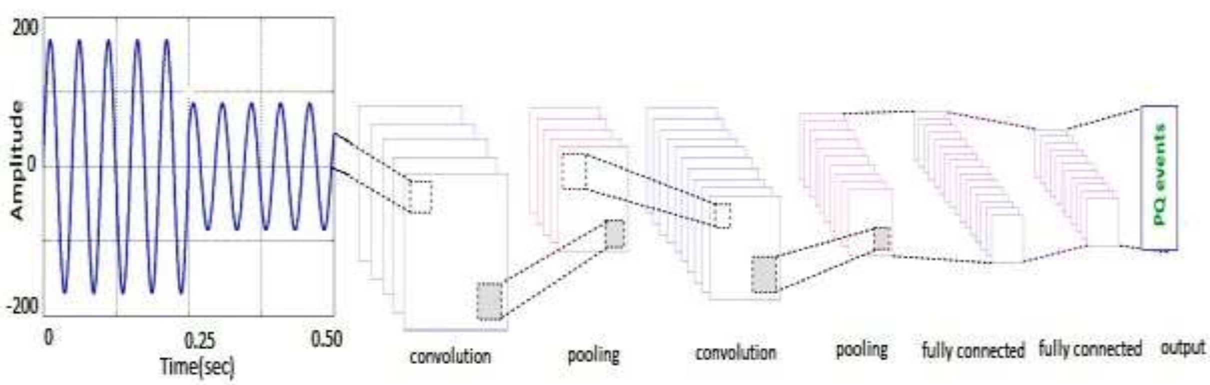


Figure 4.3: CNN architecture for power quality disturbance.

The CNN architectures made up of three main layers, first layer is convolution layer, pooling layer is second layer, and fully-connected layer is the last layer. The role of fully-connected layer is same as in the general neural networks and convolution layer do the job of convolution on the previous layer many times [253]. The task of down sampling is assigned to pooling layer, maximum of each stage of the previous layer. The stacked network of three layers makes complete CNN architecture as shown in fig. 4.3. A convolution neural network (CNN) is a generalized form of recursive neural network (RNN). In case of RNNs, iteration process is executed to recursively restore the weights of the neurons based on the loss function obtained after each learning stage. In the architecture of CNN, alternating convolution and pooling layers are combined before fully connected layer. The task of convolution layers is to filter out huge multidimensional matrices [254]. The function of pooling layer is to spatially shorten the size of the feature vectors into a smaller and more feasible matrix. In abstract, the convolution layers overcome the complexity of the power quality disturbance image by some filtering operation which do the job of sharpening and edge detection and the pooling layers performs crucial task of compression of filtered data. Role of multiple filters are generally to extract parallel and comprehensive features.

4.5 Detection and Classification of PQ Disturbances

In this work, to enhance the efficiency of power quality disturbance classification by learning some supplementary features, hybrid architecture of LSTM-CNN is implemented here as shown in fig. 4.4, many steps involved in the novel hybrid architecture. The proposed architecture comprises of an initial layer of CNN then next stage is max pooling which perform the task of finding low level dependencies in layers. To develop a concise feature map, the features extracted in first stage are applied as input to subsequent layer of CNN and max pooling layers. The first CNN layer contains 128 filters with a filter length of four for convolving input information. The next CNN layer has 256 filters with length of four. The max pooling layer has normal size of 3, which mixes the features from last layer. The final combined feature matrix developed from max pooling layer are then applied to an LSTM layer having memory cells. The LSTM layer finds large temporal dependencies and develops a more concise feature vector. The LSTM-CNN novel architecture having 100 memory cells containing many gates and activation controllers. The final output of LSTM layer has passed to a last stage i.e. fully connected layer. Commonly, a feed-forward neural network layer performs the job of fully connected layer, which involves units conforms to the number of power quality events classification. The fully connected layer having non-linear activation module termed as softmax task is to evaluate the probabilities of accurate classification of power quality events.

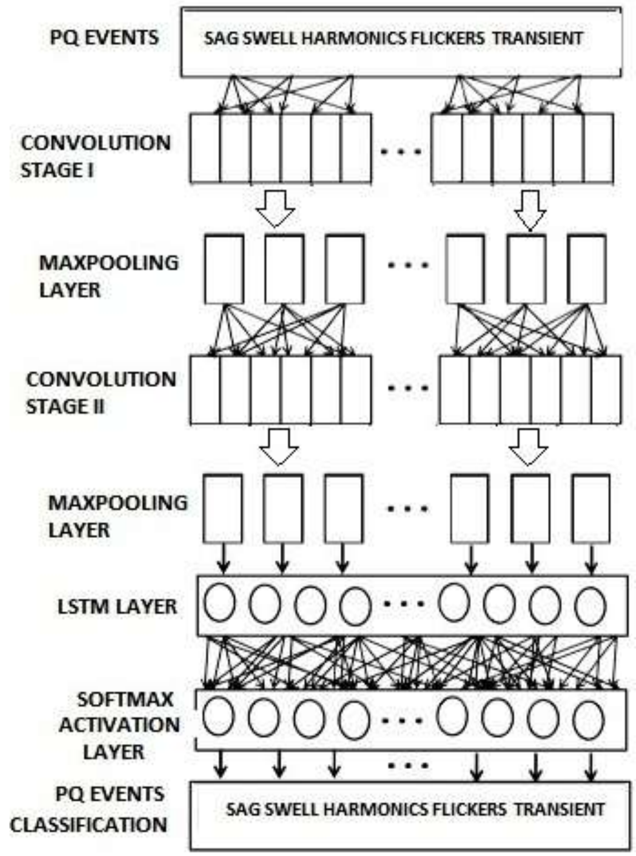


Figure 4.4: Hybrid architecture of LTSM-CNN for PQ events classification

For LSTM-CNN, the performance is totally relying on the number of filters used in the network. In the article two form of experiments performed with novel LSTM- CNN architecture and max-pooling layer by changing the number of filters as 64, 128, 256 and filter length as 4, 5 and 6. The CNN model with number of filters as 128, each filter having a length of 4 has achieved the highest accuracy and hence these values are appropriate for detailed study of power quality disturbances. After setting the network parameters, experiments are performed to select the most suitable network model for all deep learning process.

4.6 Results and Discussion

In the proposed novel architecture of LSTM-CNN, power quality events such as voltage sag, swell, harmonics, flickers and transient events are taken into consideration for analysis. These events then applied as a raw image data to the proposed architecture; first the various features are extracted by LSTM network. Features extracted in each layers are flowing through to next subsequent layer and last activation layer is capable to separate the data into different classes of power quality events and then extracted features fed as input to the CNN network which performs the function of classification for various power quality events. The results obtained for different PQ events are mentioned in table 4.1.

Table 4.1. Comparison of Hybrid Approach Accuracy

	LSTM		CNN		LSTM-CNN	
PQ EVENTS	**TPR**	**FPR**	**TPR**	**FPR**	**TPR**	**FPR**
SAG	0.91	0.098	0.91	0.098	0.097	0.007
SWELL	0.97	0.003	1	0	1	0
HARMONICS	1	0	0.99	0.098	1	0
FLICKER	0.97	0.039	1	0	1	0
TRANSIENT	0.99	0.05	0.94	0.099	0.98	0.006
ACCURACY	0.956		0.97		**0.989**	

The LSTM model has attained an accuracy of 95.6 percent for five different power quality disturbances occurring in power system. The second model of CNN achieve the accuracy of 97 percent little better performance than LSTM model, but proposed novel architecture of LSTM-CNN model attained the highest accuracy of 98.90 percent. In comparison of conventional classifiers such as artificial neural network (ANN)[255] and probabilistic neural network(PNN)[256], support vector machine[256], decision tree(DT)[258] proposed novel methodology of LSTM-CNN achieved highest accuracy of 98.90 percent. The conventional PQ disturbance classification techniques are not time efficient mainly because of extraction of features. While the deep learning architecture has eliminated the stage of the feature extraction and that's why the processing time is less than other methods.

4.7 Conclusions

In the proposed methodology, a deep learning based novel model is developed for five different power quality events such as voltage sag, swell, harmonics, flicker and transient. In contrast with the previously proposed techniques of PQ disturbances sampled data set of the PQ events are not utilized for feature extraction, but image files of the PQ disturbances are implemented by taking the advantage of the deep learning architecture on image based classification. This justify, the novelty of the proposed method to classify PQ disturbances with 98.90 % accuracy, rather than classifying the sampled data set of PQ events with low accuracy. This reveals that the proposed novel approach generates a more inventive system with classification performance better than that of each and every approach discussed in table 4.1. This confirm that the proposed novel approach generates a more inventive system with classification performance better than that of earlier state of art which is using time-frequency based method for analysis of power quality events.

This Chapter is based on following work:

1. **Rahul,** Rajiv Kapoor and M M Tripathi "Long Short-Term Memory-Convolution Neural Network Based Hybrid Deep Learning Approach for Power Quality Events Classification Innovation in electronics and communication engineering, Vol 65, p. 501-510, 2018.DOI 10.1007/978-981-13-3765-9_52. [260**](Pub.: Springer)(Indexing –Scopus)**

Chapter 5

Conclusions and Future Research Scope

This chapter falls the light on conclusions drawn from this study on the basis of work reported either experimentally or theoretically and covers the future research scope in the field of power quality disturbances.

