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A CRITICAL ANALYSIS OF METHODOLOGIES FOR DETECTION AND CLASSIFICATION OF POWER QUALITY EVENTS IN SMART GRID

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ABSTRACT Recently, power quality (PQ) issues have drawn considerable attention of the researchers due to the increasing awareness of the customers towards power quality. The PQ issues maintain its pre-eminence because of the significant growth encountered in the smart grid technology, distributed generation, usage of sensitive and power electronic equipments with the integration of renewable energy resources. The IoT and 5G networks technologies have a number of advantages like smart sensor interfacing, remote sensing and monitoring, data transmission at high speed. Due to this, applications of these two are highly adopted in smart grid. The prime focus of the paper is to present an exhaustive survey of detection and classification of power quality disturbances by discussing signal processing techniques and artificial intelligence tools with their respective pros and cons. Further, critical analysis of automatic recognition techniques for the concerned field is posited with the viewpoint of the types of power input signal (synthetic/real/noisy), pre-processing tools, feature selection methods, artificial intelligence techniques and modes of operation (online/offline) as per the reported articles. The present work also elaborates the future scope of the said field for the reader. This paper provides valuable guidelines to the researchers those having interest in the field of PQ analysis and exploring the better methodologies for further improvement. Comprehensive comparisons have been presented with the help of tabular presentations. Although this critical survey cannot be collectively exhaustive, still this survey comprises the most significant works in the concerned paradigm by examining more than 300 research publications.

INDEX TERMS Power Quality Disturbance, Detection and Classification, Smart Grid, IoT, Signal Processing, Artificial Intelligence, Renewable Energy.

I. INTRODUCTION

Nowadays, non-linear loads and sensitive power electronic equipments in the industrial, commercial and domestic applications are extensively used. With the advancement in research and manufacturing technologies, use of sensitive electronic components, programmable logic controller, computers, CNC machines, protection, control and relaying devices has increased the power consumption [1] and side by side also increased the pollution in electricity due to nonlinear behaviour. To meet the increasing energy demand and green energy motive, integration of renewable energy resources in grid with power electronics interface further increased the

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complexity and power quality (PQ) issues. As compared to old electro-mechanical technologies, solid-state devices are having smaller size and lesser weight, high versatility and reduction in initial and maintenance cost but these devices are highly sensitive to fluctuations in power systems. The term power quality describes the electrical power as the power that drives an electrical load and load's ability for proper functioning. PQ disturbance is any variation recorded in voltage, wave-shape or in frequency who's outcome is in failure or misoperation of utility or consumers' electrical gadgets [2] due to disturbances in power lines [3], [4]. The normal working operation of each electrical equipment is affected by PQ issues [5] and the impact of same PQ issue on these equipments is different.

PQ disturbances (PQD) like power surges, poor frequency and voltage regulation, transients, harmonics, notch, noise and electromagnetic interference effects, frequently occur in power system. These PQD are results of system faults, types of load or due to environmental factors. Hence, it is necessary to trace out the type of PQD and preventive action should be taken. Therefore, monitoring of PQ disturbances becomes necessary and many researches have proposed continuous monitoring of electric power [6]–[8]. In monitoring, signal processing techniques are applied to detect the disturbance and then artificial intelligence (AI) methods are adopted to classify the type of disturbance. The size of the power system network is very large, this results in voluminous data during monitoring, stored into equipment and large memory size is needed for storing this data. To reduce the storage volume, only the useful data is saved in compressed form [9], [10].

As per [11], the impact of PQ issues on US economy was up to USD 164 billion due to power outage and up to USD 24 billion for PQ phenomena and it was greater than 150 billion Euros every year in EU-25 countries [12]. A study was carried out in 2004 by European Copper Institute (ECI) and Leonardo Power Quality Initiative (LPQI) on 24 utilities in the United States (US) about the occurrences of PQ disturbances and the share was- voltage dips (23.6%), short interruptions (18.8%), long interruptions (12.5%), harmonics (5.4%), transients and surges (29%) and other PQ related problems (10.7%) [13]. Different methodologies are discussed in [14], to calculate the losses owing to voltage sag and interruption and a methodology was proposed for evaluation of power losses. Paper [15] shows the economic impact of PQ disturbances in a paper mill. Norbert also shows the impact of poor PQ on the Nigerian industries that results in loss of USD 50000 every year in the form of equipment damage [16]. In this paper author explains four sources from which PQ disturbances originate i.e. Unpredictable events; electric utility; consumer/customer and the manufacturers. A study on economics of PQ is presented by Sharma et.al. [17].

As per above discussion it is clear that these power quality disturbances results in a very large financial loss, degrade the power quality and overall system reliability [18]. Reliability study due to voltage sag and reliability indices for distribution side is presented in [19], [20] respectively. Due to these reasons the power quality studies are very popular from last three decades. In addition to this the restructuring of electrical power system and increased awareness of the customers about the quality of supply escalate its impact as well. Therefore this domain get extensive attention from academicians and researchers. Hence, a lot of work on PQD detection and classification has been done by the researchers and a number of signal processing and AI based techniques are proposed. A number of review papers are available in literature, covering different aspects of PQ assessment [21]–[30]. Ibrahim et al. presented a survey on applications of mathematical tools and AI techniques in PQ. Different techniques and methodologies used in PQ analysis are reviewed in [22]. Comprehensive study about signal processing and intelligent methods with optimization techniques used in PQ analysis is discussed in refs. [23], [24]. A detailed and extensive review on detection and classification of PQD is presented by Khokar et al. with the application of wavelet in data compression and de-noising. In another paper authors present only detection methods and also show the results of Daubechies (db) wavelet in PQD detection [26]. Liang discussed the different challenges of PQ due to integration of renewable energy resources and proposed two control methods i.e. virtual synchronous machine (VSM) method and virtual impedance control, to improve PQ. Mishra presented a review on signal processing and soft computing techniques and also include issues related to distributed generation [28]. Alimi et al. presented a review of various machine learning techniques used for security and stability analysis of power system. A detailed review of PQ detection and classification methods in grid is presented by Chawda et al. [29], with hardware/software structure used for the PQ monitoring in the presence of renewable energy sources. However, it is very necessary to monitor the PQ and fast detection and classification methods play a significant role in early detection of disturbances. The current researches on renewable energy and power electronics interface with grid demands more attention on power quality. Therefore, main focus of this manuscript is to present a up-to-date and detailed review on PQ analysis with PQ standards, signal processing techniques for detection, AI based classification methods and optimization techniques. Power quality issues faced in integration of renewable energy and smart grid also presented with researches on real time and experimental studies. Remarks on further improvement and future research are also given.

Before going in more depth, the objectives and main contributions of this paper are as follows:

1. In this paper more than 300 published articles are reviewed for the deep insight in the PQ disturbances detection and classification.
2. PQ disturbances due to renewable integration to grid as well as in smart grid environment with some real time applications are also discussed with application of IoT and 5G network.
3. In PQ disturbance detection and classification three main