5.1 Conclusions

The three major approaches of power quality disturbances recognition and classification are presented and these approaches are as follows:

- In the first approach Volterra series(VS) is applied for feature extraction and interval type-2 fuzzy logic based classifier is utilized for classification of power quality events. The most of similar work only detect single power quality events rarely detect multiple power quality events, this problem has been addressed here by employing: (a) Accurate feature extraction through spectral entropy and kurtosis of Volterra series based patterns ; (b) Simple and minimum effective feature sets are utilized of power quality events detection; (c) Fast, accurate and simple classification of power quality disturbances with type- 2 fuzzy classifier under noiseless and heavy noisy conditions. The effectiveness of the proposed method is tested on three different conditions, i.e. ideal, SNR 30 and 20 dB. The overall classification efficiency of IT2FLS is 99.27 percent if taken as the average of all three conditions mentioned in this chapter. The simulation results show that IT2FLS has higher performance than NN, PNN and support vector machines. The performance of the hybrid approach successfully verified. The future work includes hardware implementation of hybrid technique of VS+IT2FLS so that this novel hybrid technique may be applied in real time detection and classification of power quality events.
- The second approach of power quality disturbances analysis is based on adaptive FEM based intelligent system for detection and classification of power quality events which enhances the PQ events detection accuracy with minimum error. The adaptive FEM algorithm automatically changes triangular mesh size based on size of power quality disturbances with the help of sparse signal decomposition based method. The features

based on stiffness matrix are extracted and fed as input to type-2 fuzzy based classifiers. The performance of proposed method is much better in terms of only three feature set are required for detection of power quality events than other signal processing based techniques such as Fourier transform, short time Fourier transform, wavelet transform and Hilbert transform, which requires at least five to ten features for detection of PQ events and the performance of type -2 fuzzy based classifier is comprehensively compared in with type-1 fuzzy ,in terms of type-1 fuzzy system, support vector machine and artificial intelligence based classifiers. If we combine all the three conditions of SNR i.e. ideal 30 and 20dB then the average accuracy comes out to be 99.30 percent this shows that the proposed method has much better performance than RBFNN, PNN support vector machine and type-1 fuzzy based classifiers. So, the proposed intelligent system developed in this work is capable of monitoring PQ events in real time scenario.

- In the third approach hybrid technique is developed by combining long short-term memory and convolution neural network which developed totally different concept for detection and classification of power quality events in terms of image which is utilized the concept of edge detection and sharpening as a feature for fast and automatic classification of power of power quality disturbances. In contrast with the previously proposed techniques of PQ disturbances sampled data set of the PQ events are not utilized for feature extraction, but image files of the PQ disturbances are implemented by taking the advantage of the deep learning architecture on image based classification. This justify the novelty of the proposed method to classify PQ disturbances with 98.90 % accuracy, rather than classifying the sampled data set of PQ events with low accuracy. This reveals that the proposed novel approach generates a more inventive system with classification performance better than that of earlier state of art which is using time-frequency based method for analysis of power quality events.

5.2 New Innovations and Future Scope

For the power industries point of view, this work is based on low memory requirements and subsequently it requires less computation time and enhances performance in terms of accuracy, speediness, reliability and lower cost. This work paves the path for early detection &

classification techniques of power quality events, with the existing methods S-transform, wavelet, neural networks and type-1 fuzzy. This study can further be extended by exploring new techniques with less computational overhead in detection and classification of power quality events with maintaining high accuracy.

The concept of Non-dominated sorting genetic algorithm-III has been a reliable evolutionary algorithm (EA) inspired by Darwin's theory of evolution but it has not been explored in the field of PQ disturbance monitoring. NSGA III algorithm and Directed Acyclic Graph –Support Vector Machine (DAG-SVM) based combined approach can be explored for recognition and classification of power quality events. The function of NSGA III is to extract features and DAG-SVM for the purpose of classification of power quality events with minimum error. The non-stationary and non- linear nature of power quality disturbances makes it a suitable choice for NSGA III as this algorithm is adaptive and can change shape and size of data set as per requirement by utilizing the concept of mutation and crossover probabilities. This technique will give unique Pareto-optimal solutions based on multi objective optimization. Considering equal priority for all the objectives, a fitness function is used to obtain the best solution set from the first Pareto front. Non-dominated sorting sets a dominated count and assigns domination to each individual. Dominated count means the number of times an individual data point has been dominated by another data point. The obtained unique feature vectors are used for training DAG -SVM to classify the power quality disturbances. Therefore this combined approach may give good results for accurate and fast detection of power quality events.

The design of new wavelets can also be possible in an alternative way so that effective features can be extracted for fast and accurate analysis of power quality events. Consequently, a new approach may be developed in the form of Hybrid Fuzzy Wavelet Neural Networks Architecture. This concept is a better option for improvement in time-frequency analysis of PQ events for the purpose of further optimization of feature sets. Based on the concept of fuzzy, wavelet, and neural network, new signal processing techniques can be further devised for analysis of PQ disturbances.

REFERENCES:

[1] M. H. J. Bollen and H. Y. I. Gu, Signal Processing of Power Quality Disturbances. John Wiley and Sons, 1st ed., 2006.

[2] H. Eristi, O. Yildirim, B. Eristi, and Y. Demir,, "Optimal feature selection for classification of power quality events using wavelet transform and least squares support vector machines",‖ International Journal of Electrical Power & Energy Systems, vol. 49, pp. 95-103, 2013.

[3] H. Dehghani, B. Vahidi, R. A. Naghizadeh, and S. H. Hosseinian, "Power quality disturbance classification using a statistical and wavelet-based hidden Markov model with Dempster-Shafer algorithm" International Journal of Electrical Power & Energy Systems, vol. 47, pp. 368-377, 2013.

[4] H. Eristi and Y. Demir, "A new algorithm for automatic classification of power quality events based on wavelet transform and SVM" Expert Systems with Applications, vol. 37, no. 6, pp. 4094-4102, 2010.

[5] M. A. S. Masoum, S. Jamali, and N. Ghaffarzadeh, "Detection and classification of power quality disturbances using discrete wavelet transform and wavelet networks" IET Science, Measurement &Technology, vol. 4, no. 4, pp. 193-205, 2010.

[6] M. Uyar, S. Yildirim, and M. T. Gencoglu, "An expert system based on S transform and neural network for automatic classification of power quality disturbances" Expert Systems with Applications, vol. 36, no. 3, pp. 5962-5975, 2009.

[7] P. S. Wright, "Short-time Fourier transforms and Wigner-Ville distributions applied to the calibration of power frequency harmonic analyzers" IEEE Transaction on Instrumentation and Measurement, vol. 48, no. 2, pp. 475 -478, 1999.

[8] C. Zhao, M. He, and X. Zhao, "Analysis of transient waveform based on combined short time Fourier transform and wavelet transform" International Conference on Power System Technology pp.1122-1126,2004.

[9] F. Hashemi and M. Mohammadi, "Islanding detection approach with negligible non-detection zone based on feature extraction discrete wavelet transform and artificial neural

network" International Transaction on Electrical Energy Systems, vol 26, no.10, pp. 2172-2192, 2016.

[10]L. C. M. Andrade, M. Oleskovicz, and R. A. S. Fernandes, "Adaptive threshold based on wavelet transform applied to the segmentation of single and combined power quality disturbances," Applied Soft Computing, vol. 38, pp. 967–977, 2016.

[11]O. P. Mahela and A. G. Shaik, "Power quality detection in distribution system with wind energy penetration using discrete wavelet transform" 2nd International Conference on Advances in Computing and Communication Engineering, 2015, pp. 328-333.

[12]S. Shukla, S. Mishra, and B. Singh, "Empirical-mode decomposition with Hilbert transform for power-quality assessment" IEEE Transaction on Power Delivery, vol. 24, no. 4, pp. 2159 - 2165, 2009.

[13]R. G. Stockwell, L. Mansinha, and R. P. Lowe, "Localization of the complex spectrum: the S-transform" IEEE Transaction on Signal Processing, vol. 44, no. 4, pp. 998-1001, 1996.

[14]M. S. Azam, T. Fang, K. R. Pattipati, and R. Karanam, "A dependency model-based approach for identifying and evaluating power quality problems" IEEE Transaction on Power Delivery, vol. 19, no. 3, pp. 1154-1166, 2004.

[15]F. Choong, M. B. I. Reaz, and F. Mohd-Yasin, "Advances in signal processing and artificial intelligence technologies in the classification of power quality events: a survey" Electric Power Components and Systems, vol. 33, no.12, pp. 1333-1349, 2005.

[16]G. T. Heydt, P. S. Fjeld, C. C. Liu, D. Pierce, and L. Tu, G. Hensley, "Applications of the windowed FFT to electric power quality assessment" IEEE Transaction on Power Delivery, vol. 14, no. 4, pp. 1411-1416, 1999.

[17]I. Y. H. Gu and M. H. J. Bollen, "Time-frequency and time-scale domain analysis of voltage disturbances" IEEE Transaction on Power Delivery, vol. 15, no. 4, pp. 1279-1284, 2000.

[18]S. Santoso, W. M. Grady, E. J. Powers, J. Lamoree, and S. C. Bhatt, "Characterization of distribution power quality events with Fourier and wavelet transforms" IEEE Transaction on Power Delivery, vol.15, no. 1,pp. 247-254, 2000.

[19]S. Avdakovic and N. Cisija, “Wavelets as a tool for power system dynamic events analysis –state-of-the-art and future applications” Journal of Electrical Systems and Information Technology, vol. 2, no. 1, pp. 47-57,2015.

[20]J. Barros, R. I. Diego, and M. d. Apraiz, “Applications of wavelets in electric power quality: voltage events” Electric Power Systems Research, vol. 88, pp. 130–136, 2012.

[21]A. M. Gaouda, M. M. A. Salama, M. R Sultan, and A. Y. Chikhani, “Power quality detection and classification using wavelet-multiresolution signal decomposition,” IEEE Transaction on Power Delivery, vol. 14, no. 4, pp. 1469-1476, 1999.

[22]M. Oleskovicz, D. V. Coury, O. D. Felho, W. F. Usida, A. A. F. M. Carneiro, and L. R. S. Pires, “Power quality analysis applying a hybrid methodology with wavelet transforms and neural network,” International Journal of Electrical Power & Energy Systems, vol. 31, no. 5, pp. 206-212, 2009.

[23]M. Sahani, S. Mishra, A. Ipsita, and B. Upadhyay, “Detection and classification of power quality event using wavelet transform and weighted extreme learning machine” International Conference on Circuit, Power and Computing Technologies (ICCPCT), 2016, pp. 1-6.

[24]S. Divya and K. Uma Rao,, “Comparative performance of different wavelets in Power Quality disturbance detection and quantification” 2nd International Conference on Cognitive Computing and Information Processing (CCIP), 2016, pp. 1-5.

[25]M. F. Faisal and A. Mohamed, “Comparing the performance of various mother wavelet functions in detecting actual 3-phase voltage sags” 2nd IEEE International Power and Energy Conference, 2008, pp. 657-661.

[26]R. Kapoor and M. K. Saini, “Multiwavelet transform based classification of PQ events” International Transaction on Electrical Energy System, vol. 22,no. 4, pp. 518-532, 2011.

[27]M. Hajian and A. A. Foroud, “A new hybrid pattern recognition scheme for automatic discrimination of power quality disturbances” Measurement, vol.51, pp. 265-280, 2014.

[28]S. A. Deokar and L. M. Waghmare, “Integrated DWT-FFT approach for detection and classification of power quality disturbances” International Journal of Electrical Power & Energy Systems, vol. 61, pp. 594-605, 2014.

[29]C. Xiangxun, “Wavelet-based detection, localization, quantification and classification of short duration power quality disturbances” IEEE Power Engineering Society Winter Meetingpp. 931 - 936, 2002.

[30]S. Santoso, E. J. Powers, W. M. Grady, and P. Hofmann, “Power quality assessment via wavelet transform analysis” IEEE Transaction on Power Delivery, vol. 11, no. 2, pp. 924 - 930, 1996.

[31]H. Eristi, O. Yildirim, B. Eristi, and Y. Demir, “Automatic recognition system of underlying causes of power quality disturbances based on S-transform and extreme learning machine” International Journal of Electrical Power & Energy Systems, vol. 61, pp. 553 - 562, 2014.

[32]J. Chung, E. J. Powers, M. W. Grady, and S. C. Bhatt, “Power disturbance classifier using a rule-based method and wavelet packet-based hidden Markov model” IEEE Transactions on Power Delivery, vol. 17, no. 1, pp. 233-241, 2002.

[33]H. Eristi and Y. Demir, “Automatic classification of power quality events and disturbances using wavelet transform and support vector machines” IET Generation, Transmission & Distribution, vol. 6, no. 10, pp. 968-976, 2012.

[34]S. Santoso, J. Lamoree, W. M. Grady, E. J. Powers, and S. C. Bhatt, “A scalable PQ event identification system” IEEE Transaction on Power Delivery, vol. 15, no. 2, pp. 738 - 743, 2000.

[35]W. M. Lin, C. H. Wu, C. H. Lin, and F. S. Cheng, “Detection and classification of multiple power-quality disturbances with wavelet multiclass SVM” IEEE Transaction on Power Delivery, vol. 23, no. 4, pp. 2575-2582, 2008.

[36]A. M. Gaouda, S. H. Kanoun, and M. M. A. Salama, “On-line disturbance classification using nearest neighbor rule” Electric Power Systems Research, vol. 57, no. 1, pp. 1-8, 2001.

[37]H. He and J. A. Starzyk, “A self-organizing learning array system for power quality classification based on wavelet transform” IEEE Transactions on Power Delivery, vol. 21, no. 1, pp. 286-295, 2006.

[38]D. G. Ece and O. N. Gerek, “Power quality events using joint 2-D wavelet subspaces” IEEE Transaction on Instrumentation and Measurement, vol.53, no. 4, pp. 1040-1046, 2004.

[39]O. N. Gerek and D. G. Ece, “Compression of power quality event data using 2D representation,” Electric Power Systems Research, vol. 78, no. 6, pp. 1047-1052, 2008.

[40]M. A. S. Masoum, S. Jamali, and N. Ghaffarzadeh, “Detection and classification of power quality disturbances using discrete wavelet transform and wavelet networks” IET Science, Measurement & Technology, vol. 4, no. 4, pp. 193-205, 2010.

[41]C.-H. Lin and C.-H. Wang, “Adaptive wavelet networks power quality detection and discrimination in a power system” IEEE Transaction on Power Delivery, vol. 21, no. 3, pp. 1106-1113, 2006.

[42]U. D. Dwivedi and S. N. Singh, “Enhanced detection of power-quality events using intra and interscale dependencies of wavelet coefficients” IEEE Transaction on Power Delivery, vol. 25, no. 1, pp. 358-366, 2010.

[43]Y.-Y. Hong and C.-W. Wang, “Switching detection classification using discrete wavelet transform and self-organizing mapping network” IEEE Transaction on Power Delivery, vol. 20, no. 2, pp. 1662-1668, 2005.

[44]M. K. Saini, R. Kapoor, A. K. Singh, and Manisha, “Performance comparison between orthogonal, bi-orthogonal and semi-orthogonal wavelets” Advanced Materials Research, vol. 433-440, pp. 6521-6526, 2012.

[45]R. Kapoor and M. K. Saini, “Multiwavelet transform based classification of PQ events” International Transaction on Electrical Energy System, vol. 22, no. 4, pp. 518-532, 2011.`

[46]M. K. Saini and R. Kapoor, “Power quality events classification using MWT and MLP” International Conference on Control, Robotics and Cybernetics (ICCRC, pp. 37-40), 2011.

[47]S. Dahiya, D. K. Jain, A. Kumar, R. Kapoor, and M. Kumar, “Detection and classification of power quality events using multiwavelet,” International Journal of Energy Technology and Policy, vol. 5, no. 6, pp. 673-683, 2007.

[48]R. Kapoor and M. K. Saini “A new signal processing technique for power system disturbance detection and classification” International Journal of Electrical Engineering, pp. 9-14, 2007.

[49]I. Y. H. Gu and M. H. J. Bollen, “Time-frequency and time-scale domain analysis of voltage disturbances” IEEE Transaction on Power Delivery, vol. 15, no. 4, pp. 1279-1284, 2000.

[50]F. Jurado and J. R. Saenz, “Comparison between discrete STFT and wavelets for the analysis of power quality events” Electric Power Systems Research, vol. 62, no. 3, pp. 183-190, 2002.

[51]F. Uçar, O. F. Alçin, B. Dandil, and F. Ata, “Machine learning based power quality event classification using wavelet-entropy and basic statistical features” 21st International Conference on Methods and Models in Automation and Robotics (MMAR), pp. 414-419, , 2016.

[52]Z. He, S. Gao, X. Chen, J. Zhang, Z. Bo, and Q. Qian, “Study of a new method for power system transients classification based on wavelet entropy and neural network” International Journal of Electrical Power & Energy Systems, vol. 33 , no. 3, pp. 402–410, 2011.

[53]P. Sinha, S. K. Goswami, and S. Nath, “Wavelet-based technique for identification of harmonic source in distribution system” International Transaction on Electrical Energy Systems, vol. 26, no. 12, pp. 2552-2572, 2016.

[54]A. Moschitta, P. Carbone, and C. Muscas, “Performance comparison of advanced techniques for voltage dip detection” IEEE Transaction on Instrumentation and Measurement, vol. 61, no. 5, pp. 1494–1502, 2012.

[55]V. F. Pires, T. G. Amaral, and J. F. Martins, “Power quality disturbances classification using 3-D representation and PCA based neuro-fuzzy approach” Expert Systems with Applications, vol. 38, no. 9, pp. 11911– 11917, 2011.

[56]A. Rodriguez, I.E. Ruiz, J. Aguado, J.J. Lopez, F.I. Martin, and F. Munoz, “Classification of power quality disturbances using S-transform and artificial neural networks” International Conference on Power Engineering, Energy and Electrical Drives (POWERENG) , pp. 1-6, 2011.

[57]R. G. Stockwell, L. Mansinha, and R. P. Lowe, “Localization of the complex spectrum: the S-transform” IEEE Transaction on Signal Processing, vol. 44, no. 4, pp. 998-1001, 1996.

[58]S. R. Mohanty, P. K. Ray, N. Kishor, and B. K. Panigrahi, "Classification of disturbances in hybrid DG system using modular PNN and SVM" International Journal of Electrical Power & Energy Systems, vol. 44, no. 1, pp. 764-777, 2013.

[59]F. Zhao and R. Yang, "Power-quality disturbance recognition using S-transform" IEEE Transaction on Power Delivery, vol. 22, no. 2, pp. 944-950, 2007.

[60]P. K. Dash, B. K. Panigrahi, D. K. Sahoo, and G. Panda, "Power quality disturbance data compression, detection and classification using spline wavelet and S-transform" IEEE Transaction on Power Delivery, vol. 18, no. 2, pp. 595-600, 2003.

[61]P. K. Dash and M. V. Chilukuri, "Multiresolution S-transform-based fuzzy recognition system for power quality events" IEEE Transaction on Power Delivery, vol. 19, no. 1, pp. 323-330, 2004.

[62]S. R. Shaw, C. R. Laughman, S. B. Leeb, and R. F. Lepard, "A power quality prediction system" IEEE Transaction on Industrial Electronics, vol. 47, no. 3, pp. 511-517, 2000.

[63]R. Ahila and V. Sadasivam, "S-transform based extreme learning machine for power system disturbances classification" Journal of The Institution of Engineers (India): Series B,‖ vol. 94, no. 3, pp.179-191, 2013.

[64]A. M. Gargoom, N. Ertugrul, and W. L. Soong, "Automatic classification and characterization of power quality events" IEEE Transaction on Power Delivery, vol. 23, no. 4, pp. 2417-2425, 2008.