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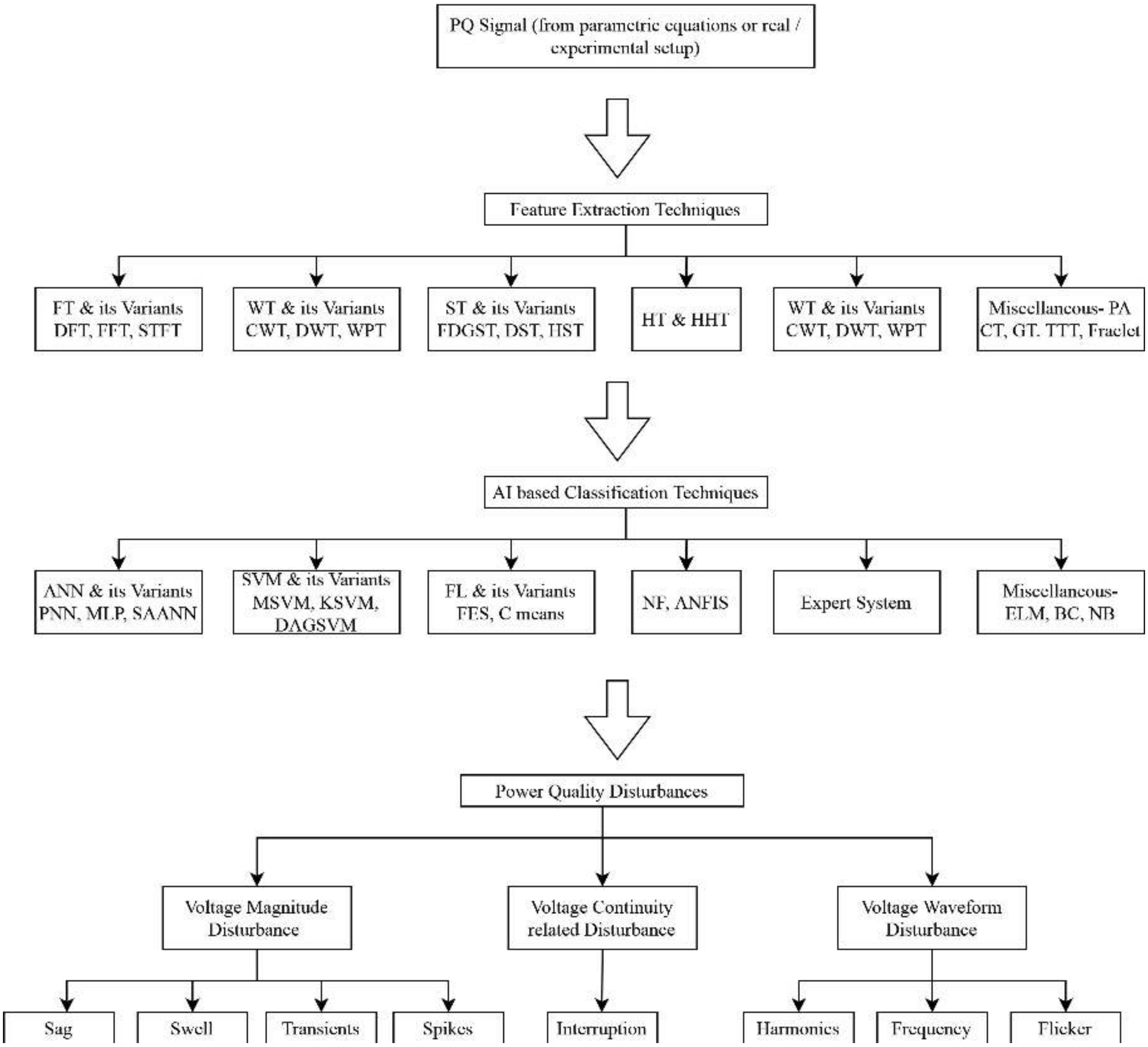

FIGURE 1. Categorization Tree of Power Quality Disturbances Analysis.

steps pre-processing, feature extraction and classification are clearly explained with different techniques proposed by the researchers in literature.
4. Additional processing like feature selection and optimization techniques are also included in this study to give detailed knowledge to the readers.
5. All the major techniques are compared and presented with their advantages and drawbacks, with their effectiveness.
6. Comparison has been made by different parameters like type of PQ data (real/simulated), PQ disturbance type (single/multiple), feature selection technique used or not, any additional algorithm or optimization used and effect of noise on classification accuracy.

This paper is organized in ten sections. Section 2 describes basic terminology in PQ analysis and section 3 gives an introduction to PQ issues, section 4 and 5 give details about pre-processing and signal processing techniques. Feature selection and classification methods are discussed in section 6 and 7 respectively. Section 8 presents optimization techniques. Comparative analysis is analyzed in section 9. Section 10 conclude the paper with future scope.

II. PQ STANDARDS AND TERMINOLOGY

A. PQ STANDARDS

Standards provide a common point of reference in PQ domain. International working organizations provides definitions, guidelines, parameters and variation limits for PQ. The development of these standards increased the effectiveness of PQ analysis. The PQ indices (PQI) have been presented by IEEE 1159, IEC 61000-4-30 and EN 50160 standards, given in [31]–[33] respectively. These standards characterized the different types of PQ event or disturbance. IEEE 1159 standard associated with power quality monitoring and gives definitions for various categories of PQD. IEC 61000-4-30 standard related with PQ testing and measurement methods and EN 50160 categorized voltage characteristics in public distribution system. These standards helps the user to obtain same results on different places or systems. With the common guidelines it is easy to compare the results obtained with different methods/techniques. The calculation of PQI's is also based on these standards and it is a powerfull technique to quantifying PQD. Table 1 enlist some standards used in PQ analysis.

B. PQ TERMINOLOGY

Power Quality: Fixed magnitude, phase and frequency signals just like pure sine wave, defines the quality of power supplied by the power system [34].

Power Quality Disturbance: Any deviation from fixed magnitude, phase and frequency of the signal is considered as PQD. As per standard different types of PQ disturbance are presented in Table 2. Figure 1 depicts categorization tree of PQ analysis.

Any disturbance recorded by monitoring equipment is used for analysis and event classification. The PQ event classification using digital signal processing (DSP) tools is completed in three steps. First, the online/offline disturbance signal is pre-processed, then features are extracted from it and useful features are selected to apply classifiers on them. Figure 2 shows the generalized block diagram of PQ analysis system. Each of the block of Figure 2 is briefly discussed as below (detailed discussion in section 3-7).

Pre-Processing: The input power signal is fed to the pre-processing stage where normalization and segmentation thereafter feature extraction takes place.

Normalization and Segmentation: In segmentation event data size is reduced so that relevant part of the signal is extracted. In normalization, the different magnitude values are converted in a scale i.e., per unit (pu).

Feature Extraction: Feature extraction stage includes certain signal processing technique depending upon the different strategy.

Feature Selection/Optimization: This is optional step. Feature selection and optimization block reduce the dimension of the feature space which helps in improving the performance of classification.

Classification: Classifiers are applied on the selected feature set and then finally decision is made for the type of disturbance.

Decision Making: In this stage final decision is made about type of disturbance present in input signal.

Additional Processing: Additional processing blocks are used for the activation of the recording instruments.

III. POWER QUALITY ISSUES

Fixed voltage, current and frequency signals (pure sine wave) define the quality of power supplied by the power system [34]. PQ is becoming increasingly important for both the utilities and the customers. Due to variation in voltage, current magnitude and waveshape, electric equipments can malfunction in operation, giving erroneous result or may be damaged [35]. These variations are results of switching on/off of high loads, transformer energizing, line energizing, unbalance in three phases, due to capacitor/protective equipment switching or faults and the details are given in [2], [36], [37]. Due to these causes, PQ disturbances like transient, voltage sag/swell, frequency variation, notch, spike and flicker are generated in power lines. The PQ event detection and classification are the most interesting area of research in PQ analysis [38]–[40].

The literature of PQ analysis can be divided into two categories, PQ event classification and identification of PQ event's causes [41], which may be stationary or non-stationary. PQ signals may be sinusoidal or non-sinusoidal [38]. Non-stationary signals are difficult to analyze [42]; these can be monitored [43] and classified by voltage and current waveform characteristics [44]–[46].

In the last decade, restructuring of power system was carried out at different levels; subsequently the independent power producers (IPP) in generation business and distribution companies (DISCOs) in distribution sector increased the competition and responsibilities to customers. The demand of electric power is continually growing every year in India. To meet the energy demand of the country, the focus is on the renewable energy. Furthermore, the advancement, new innovations in technology and need of clean and green power have put emphasis on renewable energy sources (RES). Solar PV and wind energy are the main renewable energy sources. Therefore, these renewable energy resources are integrated with smart grid. These renewable energy sources use semi-conductor switching and non-linear equipments which degrade the power quality and exaggerate problems in integration with the grid.

Renewable energy sources in distributed generation (DG) have become increasingly popular therefore demand new techniques for efficient control and management of electrical grid to enhance PQ. Wind energy conversion system integrated with small network gives disruptive effects at customer end due to direct drive wind turbines [47], adversely affecting the PQ in terms of fluctuations and harmonics. IEC 61400-21 standard provides the PQ characteristics of wind turbine [48]. Due to RES, the effect of PQ has to be assessed for preventing the malfunctioning of the equipments. In modern world, PQ analysis is very important due to sensitive and large loads like Metro rails, large manufacturing industries and IT parks.Hence, PQ issues related with the integration of renewable energy with grid and smart grid are further discussed in coming sub-section.

A. PQ ISSUES IN INTEGRATION OF RENEWABLE ENERGY WITH GRID

To reduce the greenhouse gas effect, efforts of power system researches toward the renewable energy resources have increased, which give rise to integration of RES with grid. Distributed energy resources (DER) based distribution increases the efficiency, reduces the line losses and enhances customer reliability through islanding though it increases the system complexity [49]. In this the author proposes distributed en-

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TABLE 1. Standards from International bodies for PQ analysis

Guidelines for	**Standards**
Classification of PQ	IEC61000-2-1:1990, IEC 61000-2-5:1995
Monitoring of PQ	IEEE 1159:1995
Transients	IEC 816:1984, IEC 61000-2-1:1990, IEEE C62:41:1991, IEEE 1159:1995
Voltage sag/swell and interruptions	IEC 61009-2-1:1990, IEEE 519:1992
Harmonics	IEC 61000-2-1:1990, IEEE 519:1992
Voltage flicker	IEC 61000-4-15:1997
Voltage characteristics in Public distribution	EN 50160:1999
Powering and grounding	IEEE 1100:1999
DG/RES interconnection	IEEE P1547: 2015

TABLE 2. Classification of PQ Events on the basis of different parameters [31]–[33]

		Spectral content	Duration	Voltage magnitude
Transients (Impulsive)	Nanosecond	5-ns rise	<50 ns	
	Microsecond	1-µs rise	50 ns -1 ms	
	Millisecond	0.1 ms	>1 ms	
Transients (Oscillatory)	Low Frequency	<5 Khz	03 – 50 ms	0 - 4 pu
	Medium Frequency	5 - 500 kHz	20 µs	0 - 8 pu
	High Frequency	0.5 - 5 MHz	5 µs	0 – 4 pu
Short duration variations (Instantaneous)	Interruption		0.5 – 30 cyc	<0.1 pu
	Sag(Dip)		0.5 – 30 cyc	0.1 – 0.9 pu
	Swell		0.5 – 30 cyc	1.1 – 1.8 pu
Short duration variations (Momentary)	Interruption		30 cyc – 3 s	<0.1 pu
	Sag(Dip)		30 cyc – 3 s	0.1 - 0.9 pu
	Swell		30 cyc – 3 s	1.1 - 1.4 pu
Short duration variations (Temporary)	Interruption		3 s – 1 min	<0.1 pu
	Sag(Dip)		3 s – 1 min	0.1 - 0.9 pu
	Swell		3 s – 1 min	1.1 - 1.2 pu
Long duration variation	Interruption,Sustained		>1 min	0.0 pu
	Under voltage		>1 min	0.8 - 0.9 pu
	Over voltage		>1 min	1.1 - 1.2 pu
Voltage unbalance			Steady state	0.5 – 2 %
Waveform Distortion	DC Offset		Steady state	0 – 0.1 %
	Harmonics	0 – 100 harmonic	Steady state	0 – 20 %
	Inter-harmonics	0 – 6 kHz	Steady state	0 – 2 %
	Notching		Steady state	
	Noise	Broadband	Steady state	0 – 1 %
Voltage Fluctuation		<25 Hz	intermittent	0.1 – 7 % 0.2 2 Pst
Power Frequency Variation			<10 s	

ergy resources as a small cluster or micro grids for improved reliability, maximization of renewable resources, islanding, increased efficiency and distributed control, as an alternative to smart grid. Integration of RES with grid, causes many PQ problems such as voltage fluctuation, transients, flickers, harmonics and frequency variations etc. in the power system. Characterization of flickers under multiple control techniques (power factor control, voltage control, fixed reactive power dispatch) is implemented for doubly fed induction generator (DFIG) in wind plant [50]. Three operating schemes are adopted for analysis of flicker's effect on distribution network. Manas and Bilik [51] have developed an analyzer for measurement of flickers in distribution system, caused by RES with varying power of wind and photovoltaic (PV) cells, i.e., wind speed and level of radiation. The authors in [52], present work focused on quantitative model based approach to FDIR (fault detection, isolation and reconfiguration). Here, an embedded system technique is developed for an inverter to integrate RES in the grid. This proposed approach for PQ events uses skewness and kurtosis as statistical estimators and real time cumulative sum (CUSUM) algorithm for detection of events in real time. Analysis of renewable energy systems is presented in [53] using hybrid wind-solar-diesel system integration. Reactive power compensation, short circuit, total harmonic distortion and flicker is considered during fault analysis. PQ analysis in off grid power system is presented by authors in [54]. Wind power and solar power resources are used as RES and effects of solar irradiation and wind speed on PQ are discussed. PQ analysis is presented on the basis of frequency, total harmonic distortion of current (THD_i) and total harmonic distortion of voltage (THD_v).

Farhoodnea et al. present PQ problems faced in renewable energy based generation and electric vehicle charging stations [55]. The problems related to PQ issues, such as inrush current, safety and protection issues, under and over voltage, output power fluctuation, harmonic distortion and frequency fluctuation are discussed. Authors of this paper proves that frequency and voltage fluctuations are mainly due to PV and

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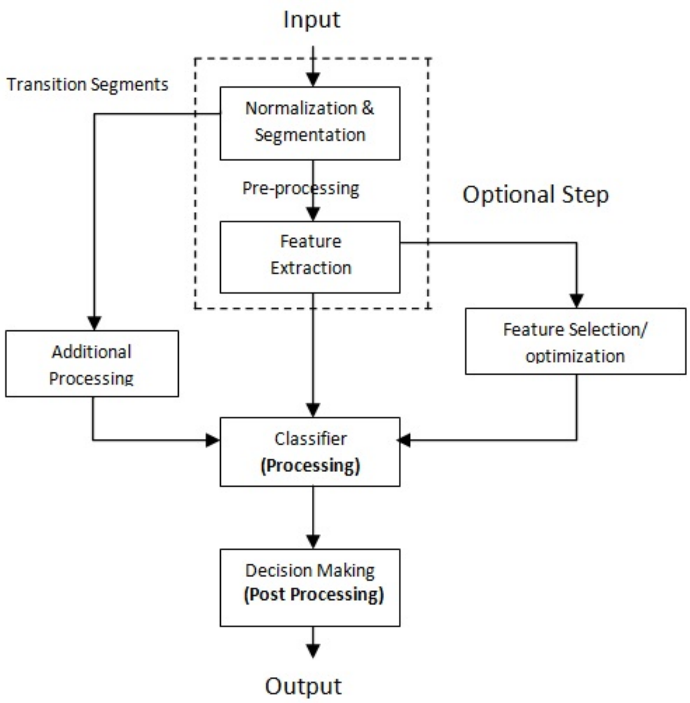

FIGURE 2. Generalized block diagram of Power Quality Disturbance analysis [24].

wind systems based on simulation results. Hsu et al. [56] proposed the impact of wind generation on PQ analysis in DG environment. Steady state voltage ratio, reverse power flow, voltage fluctuation, fault current and harmonics are considered in this paper. Here, authors shows how wind plants effects the distribution system in operation, planing and maintenance schedules. Islanding detection using phase space technique and probabilistic neural networks (PNN) classifier is presented by the authors in DG integrated power system [57].