[65]M. Biswal and P.K. Dash, "Detection and characterization of multiple power quality disturbances with a fast S-transform and decision tree base classifier" Digital Signal Processing, vol. 23, no. 4, pp. 1071-1083, 2013.

[66]B. Biswal, P.K. Dash, and K.B. Panigrahi, "Power quality disturbance classification using fuzzy c-means algorithm and adaptive particle swarm optimization" IEEE Transaction on Industrial Electronics, vol. 56, no. 1, pp. 212-220, 2009.

[67]M. Biswal and P.K. Dash, "Estimation of time-varying power quality indices with an adaptive window-based fast generalised S-transform" IET Science, Measurement & Technology, vol. 6, no. 4, pp. 189-197, 2012.

[68]S. R. Mohanty, N. Kishor, P. K. Ray, and J. P. S. Catalao, “Comparative study of advanced signal processing techniques for islanding detection in a hybrid distributed generation system” IEEE Transactions on Sustainable Energy, vol. 6, no. 1, pp. 122–131, 2015.

[69]P. K. Dash and M. V. Chilukuri, “Multiresolution S-transform-based fuzzy recognition system for power quality events” IEEE Transaction on Power Delivery, vol. 19, no. 1, pp. 323-330, 2004.

[70]P. R. Babu, P. K. Dash, S. K. Swain, and S. Sivanagaraju, “A new fast discrete S-transform and decision tree for the classification and monitoring of power quality disturbance waveforms” International Transaction on Electrical Energy Systems, vol. 24, no. 9, pp. 1279-1300, 2013.

[71]B. Biswal, P. K. Dash, and B. K. Panigrahi, “Non-stationary power signal processing for pattern recognition using HS-transform” Applied Soft Computing, vol. 9, no. 1, pp. 107-117, 2009.

[72]M. Hajian and A. A. Foroud, “A new hybrid pattern recognition scheme for automatic discrimination of power quality disturbances” Measurement, vol. 51, pp. 265-280, 2014.

[73]T. Nguyen and Y. Liao, “Power quality disturbance classification utilizing S-transform and binary feature matrix method” Electric Power Systems Research, vol. 79, no. 4, pp. 569-575, 2009.

[74]P. K. Ray, N. Kishor, and S. R. Mohanty, “Islanding and power quality disturbance detection in grid-connected hybrid power system using wavelet and S-transform” IEEE Transaction on Smart Grid, vol. 3, no. 3, pp. 1082- 1094, 2012.

[75]S. R. Mohanty, P. K. Ray, N. Kishor, and B. K. Panigrahi, “Classification of disturbances in hybrid DG system using modular PNN and SVM” International Journal of Electrical Power & Energy Systems, vol. 44, no. 1, pp. 764-777, 2013.

[76]P. K. Ray, S. R. Mohanty, N. Kishor, and J. P. S. Catalao, “Optimal feature and decision tree-based classification of power quality disturbances in distributed generation systems” IEEE Transaction on Sustainable Energy, vol. 5. No. 1, pp. 200-208, 2014.

[77]M. Biswal and P.K. Dash, “Detection and characterization of multiple power quality disturbances with a fast S-transform and decision tree based classifier” Digital Signal Processing, vol. 23, no. 4, pp. 1071-1083, 2013.

[78]A. Khamis, H. Shareef, and M. Z. C Wanik, ‘Pattern recognition of islanding detection using TT-transform” Journal of Asian Scientific Research, vol. 2, no. 11, pp. 607-613, 2012.

[79]N. Senroy, S. Suryanarayanan, and P. F. Ribeiro, “An improved Hilbert- Huang method for analysis of time-varying waveforms in power quality” IEEE Transaction on Power System, vol. 22, no. 4, pp. 1843-1850, 2007.

[80]J. Faiz, S. Lotfi-fard, and S. H. Shahri, “Prony-based optimal bayes fault classification of overcurrent protection” IEEE Transactions on Power Delivery, vol. 22, no. 3, pp. 1326-1334, 2007.

[81]A. Andreotti, A. Bracale, P. Caramia, and G. Carpinelli, “Adaptive Prony method for the calculation of power-quality indices in the presence of non-stationary disturbance waveforms” IEEE Transaction on Power Delivery, vol. 24, no. 2, pp. 874-883, 2009.

[82]J. C. H. Peng and N. K. C. Nair, “Adaptive sampling scheme for monitoring oscillations using Prony analysis” IET Generation, Transmission & Distribution, vol. 3, no. 12, pp. 1052-1060, 2009.

[83]L. Qi, L. Qian, S. Woodruff, and D. Cartes, “Prony analysis for power system transient harmonics” EURASIP Journal on Advances in Signal Processing, vol. 2007, pp. 1-12, 2007.

[84]T. Lin and A. Domijan, “Recursive algorithm for real-time measurement of electrical variables in power systems” IEEE Transaction on Power Delivery, vol. 21, no. 1, pp. 15-22, 2006.

[85]J. J. G. de la Rosa, A. M. Munoz, and A. Luque, “Power transients characterization and classification using higher-order cumulants and neural networks” IEEE Conference on Instrumentation and Measurement Technology, pp. 1-4,. 2007.

[86]P. K. Dash, M. Nayak, M. R. Senepati, and I. W. C. Lee, “Mining for similarities in time series data using wavelet-based feature vectors and neural networks” Engineering Application of Artificial Intelligence, vol. 20, no. 2, pp. 185-201, 2007.

[87]B.V. Krishna and K. Baskaran, “Parallel computing for efficient time frequency feature extraction of power quality disturbances” IET Signal Processing, vol. 7, no. 4, pp. 312 - 326, 2013.

[88]Z. Moravej, A. A. Abdoos, and M. Pazoki, “Detection and classification of power quality disturbances using wavelet transform and support vector machine” Electric Power Components and Systems, vol. 38, no. 2, pp. 182- 196, 2010.

[89]A. M. Gargoom, N. Ertugrul, and W. L. Soong, "Investigation of effective automatic recognition systems of power-quality events," IEEE Transactions on Power Delivery, vol. 22, no. 4, pp. 2319-2326, 2007.

[90]S. Naderian and A. Salemnia, ‘Method for classification of PQ events based on discrete Gabor transform with FIR window and T2FK-based SVM and its experimental verification” IET Generation, Transmission & Distribution, vol. 11, no. 1, pp. 133-141, 2017.

[91]E. Perez and J. Barros, “An extended Kalman filtering approach for detection and analysis of voltage dips in power system” Electric Power Systems Research, vol. 78, no. 4, pp. 618-625, 2008.

[92]E. Perez and J. Barros, “Voltage event detection and characterization methods: a comparative study” Transmission & Distribution Conference & Exposition: Latin America, pp. 1-6, 2006.

[93]E. Styvaktakis, I. Y. H. Gu, and M. H. J. Bollen, “Voltage dip detection and power systems transients” Power Engineering Society Summer Meeting, pp. 683-688, 2001.

[94]E. Styvaktakis, M. H. J. Bollen, and I. Y. H. Gu, “Expert system for classification and analysis of power system events” IEEE Transaction on Power Delivery, vol. 17, no. 2, pp. 423-428, 2002.

[95]J. A. R. Macias and A. G. Exposito, “Self-tuning of Kalman filters for harmonic computation” IEEE Transaction on Power Delivery, vol. 21, no. 1, pp. 501 - 503, 2006.

[96]S.-H. Cho, G. Jang, and S.-H. Kwon, “Time-Frequency analysis of power quality disturbances via the Gabor-Wigner transform” IEEE Transaction on Power Delivery, vol. 25, no. 1, pp. 494 - 499, 2010.

[97]Z. Chen, and P. Urwin, "Power quality detection and classification using digital filters" IEEE Porto Power Tech Proceedings, pp. 1-6 2001.

[98]S. Suja and J. Jerome, "Pattern recognition of power signal disturbances using S transform and TT transform" International Journal of Electrical Power & Energy Systems, vol. 32, no. 1, pp. 37-53, 2010.

[99]S. Santoso, W. M. Grady, E. J. Powers, J. Lamoree, and S. C. Bhatt, "Characterization of distribution power quality events with Fourier and wavelet transforms" IEEE Transaction on Power Delivery, vol.15, no. 1, pp. 247-254, 2000.

[100]H. He, X. Shen, and J. A. Starzyk, "Power quality disturbances analysis based on EDMRA method" International Journal of Electrical Power & Energy Systems, vol. 31, no. 6, pp. 258-268, 2009.

[101]N. C. F. Tse, J. Y. C. Chan, W.-H. Lau, and L. L. Lai, "Hybrid wavelet and Hilbert transform with frequency-shifting decomposition for power quality analysis" IEEE Transaction on Instrumentation and Measurement, vol. 61, no.12, pp. 3225-3233, 2012.

[102]S.-J. Huang and C.-T. Hsieh, "Feasibility of fractal-based methods for visualization of power system disturbances" International Journal of Electrical Power & Energy Systems, vol. 23, no. 1, pp. 31-36, 2001.

[103]D. D. Ferreira, A. S. Cerqueira, C. A. Duque, and M. V. Ribeiro, "HOS based method for classification of power quality disturbances" IET Electronics Letters, vol. 45, no. 3, pp. 183-185, 2009.

[104]M. V. Ribeiro, C. A. Marques, C. A. Duque, A. S. Cerqueira, and J. L. R. Pereira, "Power quality disturbance detection using HOS" IEEE Power Engineering Society General Meeting, 2006

[105]U. D. Dwivedi and S. N. Singh, "De-noising techniques with change-point approach for wavelet-based power-quality monitoring" IEEE Transaction on Power Delivery, vol. 24, no. 3, pp. 1719-1727, 2009.