The main challenge with renewable energy is that it is highly unpredictable. The uncertainties of these resources such as wind speed in case of wind turbine, solar radiation in solar cell and PV systems are generating disturbance in voltage e.g. fluctuation and harmonics. Therefore, this may be the major reason for degradation of power quality. In the literature, voltage fluctuation or voltage waveform variation has been considered for the mitigation. There are some techniques available in the reported articles, which suggests that the mitigation of various types of disturbances is possible. Some of the major reported articles in different renewable sources or DGs are discussed here. In [58], characteristics of wind resource and wind turbine are presented. In this, the authors propose a method of wind power estimation based on Gaussian regression. To reduce the variableness in the voltage, the authors suggested a method of selecting wind turbine on the basis of analysis between wind power's quantity and quality, according to size of wind farms and as per their geographical location. Energy sources in DG environment are interfaced with grid system using voltage source converters (VSCs). The modeling, design and control methods of DC-DC boost converter and VSC's in grid connected PV system is presented in [59]. Two control techniques i.e. Instantaneous Reactive Power Theory and Perturb and Observe based maximum power point tracking are used by the authors. This system mitigate harmonics, provides reactive power compensation, correction in power factor and performs grid currents balancing. Current controlled voltage source inverter is used for PQ improvement and renewable energy sources integration at distribution side in [60]. For PQ improvement, inverter is used as shunt active power filter and output power of RES is controlled by controller. This system injects surplus power into the mains and has reactive power support, harmonics mitigation capability and compensation of neutral current. Multi-functional grid-tied inverter (MFGTI) is used for interfacing RES in grid and for compensation of harmonics and reactive current in micro-grid for PQ improvement. Two control objectives of MFGTIs are presented; first is for obtaining expected PQ using minimal apparent capacity of MFGTI and second for enhancing the PQ [61]. In [62], [63], authors proposed a novel methodology using S-transform and Fuzzy C-mean clustering for the PQ events, generated using solar penetration in grid and are tested on Real-Time Digital Simulator on IEEE-13 bus system. Sanchez et al. proposed a statistical method using principle component analysis and k-mean clustering process to identify the voltage dips disturbances collected in Wind Farms [64].

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Reactive power compensation algorithm (RPCA) is proposed in [65] for improvement, operational stability and reliability of system. A control system with RPCA is designed for effective distribution and dynamic voltage regulation in grid interactive cascaded PV system. A review on PV grid related PQ event mitigation is presented by comparing the conventional and AI techniques [66]. Marei et al. [67] present flexible distribution generation at distribution level, with recursive least square (RLS) algorithm for mitigation of PQ disturbances in distribution system. In [68], secondary level control is suggested by authors for compensation of sensitive load bus (SLB) voltage and harmonics by using hierarchical control scheme. A control scheme is designed for unified power quality conditioner (UPQC) based on output regulation with Kalman filter for mitigation of PQ problems and a self charging circuit based on linear quadratic regulator (LQR) is developed to avoid need of external DC source for operation of UPQC in [69]. A comprehensive review of voltage dip mitigation techniques in DG is presented in [70]. Hossain et al. presents a review on PQ issues in DG and mitigation techniques using custom power devices [71].

RES/DGs provide security in supply system, minimize the transmission losses and also protect the environment from green house gases in grid connected mode but they cause PQ problems in power systems. Hence, to increase the reliability and efficiency of the highly interconnected grid systems, utilities switched to smart grid techniques.

B. PQ ISSUES WITH SMART GRID

With the maturity of power system network, increase in demand and service quality, the concept of smart grid is evolved to replace the conventional power grid. In the smart grid environment, the mostly equipments are sensitive i.e., intelligent, smart and sensitive control equipments are used with DG and energy efficient devices. The main functions of a smart grids are electronic power conditioning, control of production and distribution, improved reliability, security and efficiency, optimization, integration of DG includes RES, real time, interactive, automatic and energy efficient operation. To meet demand response requirements, energy forecasting, future planning, microgrid applications, power system stability and DERs integration the smart grids are becoming popular.

In [72], advanced distribution automation (ADA) application and its effect on PQ in smart grid is discussed. ADA is a set of technologies which provides remote monitoring, coordination and operation of distribution components of a utility at remote locations in real time mode. All these techniques help to control the equipments connected at remote locations in real time mode. In [73], a test system for power conditioner is presented on the basis of IEEE 1547 standard which can be used for integration of distributed energy resources or renewable energy applications with a smart grid. A low cost single phase meter for PQ measurement is presented, which detects series arc faults, load trip on failure and phase and neutral mixing indication for smart grid. Goertzel filter is used for total harmonic distortion calculation and an algorithm is proposed for peak detection and repetitive rate calculation [74]. He et al. [75]. introduce change point approach to detect PQ events in smart grid. Three statistical distributions Gaussian, gamma and gamma inverse along with a weighted CUSUM algorithm are used for PQ event detection. In [76], PQ monitoring issues and analysis techniques are presented from view point of smart grid. The issues related to PQ monitoring in smart grid along with PQ analysis and disturbance detection techniques are dealt with. For the reliable and efficient operation, monitoring plays a vital role in smart grid environment. Thence, in literature of smart grid, researchers have emphasized on monitoring.

In [77], Garcia et al. present real-time monitoring and detection of PQ events for intelligent management of distributed generation (DG) in grid. CUSUM is used for early detection of events and higher order statistics (HOS) is used to characterize the events. For analysis of PQ events in smart grid application, an eigen analysis based data clustering and classification method is proposed in [78]. Principal component analysis (PCA) and linear discriminant analysis (LDA) are used for enhancing the clustering efficiency and k-means clustering is used for classification of PQ events. These issues create problem in smooth and reliable operation of the smart grid and degrade the PQ. So, for efficient operation and maximum performance of the smart grid, these issues must be resolved by using suitable techniques.

C. APPLICATIONS OF IOT AND 5G IN SMART GRID

In the traditional power grids, PQ and reliability are the major issues, which are faced by utility and consumers. With the evolution of new technologies like internet of things (IoT), 5G, information and communication techniques (ICT), that provides a reliable solution to these issues, transforming the conventional grid into smart grid.

In the present era, IoT technology is an indispensable part of smart grid for domestic and commercial applications [79]. Here, the roll of smart meters in PQ and reliability monitoring of smart grid is presented by the authors by using IoT applications. The objective of the SG is to transfer the power effectively with low prices of time of use and maintain the security. The authors in [80], presented a energy management system using IoT in smart grid environment. In the experimental setup, the customer side power is continually monitored and data is sent to the control center. On the basis of demand output of the solar panel is controlled to meet the load using IoT module. If there is any faulty solar string or panel, it is identified and detached from the network by dedicated IoT module. IoT sensor data processing and analysis is presented in [81] whereas principles of Green IoT with challanges in [82]. A very good study on challenges faced, different opportunities and the future trends on IoT is presented in [83].

5G technology is rapidly adopted around the globe and this brings transformation in all the industries. The fast data transfer rate, high reliability, support to machine interconnections and very less delay in communication. All these qualities

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of 5G makes it suitable candidate for IoT applications in smart grid. Hui et al. [84] presented different applications of communication techniques in demand response (DR) program in smart grid using IoT and 5G network. In another paper [85], challenges faced in the security of smart grid in 5G networks are discussed. Authors give stress on the security concerns because if there is a security threat then whole grid can collapse. While Srinivas et al. [86], proposed a anonymous signature based scheme for IoT enabled smart grid to deal with security threats. The proposed scheme is tested for smart meters under real or random (RoR) model to withstand different attacks like replay, man-in-the-middle, impersonation, traceability, user anonymity and untraceability. Another researcher discussed recent cyber attacks for IoT based smart grid [87]. Kumari et al. [88] proposed fog computing for smart grid in 5G while in [89] authors used fog computing to process the huge data received from IoT devices. A review on 5G wireless network for smart grid has been presented by the Sofana and Reka [90].

To deal with PQ issues, efficient operation and reliability concerns in grid, the analysis process starts with pre-processing of power signal and further steps are used for analysis.

IV. PRE-PROCESSING OF INPUT SIGNAL

In the pre-processing stage, the power signals used for PQ analysis first undergo segmentation and then normalization. The process of segmentation is very nicely explained in [91], [92]. In the analysis of PQ disturbances, it is useful to divide the input signal into segments. Segmentation is a process in which event data size is reduced and only relevant part of the event data is further processed in next stages. In other words, the input power signal is converted into disjoint segments so that the analysis of data becomes effective. Input sequence can be divided in two categories i.e., transition segment and the event segment [36]. An event segment is sandwiched between transition segments. In normalization, event parameters are converted in a scale i.e., per unit (pu), by dividing input by the nominal RMS value of the parameter [93]. Pre-processing is an important step because the disturbances in the signal are present for a small time so instead of using complete waveform of signal, the pre and post cycles including disturbance cycle are used in analysis. This will reduce the processing time of signal. In the real signals, there is always some kind of noise mixed with the signal and in case of synthetic signals, authors add some noise to find out the performance of proposed techniques in noisy conditions [41], [94]–[96]. This noise affects the accuracy of the system or the misclassification rate increases, results in degrading the efficiency. To overcome these adverse effects in pre-processing stage, filters can be used to remove the noise and this method helps in increased performance of the subsequent stages like feature extraction and classification.

V. SIGNAL PROCESSING TOOLS IN PQ

Electrical power systems have three major areas i.e., generation, transmission and distribution. From PQ point of view, discussion of disturbances on transmission and distribution system is important because environmental and load conditions strongly affect these two. Some of these environmental factors shown in Figure 3 [97], [98].

The analysis of PQ disturbances is started from pre-processing by normalization and segmentation followed by feature extraction by applying some transformation technique like, Fourier transform (FT), Short-time Fourier Transform (STFT), Time Time (TT) transform, S-transform (ST), Wavelet transform (WT), Hilbert transform (HT) or Hilbert-Huang transform (HHT) and more. Each disturbance has different feature values; on the basis of which, power signal disturbances are differentiated from each other. For this purpose, mathematical transforms are applied on the input signals for feature extraction. Figure 4 depicts the different transforms reported in literature for feature extraction and Table 3 presents their mathematical expressions.

A. FOURIER TRANSFORM

Fourier transform (FT) is the frequently used method for frequency domain analysis of the signals, as it decomposes a signal into a number of sinusoids with different frequencies. FT is used for feature extraction of PQ events [99]. FT is suitable for analysis of stationary signals, but in case of non-stationary signals, it is unable to give correct information about fluctuations [100]. FT gives only frequency domain information of the signal under analysis. It doesn't deals with time information which is necessary for PQ analysis. The variations in the power signal are often aperiodic and time-varying, so FT and DFT (Discrete Fourier Transform) is not adequate choice for these non-stationary signals. Another variant of FT is fast FT (FFT) who's computation time is very less. FT is mainly used to find harmonics components present in the PQ signal. DFT is having many shortcoming like spectral leakage, resolution and picket-fence effects. Short-time Fourier Transform (STFT) gives better efficiency compared to FT. STFT is used for non-stationary signals as it provides the fix window size for further signal analysis [101]. The size of window in STFT is much smaller than fluctuation rate of the different disturbances. So, selection of window size is affect the performance of the STFT and the resolution. The STFT and other techniques for extraction of spectral information of a signal are used in [102]. Analysis of non-stationary signals with STFT is difficult [103], [104]. Hence, Windowed-FFT [105] that is a time windowed technique of Discrete-Time Fourier Transform (DTFT), where width of window can be adjusted as per application. For the analysis of voltage disturbance recording, discrete STFT and FT are used in [99]. A comparison between discrete STFT and WT is presented in [106], where in [42] on the basis of experimental analysis, authors prove that WT is better than STFT.

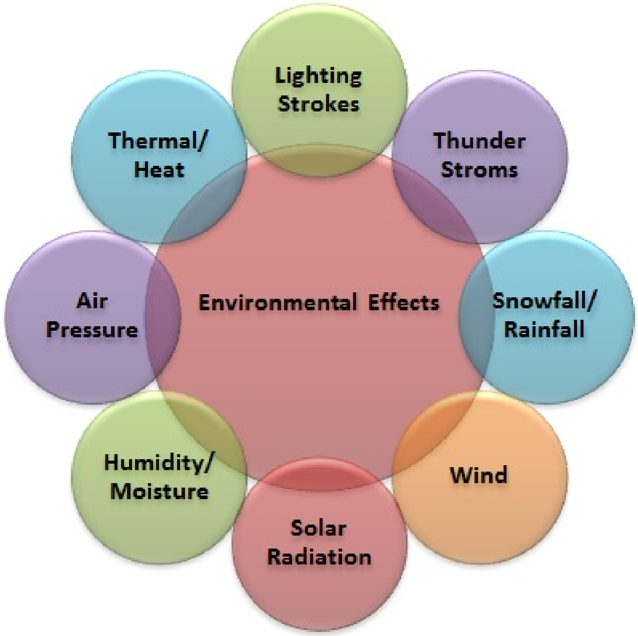

FIGURE 3. Environmental factors affecting PQ.

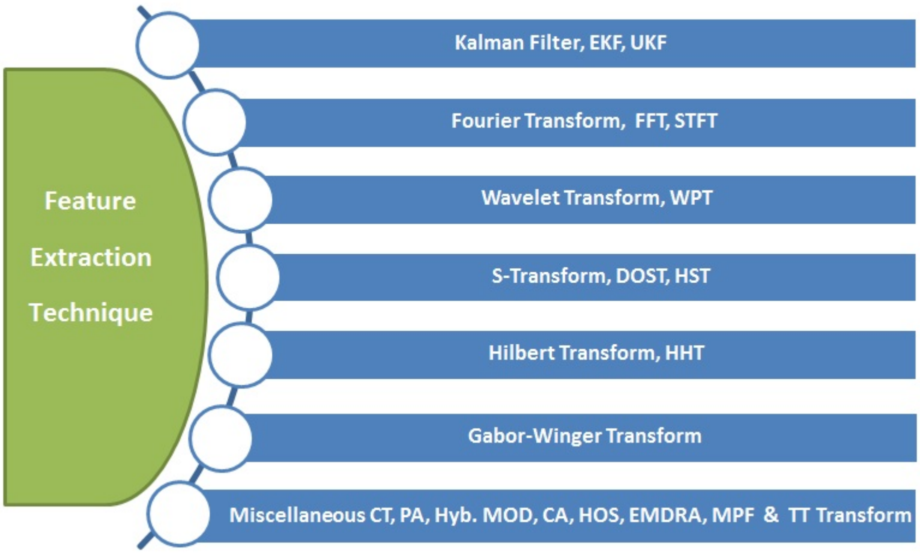

FIGURE 4. Various Transforms used for Feature Extraction.

B. WAVELET TRANSFORM

At present wavelet transform (WT) is the most popular technique used by researchers for analysis of PQ events to obtain characteristics in time-frequency plane. So, WT becomes a adequate choice where time and frequency information is required for starting and ending of event in PQ analysis. WT decomposes a signal in terms of scaled and translated form. In WT, multi-resolution analysis (MRA) technique [107] is used. In MRA, a signal is decomposed into high frequency and low frequency bands by using high-pass and low-pass filters respectively as shown in Figure 5, this process is repeated to reach desired level of details. At each level, amount of information is reduced to subsequent levels [108]. In Figure 5, high-pass filter (h_p) gives detailed coefficients (D) and low-pass filters (l_p) gives approximation coefficients (C).