[106]T. K. Abdel-Galil, E. F. El-Saadany, and M. M. A. Salama, "Power quality event detection using Adaline" Electric Power Systems Research, vol. 64, no. 2, pp. 137-144, 2003.

[107]C. T. Hsieh, J. M. Lin, and S. J. Huang, “Slant transform applied to electric power quality detection with field programmable gate array design enhanced” International Journal of Electric Power & Energy system, vol. 32, no. 5, pp. 428-432, 2010.

[108]A. A. Perez, J. C. P. Salas, J. J. G. de la Rosa, J. M. S. Fernandez, D. A. Sedeno, and A. M. Munoz, “Characterization of electrical sags and swells using higher-order statistical estimators” Measurement, vol. 44, no. 8, pp. 1453-1460, 2011.

[109]J. M. Filho, J. M. C. Filho, and A. P. Paiva, P. V. G. Souza and S. Tomasin, “A PCA-based approach for substation clustering for voltage sag studies in the Brazilian new energy context” Electric Power Systems Research, vol. 136, pp. 31-42, 2016.

[110]A. K. Goswami, C. P. Gupta, and G. K. Singh, “An analytical approach for assessment of voltage sags” International Journal of Electrical Power & Energy Systems, vol. 31, no. 7-8, pp. 418-426, 2009.

[111]Ou-yang Hua, B. Le-ping and Y. Zhong-lin, “Voltage sag detection based on DQ transform and mathematical morphology filter” Procedia Engineering, vol. 23, pp. 775-779, 2011.

[112]B. Boujoudi, N. Machkour, and E. Kheddioui, “New method for detection and characterization of voltage dips” Molecular Crystals and Liquid Crystals, vol. 641, no. 1, pp. 1542-1406, 2016.

[113]P. Thakur, A. K. Singh, and R. C. Bansal, “Novel way for classification an type detection of voltage sag,” IET Generation, Transmission & Distribution, vol. 7, no. 4, 398-404, 2013.

[114]S. Khokhar, A. A. B. M. Zin, A. S. B. Mokhtar, and M. Pesaran, “A comprehensive overview on signal processing and artificial intelligence techniques applications in classification of power quality disturbances” Renewable and Sustainable Energy Reviews, vol. 51, pp. 1650–1663, 2015.

[115]K. Manimala and K. Selvi, “Power quality disturbances classification using probabilistic neural network” International Conference on Computational Intelligence and Multimedia Applications, 2007, pp. 207-211.

[116]S. E. Jafarabadi and H. Rastegar, “Contribution to automatic detection and diagnosis of wide variety range of power quality disturbances using combined wavelet transform and neural network methods”39th International Universities Power Engineering Conference, 2004, pp. 902 - 906.

[117]Z. L. Gaing, “Wavelet-based neural network for power disturbance recognition and classification” IEEE Transaction on Power Delivery, vol. 19, no. 4, pp. 1560-1568, 2004.

[118]C. L. Chuang, Y. L. Lu, T. L. Huang, Y. T. Hsiao, and J. A. Jiang, “Recognition of multiple PQ disturbances using wavelet-based neural networks - part 2: implementation and applications” IEEE/PES Transmission and Distribution Conference and Exhibition: Asia and Pacific, 2005, pp. 1-6.

[119]B. Perunicic, M. Mallini, Z. Wang, and Y. Liu, “Power quality disturbance detection and classification using wavelets and artificial neural networks” 8th International Conference on Harmonics and Quality of Power Proceedings, 1998, pp. 77-82.

[120]N. Huang, D. Xu, X. Liu, and L. Lin, “Power quality disturbances classification based on S-transform and probabilistic neural network” Neurocomputing, vol. 98, pp. 12-23, 2012.

[121]S. Mishra, C. N. Bhende, and B. K. Panigrahi, “Detection and classification of power quality disturbances using S-transform and probabilistic neural network” IEEE Transaction on Power Delivery, vol. 23, no. 1, pp. 280-287, 2008.

[122]R. Kapoor, M. K. Saini, and P. Pramod, “Detection of PQ events using demodulation concepts: a case study” International Journal of Nonlinear Science, vol. 13, no. 1, pp. 64-77, 2012.

[123]N. Talaat and M. Ilic, “ANNs based on subtractive cluster feature for classifying power quality” 40th North American Power Symposium, pp. 1-7, 2007.

[124]J.-J. G. de-la-Rosa and A. M. Munoz, “Categorization of power quality transients using higher-order statistics and competitive layers-based neural networks” IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, pp. 83-86, 2008.

[125]C.-H. Lin and M.-C. Tsao, "Power quality detection with classification enhacible wavelet-probabilistic network in a power system" IEE Proceedings- Generation, Transmission and Distribution, vol. 152, no. 6, pp. 969-976, 2005.

[126]V. Wijayakulsooriya, G. A. Putrus, and P. D. Minns, "Electric power quality disturbance classification using self-adapting artificial neural networks" IEE Proceedings- Generation, Transmission & Distribution, vol. 149. no. 1, pp. 98-101, 2002.

[127]Y. T. Hsiao, C.-L. Chuang, and J.-A. Jiang, "Recognition of power quality events using wavelet-based dynamic structural neural networks" IEEE International Symposium on Circuits and Systems, pp. 3885-3888, 2005.

[128]P. R. Manke and S. B. Tembhurne, "Artificial neural network classification of power quality disturbances using time-frequency plane in industries" 1st International Conference on Emerging Trends in Engineering and Technology, pp. 564 – 568, 2008.

[129]C. H. Huang, C. H. Lin, and C. H. Kuo, "Chaos synchronization based detector for power quality disturbance classification in a power system" IEEE Transaction on Power Delivery, vol. 26, no. 2, pp. 944-953, 2011.

[130]M. Manjula, S. Mishra, and A. V. R. S. Sarma, "Empirical mode decomposition with Hilbert transform for classification of voltage sag causes using probabilistic neural network" International Journal of Electrical Power & Energy Systems, vol. 44, no. 1, pp. 597-603, 2013.

[131]F. Hashemi and M. Mohammadi, "Islanding detection approach with negligible non-detection zone based on feature extraction discrete wavelet transform and artificial neural network" International Transaction on Electrical Energy Systems, vol 26, no.10, pp. 2172-2192, 2016.

[132]M. Fooladi and A. A. Foroud, 'Recognition and assessment of different factors which affect flicker in wind turbines" IET Renewable Power Generation, vol. 10 no. 2, pp. 250-259, 2016.

[133]T. E. Raptis, G. A. Vokas, P. A. Langouranis, and S. D. Kaminaris, "Total power quality index for electrical networks using neural networks" Energy Procedia, vol. 74, pp. 1499-1507, 2015.

[134]G. Lv, X. Wang, H. Zhang, and C. Zhang, “PQ disturbances identification based on SVMs classifier” International Conference on neural networks and brain, pp. 222-226, 2005.

[135]A. S. Cerqueira, D. D. Ferreira, M. V. Ribeiro, and C. A. Duque, “Power quality events recognition using a SVM-based method” Electric Power Systems Research, vol. 78, no. 9, pp. 1546-1552, 2008.

[136]H. Eristi, A. Ucar, and Y. Demir, “Wavelet-based feature extraction and selection for classification of power system disturbances using support vector machine” Electrical Power Systems Research, vol. 80, no. 7, pp. 743-752, 2010.

[137]P. Janik and T. Lobos, “Automated classification of power quality disturbances using SVM and RBF networks” IEEE Transaction on Power Delivery, vol. 21, no. 3, pp. 1663-1669, 2006.

[138]Z. Moravej, A. A. Abdoos, and M. Pazoki, “Detection and classification of power quality disturbances using wavelet transform and support vector machine,” Electric Power Components and Systems, vol. 38, no. 2, pp. 182 - 196, 2010.

[139]J. C. P. Salas, A. A. Perez, and J. J. G. De la Rosa, “Support vector machine for power quality disturbances classification using higher-order statistical features” 7th International Conference-Workshop Compatibility and Power Electronics, pp. 6-10, 2001.

[140]B. Biswal, M. K. Biswal, P. K. Dash, and S. Mishra, “Power quality event characterization using support vector machine and optimization using advanced immune algorithm” Neurocomputing, vol. 103, no. 1, pp. 75-86, 2013.

[141]B. K. Panigrahi, P. K. Dash, and J. B. V. Reddy, “Hybrid signal processing and machine intelligence techniques for detection, quantification an classification of power quality disturbances” Engineering Application of Artificial Intelligence, vol. 22, no. 3, pp. 442-454, 2009.

[142]S. R. Mohanty, P. K. Ray, N. Kishor, and B. K. Panigrahi, “Classification of disturbances in hybrid DG system using modular PNN and SVM” International Journal of Electrical Power & Energy Systems, vol. 44, no. 1, pp. 764-777, 2013.

[143]S. Naderian and A. Salemnia, “Detection and classification of power-quality events using discrete Gabor transform and support vector machine” 6th Power Electronics, Drives Systems & Technologies Conference, pp. 544-549, 2015.

[144]Y. Mohammadi, M. H. Moradi, and R. C. Leborgne, “A novel method for voltage-sag source location using a robust machine learning approach” Electric Power Systems Research, vol. 145, pp. 122-136, 2017.

[145]H. Eristi, O. Yildirim, B. Eristi, and Y. Demir, “Optimal feature selection for classification of power quality events using wavelet transform and least squares support vector machines” International Journal of Electrical Power & Energy Systems, vol. 49, pp. 95-103, 2013.

[146]S. Gunal, O. N. Gerek, D. G. Ece, and R. Edizkan, “The search for optimal feature set in power quality event classification” Expert Systems with Applications, vol. 36, no. 7, pp. 10266–10273, 2009.