By using band-pass filters, the high frequency signals with sudden changes like transients, energizing events, switching

TABLE 3. Mathematical expression of different transforms

Sr No	Transform	Mathematical Equation	Description
1	FT	$F(W)=\int_{-\infty}^{\infty} x(t)e^{-jwt}dt$	$x(t)$= input signal
2	STFT	$STFT_x(t,w) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-jw\tau}dt$	$w(t-\tau)$= window function
3	WT	$WT_x(a,b)=\frac{1}{\sqrt{\lvert a\rvert}}\int_{-\infty}^{\infty} x(t)\Psi(\frac{t-b}{a})dt$	a= scaling function, b= translation function, $\Psi(\frac{t-b}{a})$= mother wavelet
4	HT	$HT[x(t)]=\frac{1}{\pi}P\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}d\tau$ P is the Cauchy principal value	HT convolutes a monotone signal x(t) with $\frac{1}{\pi t}$ & shifts each frequency component of x(t) by 90^o
5	HHT	$HHT = EMD+HT \,\&\, EMD = r_n(t)+\sum_{i=1}^{n} c_i(t)$	$c_i(t)$ = i-th IMF component and $r_n(t)$ = final residue
6	ST	$ST_x(\tau,f) = \frac{\lvert f\rvert}{\sqrt{2\pi}}\int_{-\infty}^{\infty} x(t)e^{\frac{(t-\tau)^2f^2}{2}}e^{-2j\pi ft}dt$	f = frequency, t, τ= time, $e^{-2j\pi ft}$ = oscillatory exponential kernel
7	GT	$GT_x(\tau,f)=\int_{-\infty}^{\infty} x(t)e^{-\pi(t-\tau)^2}e^{-j2\pi ft}dt$	$e^{-\pi(t-\tau)^2}$= Gaussian function as a window

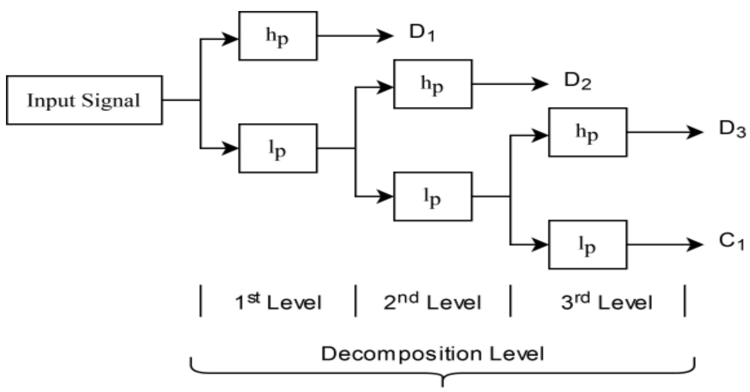

FIGURE 5. Wavelet Transform Filter Bank.

operation and quick rise or fall in voltage are detected [36], [109] while low pass filters are used for detection of slower signals such as harmonics [110].

In [111] dyadic orthonormal WT is used for automatic power quality classification. FT gives global representation of the signal while WT gives local representation. At the lowest scale (i.e., 1st decomposition level) fast and short transient while in higher decomposition level slow and long transient disturbances are identified. Detection results are on real data and to enhance the detection results, squared WT coefficients are used at each scale which gives sharp waveform and it is easy to recognize the disturbances. In [112], detection, localization, quantification and classification of short duration PQ disturbances (SDPQD). Quantification is also performed for magnitude i.e., SDPQD / orignal signal magnitude. Five binary features are extracted which results in simple feature vector and classification based on these features by converting the binary code into decimal in real time. Discrete wavelet transform (DWT) based method for power quality indices (PQI) is proposed in [113]. In this work, PQ Index is calculated from details coefficients by using weighted sum of percentage energy deviation. Here, db-6 wavelet is used and 13 level of decomposition has been performed. Transients and harmonics of real data are analysed in the range of 500 Hz to 47 kHz. In [114], DWT and FFT based approach is presented by the authors, average energy entropy of squared detailed coefficients of DWT are computed. Further classification is based on the FFT features and total 12 PQ disturbances with addition of noise are simulated and classified. Integrated approach of DWT and hyperbolic S-transform (HST) is presented in [115]. A new feature selection algorithm orthogonal forward selection and particle swarm optimization are used. Seventeen features from HST and eight features from DWT and six statistical features are extracted. Wherein, automatic classification/monitoring of PQ events for online/offline mode is proposed [116]–[118]. All these research papers are based on wavelet transform for feature extraction. Classification methods using rule-based and wavelet packet based Hidden Markov model (HMM) is presented in [119]. In WT, the MRA performed for extraction of frequency component, hence the time domain featured disturbances may not be easily classified. So author proposed a rule based approach for time featured disturbances and wavelet packet based HMM for frequency based features disturbances. DWT and HMM with Dampster-Shafer Algorithm [94] are suggested for automatic classification of PQD. In [120] and [121], features are extracted by using WT. In the former one a combination of rule base and expert system are presented, while in other wavelet multiclass SVM used for classification and localization of disturbances. A novel approach of self organizing learning array (SOLAR) system with WT is presented in [122], under different noise conditions. The main advantages of SOLAR is data driven learning, local interconnections and entropy based self organization. The energy of each decomposition level of MRA is applied to SOLAR. Transient detection schemes in real time is proposed in [123], by using WT and sliding window based algorithm. On the basis of threshold of the different signals, transients are detected. The advantage of the proposed method is that it is less sensitive to noise. A two dimensional (2D) representation of waveforms are used for transients detection. The 2D data looks alike a wave; if there is any asymmetry in the data it shows presence of any disturbance [124]. For the compression of PQ data in automatic analysis, WT is proposed by the authors and 2D representation efficiently compress the PQ data [125].

PQ event detection and de-noising is presented in [95], DWT and wavelet network is used in this work. De-noising is performed in three steps i.e., decomposition, threshold selection and reconstruction. The proposed approach is robust for different signal to noise ratio (SNR). In [126], intra and inter-scale dependencies of wavelet co-efficient with linear minimum mean square error (LMMSE) scheme are used for de-noising. A novel approach of adaptive wavelet network (AWN) is suggested in [10], which consists of two sub-network architecture of wavelet layer and adaptive probabilistic network (APN). DWT and self organizing mapping neural network (SOMNN) are used by the authors for detection/classification of load and capacitor switching in [127]. Differences in orthogonal, bi-orthogonal and semi-orthogonal wavelets is presented in [128], from PQ view point and fractionally delayed biorthogonal wavelet in [129] . Multiwavelet transform based classification of PQ events is presented in [130], [131], whereas multiwavelet and Dampster-Shafer technique is proposed in [132], [133]. In [134], authors proposed a framework for the synthetic PQ signal classification system using DWT and Probabilistic Neural Network based Artificial Bee Colony (PNN-ABC).

Islanding detection and load rejection disturbances are detected by a hybrid system of WT and ST in DG [135]. Bhadane et al. present the effect of wind speed on the grid. For the analysis of PQD, WT is used in grid connected wind plant [136]; with increase in number of machines, more PQ problems are faced. A comparative analysis is presented between WT and WPT for PQD and islanding detection in a grid connected PV system [137]. For the identification of harmonics source in DG, WT is used in [138]. Wavelet families vary in terms of several important properties. In PQ applications, regularity, orthogonality, vanishing moments, exact reconstruction and compact support properties are commonly used. In the literature, Daubechies wavelet family is the most commonly used because of relatively good energy compaction ratio and small computational cost, followed by Symlets, Coiflets, Haar and Morlet. Different wavelets and their properties are listed in Table 4. The main disadvantage of WT is the proper choice of mother wavelet function which affects the test results. As the decomposition level increases in WT, the number of filters needed is more and consequently computational time also increases. WT is more sensitive to noise. Therefore, to avoid these limitations S-transform is used, which is a modification of wavelet transform.

C. S-TRANSFORM

S-transform (ST) is a generalized form of variable windowed STFT or an extension to WT or a combination of STFT and WT [139]. It is a time-frequency analysis tool used in Geoscience and power system engineering [140]. A frequency dependent resolution is provided in ST by decreasing the width of analysis window with frequency. ST [141] and WT are similar except the phase correction as well as amplitude and phase spectrum. In Refs. [142]–[145], ST is used for feature extraction from distorted PQ signals. Automatic classification/characterization of PQ events is presented in [146], where ST is used to find instantaneous frequency vector and Parsval's theorem is used for classification. In [147], automatic recognition system is based on ST and extreme learning machine (ELM) for PQ disturbances where real, synthetic and synthetic signals with noise are used for the analysis of suggested system. ST with adaptive practical swarm optimization (APSO) technique is used for feature extraction [148]. Authors presented a fast adaptive discrete generalized ST (FDGST) algorithm [149]. Which is based on frequency scaling, window cropping and adaptive window frame estimation of the time varying PQ indices.