[147]K. Manimala, K. Selvi, and R. Ahila, “Optimization techniques for improving power quality data mining using wavelet packet based support vector machine” Neurocomputing, vol. 77, no. 1, pp. 36-47, 2012.

[148]S. R. Mohanty, P. K. Ray, N. Kishor, and B. K. Panigrahi, “Classification of disturbances in hybrid DG system using modular PNN and SVM” International Journal of Electrical Power & Energy Systems, vol. 44, no. 1, pp. 764-777, 2013.

[149]P. K. Ray, S. R. Mohanty, and N. Kishor, “Classification of power quality disturbances due to environmental characteristics in distributed generation system” IEEE Transaction on Sustainable Energy, vol. 4, no. 2, pp. 302- 313, 2013.

[150]B.V Krishna and K. Baskaran, “Hybrid learning using multi-objective genetic algorithms and decision trees for power quality disturbance pattern recognition” International Conference on Computational Intelligence and Multimedia Applications, pp. 276 – 280, 2007.

[151]O. Sen, S. Zhengxiang, W. Jianhua, and C. Degui, “Application of LVQ neural networks combined with genetic algorithm in power quality signals classification” International Conference on Power System Technology, pp. 491-495, 2002.

[152]G. Li, Z. Ming and Z. Zhang, "Power quality disturbance automatic recognition based on wavelet and genetic network" IEEE Region 1 Conference on Computers, Communications, Control and Power Engineering, pp. 1923–926, 2002.

[153]Yusran, "Electrical network power quality improvement through distributed generation optimum placement based on Breeder genetic algorithm method" Makassar International Conference on Electrical Engineering and Informatics (MICEEI), pp. 20-22, 2014.

[154]M. H. Wang and Y. F. Tseng, "A novel analytic method of power quality using extension genetic algorithm and wavelet transform" Expert Systems with Applications, vol. 38, no. 10, pp. 12491-12496, 2011.

[155]A. Kazemi, A. Mohamed, H. Shareef, and H. Zayandehroodi, "Optimal power quality monitor placement using genetic algorithm and Mallow's Cp" International Journal of Electrical Power & Energy Systems, vol. 53, pp 564-575, 2013.

[156]Y. Y. Hong and Y. Y. Chen, "Placement of power quality monitors using enhanced genetic algorithm and wavelet transform" IET Generation, Transmission & Distribution, vol. 5, no. 4, pp. 461 - 466, 2011.

[157]P. K. Ray, N. Kishor, and S. R. Mohanty, "Islanding and power quality disturbance detection in grid-connected hybrid power system using wavelet and S-transform" IEEE Transaction on Smart Grid, vol. 3, no. 3, pp. 1082- 1094, 2012.

[158]T. X. Zhu, S. K. Tso, and K. L. Lo, "Wavelet-based fuzzy reasoning approach to power quality disturbance recognition" IEEE Transaction on Power Delivery, vol. 19, no. 4, pp. 928-1935, 2004.

[159]B. Bizjak and P. Planinsic, "Classification of power disturbances using fuzzy logic" International Conference on Power Electronics Motion Control, pp. 1356-1360, 2006.

[160]Y. Liao and J.-B. Lee, "A fuzzy-expert system for classifying power quality disturbances" International Journal of Electrical Power & Energy Systems, vol. 26, no. 3, pp. 199-205, 2004.

[161]B. Biswal, H. S. Behera, R. Bisoi, and P. K. Dash, “Classification of power quality data using decision tree and chemotactic differential evolution based fuzzy clustering” Swarm and Evolutionary Computation, vol. 4, pp. 12-24, 2012.

[162]B. Biswal, P.K. Dash, and K.B. Panigrahi, “Power quality disturbance classification using fuzzy c-means algorithm and adaptive particle swarm optimization” IEEE Transaction on Industrial Electronics, vol. 56, no. 1, pp. 212-220, 2009.

[163]H. S. Behera, P. K. Dash, and B. Biswal, “Power quality time series data mining using S-transform and fuzzy expert system” Applied Soft Computing, vol. 10, no. 3, pp. 945-955, 2010.

[164]R. Hooshmand and A. Enshaee, “Detection and classification of single and combined power quality disturbances using fuzzy systems oriented by particle swarm optimization algorithm” Electric Power Systems Research, vol. 80, no. 12, pp. 1552-1561, 2010.

[165]R. Kapoor and M. K. Saini, “Classification of nonlinear power quality events based on multiwavelet transform” International Journal of Nonlinear Science, vol. 10, no. 3, pp. 279-286, 2010.

[166]S. K. Meher and A. K. Pradhan, “Fuzzy classifiers for power quality events analysis,” Electric Power Systems Research, vol. 80, No. 1, pp. 71-76, 2010.

[167]R. Bhavani, N. R. Prabha, and C. Kanmani, “Fuzzy controlled UPQC for power quality enhancement in a DFIG based grid connected wind power system,” International Conference on Circuit, Power and Computing Technologies, pp. 1-7, 2015..

[168]R. K. Patnaik and P. K. Dash, “Impact of wind farms on disturbance detection and classification in distributed generation using modified adaline network and an adaptive neuro-fuzzy information system” Applied Soft Computing, vol. 30, pp. 549–566, 2015.

[169]V. F. Pires, T. G. Amaral, and J. F. Martins, “Power quality disturbances classification using the 3-D space representation and PCA based neurofuzzy approach” Expert Systems with Applications, vol. 38, no. 9, pp. 11911-11917, 2011.

[170]N. R. Prabha, N. S. Marimuthu, and C. K. Babulal, “Adaptive neuro-fuzzy inference system based representative quality power factor for power quality assessment,” Neurocomputing, vol. 73, no. 13-15, pp. 2737-2743, 2010.

[171]M. Negnevitsky and M. Ringrose, "A neuro-fuzzy system for recognition of power quality disturbances" IEEE Power Engineering Society General Meeting, pp. 2295-2300, 2005.

[172]M. Savaghebi, A. Jalilian, J. C. Vasquez, and J. M. Guerrero, "Secondary control for voltage quality enhancement in microgrids" IEEE Transaction on Smart Grid, vol. 3, no. 4, pp. 1893-1902, 2012.

[173]W. R. A. Ibrahim and M. M. Morcos, "Novel data compression technique for power waveforms using adaptive fuzzy logic" IEEE Transaction on Power Delivery, vol. 20, no. 3, pp. 2136-2143, 2005.

[174]F. Hashemi, N. Ghadimi, and B. Sobhani, "Islanding detection for inverter based DG coupled with using an adaptive neuro-fuzzy inference system" International Journal of Electrical Power & Energy Systems, vol. 45, no. 1, pp. 443-455, 2013.

[175]L. Reznik and M. Negnevitsky, "A neuro-fuzzy method of power disturbances recognition and reduction" IEEE International Conference on Fuzzy Systems, pp. 1517-1522, 2002.

[176]I.C. Franco, M. Dall'Agnol, T.V. Costa, A.M.F. Fileti, and F.V. Silva, "A neuro-fuzzy identification of non-linear transient systems: application to a pilot refrigeration plant" International Journal of Refrigeration" vol. 34, no. 8, pp. 2063-2075, 2011.

[177]F. Lin, K. Lu, and T. Ke, "Probabilistic wavelet fuzzy neural network based reactive power control for grid-connected three-phase PV system during grid faults" Renewable Energy, vol. 92, pp. 437-449, 2016.

[178]N. Praditphol and S. Premrudeepreechacharn, "Classification fault events using wavelet transform and expert rules" North American Power Symposium (NAPS), Starkville, USA, pp. 2009.

[179]C.-I. Chen, H.-L. Wang, and Y.-C. Chin, "A simple rule-based approach for detection and classification of voltage sag, swell, and interruption in power systems" 9th IEEE International Conference on Power Electronics and Drive Systems (PEDS), pp. 756 -762, 2011.

[180]M. B. I. Reaz, F. Choong, M. S. Sulaiman, F. Mohd-Yasin, and M. Kamada, “Expert system for power quality disturbance classifier” IEEE Transaction on Power Delivery, vol. 22, no. 3, pp. 1979-1988, 2007.

[181]E. Styvaktakis, M. H. J. Bollen, and I. Y. H. Gu, “Expert system for classification and analysis of power system events” IEEE Transaction o Power Delivery, vol. 17, no. 2, pp. 423-428, 2002.

[182]P. K. Dash, S. Mishra, M. M. A. Salama, and A. C. Liew, “Classification of power system disturbances using a fuzzy expert system and a Fourier linear combiner” IEEE Transaction on Power Delivery, vol. 15, no. 2, pp. 472 - 477, 2000.

[183]S. A. Chavoshi, R. Noroozian, and A. Amiri, “Islanding detection of synchronous distributed generation resources using AdaBoost algorithm” International Transaction on Electrical Energy Systems, vol. 26, no. 8, pp. 1604-1624, 2015.

[184]A. K. P. Kubendran, and A. K. Loganathan, “Detection and classification of complex power quality disturbances using S-transform amplitude matrix based decision tree for different noise levels” International Transaction on Electrical Energy System, vol. 27, no. 4, pp. 1-12, 2017.

[185]Y. Huang, Y. Liu, and Z. Hong, “Detection and location of power quality disturbances based on mathematical morphology and Hilbert-Huang transform,” 9th International Conference on Electronic Measurement & Instruments, pp. 2-319 - 2-324, 2009.

[186]Z. Chen, and P. Urwin, “Power quality detection and classification using digital filters” IEEE Porto Power Tech Proceedings, pp. 1-6, 2001.

[187]Chen, F. Zhang, and Y. Zhang, “Distribution network reconfiguration based on simulated annealing immune algorithm” Energy Procedia, vol. 12, pp. 271-277, 2011.

[188]J. Chung, E. J. Powers, M. W. Grady, and S. C. Bhatt, “Power disturbance classifier using a rule-based method and wavelet packet-based hidden Markov model” IEEE Transactions on Power Delivery, vol. 17, no. 1, pp. 233-241, 2002.

[189]T. K. Abdel-Galil, E. F. EI-Saadany, A. M. Youssef, and M. M. A Salama,"Disturbance classification using hidden Markov models and vector quantization" IEEE Transaction on Power Delivery, vol. 20, no. 3, pp. 2129-2135, 2005.

[190]A. Elnady, A. Massoud, and A. Noureldin, "Recursive implementation of Music algorithm to minimize power system disturbances" International Journal of Electrical Power & Energy System, vol 56. pp. 9-18, 2014.

[191]S. R. Samantaray, "Decision tree-initialised fuzzy rule-based approach for power quality events classification" IET Generation Transmission & Distribution, vol. 4, no. 4, pp. 538-551, 2010.

[192]V. T. Tran, F. AlThobiani, A. Ball, and B. K. Choi, "An application to transient current signal based induction motor fault diagnosis of Fourier- Bessel expansion and simplified fuzzy ARTMAP" Expert Systems with Applications, vol. 38, no. 9, pp. 5372-5384, 2013.

[193]G.-S. Hu, F.-F. Zhu, and Z. Ren, "Power quality disturbance identification using wavelet packet energy entropy and weighted support vector machines" Expert Systems with Applications, vol. 35, no. 1, pp. 143-149, 2008.

[194]H. Eristi and Y. Demir, "A new algorithm for automatic classification of power quality events based on wavelet transform and SVM" Expert Systems with Applications, vol. 37, no. 6, pp. 4094-4102, 2010.

[195]J. Huang, M. Negnevitsky, and D. T. Nguyen, "A neural-fuzzy classifier for recognition of power quality disturbances" IEEE Transaction on Power Delivery, vol. 17, no. 2, pp. 609-616, 2002.

[196]M. B. I. Reaz, F. Choong, M. S. Sulaiman, F. Mohd-Yasin, and M. Kamada, "Expert system for power quality disturbance classifier's" IEEE Transaction on Power Delivery, vol. 22, no. 3, pp. 1979-1988, 2007.

[197]S. K. Meher and A. K. Pradhan, "Fuzzy classifiers for power quality events analysis" Electric Power Systems Research, vol. 80, No. 1, pp. 71-76, 2010.

[198]T. X. Zhu, S. K. Tso, and K. L. Lo, "Wavelet-based fuzzy reasoning approach to power quality disturbance recognition" IEEE Transaction on Power Delivery, vol. 19, no. 4, pp. 1928-1935, 2004.

[199]H. S. Behera, P. K. Dash, and B. Biswal, "Power quality time series data mining using S-transform and fuzzy expert system" Applied Soft Computing, vol. 10, no. 3, pp. 945-955, 2010.

[200]M. E. Salem, A. Mohamed, and S. A. Samad, "Rule-based system for power quality disturbance classification incorporating S-transform features" Expert Systems with Applications, vol. 37, no. 4, pp. 3229-3235, 2010.

[201]M. Uyar, S. Yildirim, and M. T. Gencoglu, "An expert system based on S-transform and neural network for automatic classification of power quality disturbances" Expert Systems with Applications, vol. 36, no. 3, pp. 5962- 5975, 2009.

[202]A. A. Abdoos, P. K. Mianaei, and M. R. Ghadikolaei, "Combined VMD-SVM based feature selection method for classification of power quality events" Applied Soft Computing, vol. 38, pp. 637-646, 2016.

[203]A. A. Abdoos, Z. Moravej, and M. Pazoki, "A hybrid method based on time frequency analysis and artificial intelligence for classification of power quality events" Journal of Intelligent & Fuzzy Systems, vol. 28, no. 3, pp. 1183-1193, 2015.

[204]C. Y. Lee and Y. X. Shen, "Optimal feature selection for power-quality disturbances classification" IEEE Transaction on Power Delivery, vol. 26, no. 4, pp. 2342-2351, 2011.

[205]H. Eristi, O. Yildirim, B. Eristi, and Y. Demir, "Optimal feature selection for classification of power quality events using wavelet transform and least squares support vector machines" International Journal of Electrical Power & Energy Systems, vol. 49, pp. 95-103, 2013.

[206]M. Hajian, A. A. Foroud, and A. A. Abdoos, "New automated power quality recognition system for online/offline monitoring" Neuro computing, vol. 128, pp. 389-406, 2014.

[207]S. Zhang, P. Li, L. Zhang, H. Li, W. Jiang, and Y. Hu, "Modified S-transform and ELM algorithms and their applications in power quality analysis" Neurocomputing, vol. 185, pp. 231-241, 2016.

[208]H. Dehghani, B. Vahidi, R. A. Naghizadeh, and S. H. Hosseinian, “Power quality disturbance classification using a statistical and wavelet-based hidden Markov model with Dempster-Shafer algorithm” International Journal of Electrical Power & Energy Systems, vol. 47, pp. 368-377, 2013.

[209]M. A. S. Masoum, S. Jamali, and N. Ghaffarzadeh, “Detection and classification of power quality disturbances using discrete wavelet transform and wavelet networks,” IET Science, Measurement & Technology, vol. 4, no. 4, pp. 193-205, 2010.

[210]M. Uyar, S. Yildirim, and M. T. Gencoglu, “An expert system based on S-transform and neural network for automatic classification of power quality disturbances” Expert Systems with Applications, vol. 36, no. 3, pp. 5962- 5975, 2009.

[211]R. Hooshmand and A. Enshaee, “Detection and classification of single and combined power quality disturbances using fuzzy systems oriented by particle swarm optimization algorithm,” Electric Power Systems Research, vol. 80, no. 12, pp. 1552-1561, 2010.

[212]S. K. Meher and A. K. Pradhan, “Fuzzy classifiers for power quality events analysis” Electric Power Systems Research, vol. 80, No. 1, pp. 71-76, 2010.

[213]S. Alshahrani, M. Abbod, and B. Alamri, “Detection and classification of power quality events based on wavelet transform and artificial neural networks for smart grids,” IEEE Confrence on Smart Grid (SASG), Saudi Arabia, 2015, pp. 1-6.

[214]T. Jayasree, D. Devaraj, and R. Sukanesh, “Power quality disturbance classification using Hilbert transform and RBF networks,” Neurocomputing, vol. 73, no. 7-9, pp. 1451-1456, 2010.

[215]B. Biswal, M. Biswal, S. Hasan, and P.K. Dash, “Nonstationary power signal time series data classification using LVQ classifier” Applied Soft Computing, vol. 18, pp. 158-166, 2014.

[216]C. Y. Lee and Y. X. Shen, “Optimal feature selection for power-quality disturbances classification” IEEE Transaction on Power Delivery, vol. 26, no. 4, pp. 2342-2351, 2011.

[217]Richard Tymerski “Volterra Series Modeling of Power Conversion Systems” IEEE Transactions on power electronics. vol. 6, no. 4, October, I991.

[218]Sang-Won Nam and Edward J. Powers “Volterra Series Representation of Time-Frequency Distributions” IEEE transactions on signal processing, vol. 51, no. 6, June, 2003.

[219]S. Mishra and C. Bhinde, “Detection and Classification of Power Quality Disturbances Using S-Transform and Probabilistic Neural Network”, IEEE Transactions on Power Delivery, vol. 23, no. 1, January, 2008.

[220]Qilian Liang and Jerry M. Mendel “Interval Type-2 Fuzzy Logic Systems: Theory and Design” IEEE transactions on fuzzy systems, vol. 8, no. 5, October 2000.

[221]Jerry M. Mendel, John and Feilong Liu “Interval Type-2 Fuzzy Logic Systems Made Simple” IEEE transactions on fuzzy systems, vol. 14, no. 6, December 2006.

[222]Li-Xin Wang, “A New Look at Type-2 Fuzzy Sets and Type-2 Fuzzy Logic Systems” .IEEE Transactions on Fuzzy Systems(693-706),2017.

[223] J. M. Mendel and D. Wu, "Critique of “A New Look at Type-2 Fuzzy Sets and Type-2 Fuzzy Logic Systems”," in IEEE Transactions on Fuzzy Systems, vol. 25, no. 3, pp. 725-727, June 2017.

[224]Hongwei Wu and Jerry M. Mendel “Uncertainty Bounds and Their Use in the Design of Interval Type-2 Fuzzy Logic Systems” IEEE transactions on fuzzy systems, vol. 10, no. 5, October 2002.

[225] Mizumoto, M. and K. Tanaka, "Some Properties of Fuzzy Sets of Type-2," Information and Control, vol. 31, pp. 312-340, 1976

[226]Oscar Castillo, Leticia Cervantes, Jose Soria, Mauricio Sanchez, Juan R. Castro, “A generalized type-2 fuzzy granular approach with applications to aerospace” Inf. Sci. 354:165-177(2016).

[227] Mauricio A. Sanchez, Oscar Castillo, Juan R. Castro , “Information granule formation via the concept of uncertainty-based information with Interval Type-2 Fuzzy Sets representation and Takagi-Sugeno-Kang consequents optimized with Cuckoo search” Appl. Soft Comput. 27: 602-609(2015).

[228]Z. Moravej, A.A. Abdoos, M. Pazoki, “Detection and classification of power quality disturbances using wavelet transform and support vector machines” Electr.Power Compon. Syst. 38 (2009) 182–196.

[229]Ali Akbar Abdoos, Peyman Khorshidian Mianaei, Mostafa Rayatpanah Ghadikolaei, “Combined VMD-SVM based feature selection method for classification of power quality events,” Applied Soft Computing 38 (2016) 637–646.