In [150], a phase corrected WT is presented as hybrid ST and extended Kalman filter approach is used for short-duration power network disturbances. Multi-resolution ST with a variable window width that changes with frequency by user defined function is used in [144] for detection of PQ events. A fast S-transform is proposed by the authors in [151], which gives low computation time. Another variant of ST, hyperbolic S-transform (HST) is used in pattern recognition scheme for PQ disturbances in [115] and for localization of faults in [152]. PQD and islanding detection in hybrid DG system (PV, fuel cell, wind) is presented in [153], features are extracted using WT and ST and a comparative analysis is presented between these two. ST is used in feature extraction for islanding and PQD in a grid connected DG system [154]. A Nordic 32 bus model is used for wind and PV system based DG. HST is applied for feature extraction; SVM and decision tree (DT) are used as classifiers in [155]. A 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 for characterization of multiple PQ disturbances with fast S-transform and decision tree [156]. The main advantage of ST is multi-resolution analysis retaining absolute phase of all frequencies. Though, it does

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TABLE 4. Different wavelet families and their properties

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

not give instantaneous values of disturbances and is also not adequate for harmonics. High computation complexity and it is very sensitive to Gaussian window are other limitations. That's why, Hilbert transform is rather a good choice.

D. HILBERT AND HILBERT-HUANG TRANSFORM

Hilbert Transform (HT) is a linear operator used to derive analytic representation of a signal and a real power signal is extended into complex plane. HT is useful for the calculation of instantaneous attributes of time series such as amplitude and frequency. HHT is a method to decompose a signal in intrinsic mode functions (IMFs) by applying empirical mode decomposition (EMD) technique and HT is applied to IMFs to obtain instantaneous frequency data. Hilbert-Huang Transform (HHT) is useful in non-stationary and non-linear time series data analysis. HHT is a combination of the EMD technique and HT.

In [157], HHT is used for feature extraction in classification of causes of voltage sag using probabilistic neural network (PNN) while in [158] EMD and HT are used for PQ assessment. Ref. [159], proposed a PQ event classification approach for distribution system based on HHT and SVM with one against all (OAA) classifier and singular value decomposition (SVD) used to increase the classification accuracy. EMD and HT based approach is used in automatic classification of PQ events using balanced neural tree in [160]. EMD based de-noising techniques are used in [161] for classification of PQ events in noisy conditions. For analysis of non-stationary PQ waveforms, iterative HHT with symbolic aggregate approximation (SAX) algorithm is presented in [162] where instants of sudden changes are identified and SAX is used to convert PQ waveform into symbols then pattern detection algorithm is used. Another variant i.e., modified EMD is presented in [163]. An improved method of HHT for time varying PQ waveform analysis is discussed in [164], here EMD is used for mono component signals and then HT is employed. Adaptive waveform matching extension with HHT is implemented by the authors for detection of PQ disturbances in microgrid [165]. This technique considers depth of waveform with rise and fall time. End effect and mode mixing problems are minimized by proposed technique which is tested on a simulation model as well as field experiment. Ensemble empirical mode decomposition (EEMD) technique based demodulation tool is used for voltage sag detection in smart grid [166]. This techniques uses the instantaneous power for detection of voltage on the grid. In a DG PV plant, wavelet analysis and HHT based mathematical approach is used with different operating modes for showing the impact of DG penetration on PQ in smart grid [167]. HHT is suitable for the analysis of noisy data but it is limited to narrow band. Besides the techniques discussed in section 4, there are many other techniques presented in next subsection which are proposed by the authors in their work as per applications, for feature extraction.

E. MISCELLANEOUS TECHNIQUES

For detection and classification of PQ events or disturbances, some other techniques and algorithms are proposed in the literature apart from techniques discussed in previous subsections of section 4. Prony analysis (PA) method is used for the analysis of signal and extraction of its model information like frequency, phase shift, damping and magnitude. A Prony based optimal Bayes fault classification technique is presented by Faiz et al. [168]. Prony analysis (PA) and recursive algorithm are proposed in [169]–[172]. Higher order cumulants technique used for feature extraction is given in [173], [174]. Feature extraction in time frequency domain using parallel computing is explained in [175]. Another multi core algorithm for WT/WPT is proposed in [176], for harmonics analysis and data compression. The parallel processing of the algorithm reduces the computation time. Hybrid demodulation and harmonics analysis are presented in [177] for single/multiple PQ events. The authors present HT and Clarke transformation in [178]. In [179], the researchers used Gabor transform (GT) with FIR window and Type-2 Fuzzy Kernel (T2FK) based SVM for classification of PQ events. Kalman filters [180]–[184], Gabor-Winger transform (GWT) [185], digital filters [110], time-time (TT) transform [178], curve fitting [99], EMDRA method [186], hybrid HT and WT with frequency shifting [187], fractal based method [188], fractional delay wavelet (fraclet) [189], covariance analysis [190], modified potential function [191], higher-order-statistics (HOS) [192], [193], change point approach [194], Independent component analysis (ICA) [195], [196] and ADALINE method [197] are presented in the last decade. Slanted transform with field-programmable gate array (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 [198]. Another researcher used FPGA with Labview to detect single and multiple PQDs [199]. Comparison of general feature extraction methods used in PQ analysis are presented in Table 5.

VI. FEATURE SELECTION

The process of selection of relevant features out of the extracted features is called feature selection. The feature extraction techniques result in a large number of features including some irrelevant and unuseful features. These irrelevant features increase the complexity and the computational time of the classifiers. In case of online approach, fast trained and low computational time classifiers are required to detect the disturbances accurately and efficiently. This can be realized by selecting the important features and discarding the less important ones. If we have a set of F features, then selection of a subset of features which gives the smallest classification error is called feature selection [207]. In [208], classification of single and multiple disturbance based on principle of divide and conquer is used to decompose a signal into primitive components and the Fisher's discriminant ratio (FDR) is applied for feature selection. Manimala et al. present Genetic Algorithm and Simulation Annealing based wrapper model, a hybrid soft computing approach, for feature selection and parameter optimization for power quality data mining [209]. Norm entropy based feature selection is proposed in [210] for classification of PQ disturbances. In [211], sequential forward selection method (SFS) is used to select the useful features for PQ event classification. Hajian et al. present automated power quality recognition system for online/offline monitoring, and use modified relief, mutual information, sequential forward selection and sequential backward selection (SBS) techniques for feature selection in [116]. There are different feature selection approaches [212] which can be classified as:

1. Embedded Approach like Decision Tree, LASSO, LARS, 1-norm support vector
2. Wrapper Approach like complete search, sequential search, randomized search
3. Filter Approach like correlation, entropy, mutual information, chi-square (univariate) and correlation feature selection, minimum redundancy, maximum relevance (multivariate)
4. Hybrid Approach, which are combination of filter approach and wrapper approach.

Feature selection is a important part of power quality analysis, but there is a lack of research work on this approach. Some researchers use the feature selection techniques but they have not given any comparative analysis of these techniques. Carefully selected feature set reduces the feature dimension and classification time and hence reduces the order of complexity and computation time. The selection of relevant features gives good classification accuracy and reduces over fitting.

VII. ARTIFICIAL INTELLIGENCE IN CLASSIFICATION

Artificial Intelligence (AI) or the Knowledge based techniques are adopted as the substitute to the classical techniques. Artificial intelligence methods usually employed to find the solutions of 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, rule-based systems, artificial neural networks, fuzzy models, genetic algorithms and swarm intelligence lie under AI. The classification of PQ disturbances is done with these classifiers. Classifiers uses the information received from feature extraction stage. On the basis of these features or inputs, classifier classify the type of disturbance. The performance of classification is depends on the relevancy of the selected features as well as training and testing data. Figure 6 shows different AI techniques used in PQD classification.