[230]M. Uyar, S. Yildirim, M.T. Gencoglu, “An effective wavelet-based feature extrac-tion method for classification of power quality disturbance signals,” Electr.Power Syst. Res. 78 1747–1755, 2008.

[231]A.A. Abdoos, Z. Moravej, M. Pazoki, “A hybrid method based on time frequency analysis and artificial intelligence for classification of power quality events,” J.Intell. Fuzzy Syst. 28 1183–1193, 2015.

[232]Majid Jamil, Rajveer Singh, Sanjeev Kumar Sharma , “Fault identification in electrical power distribution system using combined discrete wavelet transform and fuzzy logic,” Journal of Electrical Systems and Information Technology 257–267, 2015.

[233]Saroj K. Mehera, Ashok K. Pradhan, “Fuzzy classifiers for power quality events analysis," Electric Power Systems Research 80, 71-76, 2015.

[234]T. Ohnishi and N. Takahashi, “Optimal design of efficient IPM motorusing finite element method,” IEEE Trans. Magn., vol. 36, no. 5,pp. 3537–3539, Sep. 2000

[235]O. P. Mahela, A. G. Shaik. “Recognition of power quality disturbances using S-transform based ruled decision tree and fuzzy C-means clustering classifiers” Applied Soft Computing, vol. 59, pp. 243–257, 2017.

[236]K. Yamazaki and M. Matsumoto, “3-D finite element meshing for skewed rotor induction motors,” IEEE Trans. Magn., vol. 51, no. 3, pp. 1-4, Mar. 2015.

[237]F. Kong, S. Li, W. Zhou, “Wavelet–Galerkin approach for power spectrum determination of nonlinear oscillators,” Mech. Syst. Signal Process. 48, 300–324, 2014.

[238]Q. Sun, Q. Ren, Q. Zhan, Q.H. Liu, "3-D domain decomposition based hybrid finite-difference time-domain/finite-element time-domain method with nonconformal meshes", IEEE Trans. Microw. Theory Techn., vol. 65, no. 10, pp. 3682-3688, Apr. 2017.

[239]Y. Marechal, B. Ramdane, D. P. Botelho, "Computational Performances of Natural Element and Finite Element Methods", IEEE Trans. Magn., vol. 50, no. 2, pp. 405-408, Feb. 2014.

[240]Diego Pereira Botelho, Yves Marechal, Brahim Ramdane, "Higher Order NEM and FEM Accuracy Comparison", Magnetics IEEE Transactions on, vol. 51, no. 3, pp. 1-4, 2015.

[241] W. Xu, G. Wang, N. Duan, S. Wang, Y. Guo, J. Zhu, "Extended finite-element method for weak discontinuities in electric fields", IEEE Trans. Appl. Supercond., vol. 26, no. 7, Oct. 2016.

[242]Bing-Kun Xie, Shie-Jue Lee, "An Extended Type-Reduction Method for General Type-2 Fuzzy Sets", Fuzzy Systems IEEE Transactions on, vol. 25, no. 3, pp. 715-724, 2017.

[243]Arjab Singh Khuman, Yingjie Yang, Robert John, "Quantification of R-fuzzy sets", Expert Systems with Applications, vol. 55, pp. 374, 2016.

[244]Yi Zeng, Hak-Keung Lam, Ligang Wu, "Model Reduction of Discrete-Time Interval Type-2 T–S Fuzzy Systems", Fuzzy Systems IEEE Transactions on, vol. 26, no. 6, pp. 3545-3554, 2018.

[245]G. A. Vijayalakshmi Pai, "Fuzzy Decision Theory Based Metaheuristic Portfolio Optimization and Active Rebalancing Using Interval Type-2 Fuzzy Sets", Fuzzy Systems IEEE Transactions on, vol. 25, no. 2, pp. 377-391, 2017.

[246]Rahul, Kapoor, R. & Tripathi, M.M. “Detection and classification of multiple power signal patterns with Volterra series and interval type-2 fuzzy logic system,” Protection and Control of Modern Power Systems, vol. 2, issue 1, 2017. DOI 10.1186/s41601-017-0039-z. (www.preview-pcmp.springeropen.com)

[247]Moravej Z, Pazoki M, Niasati M, Abdoos AA. A hybrid intelligence approach for power quality disturbances detection and classification. Euro. Trans. Electr. Power. 2013;23(7): 914-929.

[248]Khokhar S, Zin AAM, Memonb AP, Mokhtar AS. A new optimal feature selection algorithm for classification of power quality disturbances using discrete wavelet transform and probabilistic neural network. Measurement. 2017;95: 246-259.

[249]Hashemi F, Mohammadi M. “Islanding detection approach with negligible non-detection zone based on feature extraction discrete wavelet transform and artificial neural network” Int. Trans. Electr. Energ. Syst. 2016.

[250]Kanirajan P, Kumar VS. “Power quality disturbance detection and classification using wavelet and RBFNN” Applied Soft Computing. 2015;35:470-481.

[251]O. P. Mahela, A. G. Shaik. “Recognition of power quality disturbances using S-transform based ruled decision tree and fuzzy C-means clustering classifiers” Applied Soft Computing, vol. 59, pp. 243–257, 2017. DOI: 10.1016/ j.asoc.2017.05.061.

[252]K. He, X. Zhang, S. Ren, J. Sun, “Deep residual learning for image recognition”, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (2016) 770–778.

[253]F. Wu, P. Hu, and D. Kong. “Flip-rotate-pooling convolution and split dropout on convolution neural networks for image classification”. CoRR, abs/1507.08754, 2015

[254]A. Krizhevsky, I. Sutskever, G.E. Hinton, “Imagenet classification with deep convolutional neural networks,” Adv. Neural Inf. Process. Syst. (2012) 1097–1105.

[255]B. Biswal, M. Biswal, S. Mishra and R. Jalaja “Automatic Classification of Power Quality Events Using Balanced Neural Tree” IEEE transactions on industrial electronics, vol. 61, no. 1, January 2014.

[256]Bhende, S. Mishra, B. Panigrahi, “Detection and classification of power quality disturbances using S-transform and modular neural network,” Electr. Power Syst.Res. 78 (1) 122–128, 2008.

[257]D. De Yong, S. Bhowmik and F. Magnago “An effective Power Quality classifier using Wavelet Transform and Support Vector Machines” Expert Systems with Applications Volume 42, Issues 15–16, September 2015.

[258]P. K. Ray, S. R. Mohanty, N. Kishor, and J. P. Catalao, “Optimal feature and decision tree-based classification of power quality disturbances in distributed generation systems,” IEEE Transactions on Sustainable Energy, vol. 5, no. 1, pp. 200–208, 2014.

[259]Rajiv kapoor, Rahul, M M Tripathi “Volterra bound interval type- 2 fuzzy logic based approach for multiple power quality events analysis” IET Electrical Systems in Transportation, Volume 8, Issue 3, , p. 188 – 196, 2018. DOI: 10.1049/iet-est.2017.0054.

[260]Rahul, Rajiv Kapoor and M M Tripathi “Long Short-Term Memory-Convolution Neural Network Based Hybrid Deep Learning Approach for Power Quality Events Classification” "Innovations in Electronics and Communication Engineering", Springer Nature, Vol 65, p. 501-510, 2019.

LIST OF PUBLICATIONS

JOURNALS

1) Rajiv kapoor, **Rahul .** , M M Tripathi "Volterra bound interval type- 2 fuzzy logic based approach for multiple power quality events analysis" **IET Electrical Systems in Transportation**, Volume 8, Issue 3, September 2018, p. 188 – 196, DOI: 10.1049/iet-est.2017.0054 **(Pub.: IET)(Indexing-SCIE)**
2) **Rahul,** Rajiv Kapoor and M M Tripathi "Detection and classification of power signal pattern using volterra series and interval type -2 fuzzy logic system", **Protection and Control of Modern Power System**, Volume 2, Issue 1, 2017, (**Pub.: SPRINGER)(Indexing –ESCI)**
3) **Rahul,** Kapoor Rajiv and M. M. Tripathi, "Long Short-Term Memory-Convolution Neural Network Based Hybrid Deep Learning Approach for Power Quality Events Classification" **Innovations in Electronics and Communication Engineering", Springer Science and Business Media LLC**, Vol. 65, pages 501-510, 2019.**(Pub.: SPRINGER)(Indexing-Scopus)**
4) **Rahul** and Kapoor Rajiv "Adaptive FEM based Detection and classification of power disturbances" (Communicated to IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS)**(Under Review)**
5) Rahul and Kapoor Rajiv " NSGA-III and DAG-SVM based power quality disturbance recognition and classification" (Communicated to IEEE transactions on power delivery)**(Under Review)**

CONFERENCES

1) **Rahul,** Rajiv Kapoor and M M Tripathi "Hilbert-Huang transform and type-1 fuzzy based recognition and classification of power signal disturbances." International Conference on Recent Innovations in Electrical, Electronics &

Communication Engineering - (ICRIEECE) July 27TH 2018 School of Electrical Engineering, Kalinga Institute of Industrial Technology (KIIT), Bhubaneswar, India**(IEEE CONFERENCE).**

2) **Rahul,** Rajiv Kapoor and M M Tripathi "Curvelet bound type-2 fuzzy logic based detection and classification of power quality events." International Conference on Recent Innovations in Electrical, Electronics & Communication Engineering - (ICRIEECE) July 27th ,2018 School of Electrical Engineering, Kalinga Institute of Industrial Technology (KIIT), Bhubaneswar, India**(IEEE CONFERENCE).**
3) **Rahul,** R Kapoor, "Power quality events detection & classification: A review, EPEACT-2015, JNU, Delhi, 14-15th March, 2015.
4) N. Singhal, **Rahul ,** R Kapoor, "Power quality events detection & classification using Gaussian mixture model, MECIT-2015, JNU, Delhi, 16-17th May, 2015.