A. NEURAL NETWORK

Neural networks (NN) are used in estimation or recognition of output for a huge set of inputs. NN is a new generation information processing method. This works in similar manner as human brain. In [213], fifteen types of single PQ disturbances are classified. Multi layer perceptron (MLP) and radial basis function (RBF) are compared for classification efficiency. All the disturbances are low frequency DC offset to high frequency transients or short duration impulse to steady state events. Probabilistic neural network (PNN) is used for classification of different types of transients. The classification is made on the basis of duration of transients and detailed energy distribution [214]. In [215], authors propose the automatic detection and recognition of single PQDs based on wavelet transform and PNN as a classifier. The classification by proposed method retains the original properties of the disturbance signal, need less memory and short computation time. Multiple PQ disturbances are dealt in [216], which uses dynamic structure NN and a amplitude estimator for detection of momentary disturbance based on RMS voltage. Automatic detection and classification of

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TABLE 5. Comparison of feature extraction techniques for power system disturbance analysis

Sr. No	Method	Advantage	Disadvantage	References
1	STFT	Give good results for non varying signals. Simple to implement.	Not adequate for time varying signal limitation of fixed window width. Limited time-frequency resolution.	[42], [101], [104], [106]
2	HHT	Successfully extract the features from distorted signal. Evaluation of phase and magnitude is quite easy.	Applied to narrow band only.	[157], [158], [160], [161]
3	ST	Time domain to frequency domain convertible. Real and imaginary spectrum component time localization.	Not good for real time applications. False estimation of harmonics.	[139], [142]–[145]
4	WT	This gives localization in time as well as in frequency domain. Improved resolution of time and frequency.	Highly influenced by noise. Spectral leakage and picket fence effects influence the performance.	[95], [107], [108], [111], [118]
5	Filter Bank	Computational complexity is less as compared to wavelet and STFT.	Output does not correspond to the pure harmonic components. Due to overlap, the magnitude frequency response is not flat on their respective frequency bands.	[110], [200]
6	GT	High signal to noise ratio and good time–frequency resolution.	Limited use at high frequencies, Computational complexity is directly associated with sampling frequency.	[185], [201], [202]
7	Kalman Filter	Good Frequency, amplitude and harmonic change ratio estimation. High signal to noise ratio.	Diverges in some poorly chosen initial conditions. Instability may result in false estimation of fundamental and harmonic components. Both, time and frequency domains decomposition not present.	[180]–[183], [203]
8	HOSA	Robustness to noise, effectively detects transients.	Limited resolution. Difficult to analyze.	[192], [193]
9	PA	No frequency details are needed before filtering in Prony analysis and provides good accuracy.	This method gives incorrect estimation in case of model mismatch.	[170]–[172]
10	Park's Transform	Good for field-oriented control (FOC) of motors. Conversion of three-phase AC quantities to two DC quantities.	Not suitable for single phase.	[204]
11	TT - Transform	Good visual localization. Better classification of non-stationary power signals.	High complexity	[178], [205], [206]

PQ disturbances using wavelet and artificial neural network (ANN) are presented in [217]; input waveforms are classified according to type of disturbances and number of disturbances present in a cycle. ST based PNN [218] is used to for detection and classification of single and complex disturbances. Statistical feature selection method is used which reduces the number of features in feature vector which results in reduced time and complexity. PNN is also compared with back propagation neural network (BPNN) and RBF NN. PNN is employed for classification of PQD in [35], eleven different power quality disturbances are classified. Only four features are used in feature vector and comparison of the classification accuracy with feed forward multi layer NN and Learning vector quantization (LVQ) NN. A feed forward neural network classifier is used in [219], for detection of PQ events using demodulation. In this work authors use only half cycle to detect any event by using crosscorlation and multiple signal classification (MUSIC) algorithm. Talaat et al. suggest subtractive cluster feature based ANN for PQ classification, this method considers data point as a cluster center and calculates the likehood of each data point [220]. Transients level detection by using HOS and competitive layer based NN is presented in [221]. Other varients of NN like enhanced wavelet probabilistic network [222], self adapting ANN (SAANN) [223] and dynamic structural NN (DSNN) approach [224] are intoduced for detection and classification of PQD. Manke and Tembhurne [225] present NN with feed forward structure and modified Fisher's discriminant ratio kernel (MFDRK). A time frequency ambiguity plane is created using inverse FT and from this plane feature vector is selected. MFDRK is used to get the N locations from ambiguity plane. 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 [226]. In distributed generation (DG), ANN is used as a classifier for detection of islanding event in non detection zone [227]. Classification results of FFNN, RBF and PNN are compared, FFNN gives 100% result with five neurons and fast classification. A flicker recognition technique is presented for wind turbines and PSO is also used for parameter tuning (smoothing factor) of the PNN [228]. A total power quality

FIGURE 6. AI techniques for classification of PQ Disturbances.

index (TPQI) is presented by the authors for PQ deviations analysis on a specific site. An MLP type ANN is used for the classification purpose and input data are selected through a ES questionnaires [229]. Here authors use pre-processing filters to increase input output training data for ANN and this model is flexible for future requirements. Problems like initial weight setting, number of hidden nodes, higher space complexity, difficulty in stable solution, over-fitting, large number of training cycles and learning efficiency are associated with different types of NNs. SVM is having advantages over above said NN because of its leaning strategies.

B. SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is based on statistical learning theory. SVM is frequently used technique in classification and regression problems of PQ. In [230], authors propose SVM classifier for PQ disturbance identification by using N-1 SVMs for identification of N PQ disturbances. The first SVM is trained with all the samples and SVM second is trained with one lesser number of sample and so on. The proposed scheme is robust and fast and their is no local optimization problem. In ref. [231], SVM is used for automatic classification of PQ disturbances. Comparison of SVM and RBF is presented with added noise in the signals and on the basis of classification rate SVM is found better. In [232], wavelet transform and SVM is used for detection and classification purpose. The proposed approach results in reduction of data size, reduced memory space, increase computation rate and classification with noise. In another work, a sequential forward selection feature selection algorithm is used with SVM classifier which gives high classification rate [233]. SVM classifier and a simple approach of feature selection is presented in [234]. In this approach fundamental component is subtracted from the acquired voltage signal. The SVM is compared with low complexity event classification method (LCEC) and optimal time frequency representation (OTFR) method. Authors present application of SVM in PQ disturbances based on HOS by using geometrical pattern establishment for automatic PQ classification [235]. Automatic recognition of PQD with kernel based SVM clustering is proposed in [236], where a modified immune optimization algorithm is used for improvement of compactness of the clusters and for classification accuracy by refining center of SVM clusters. Different multiclass SVM algorithms such as K-SVM (number of class in one against rest), fuzzy SVM (FSVM), directed acyclic graph SVM (DAGSVM) and multi layer ANN are compared in [237] and the performance of DAGSVM is better even in presence of noise. Mohanty et al. [238], present islanding and PQD classification using MPNN and SVM classifier in grid connected power network in distributed generation. Authors used practical data collected from laboratory setup for classification and performance of SVM is outperforming. while [239] classifies transients due to power transformer using SVM and PSO is used for tuning the SVM parameters. In this scheme no threshold is required and it takes less than a quarter of a cycle which reduces the complexity. In paper [240], SVM is used for PQ disturbance classification and optimization with GA and simulated annealing. The results are also presented with RBF kernel and polynomial kernel. Islanding and PQ disturbance detection in a grid connected DG system using MPNN and SVM are presented in [154]. Wind energy and PV based DG system are presented in [241]. 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 [242]. While there is no need of training in the fuzzy systems. Other disadvantages like selection of parameters and extension to multi-class problems. 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.

C. FUZZY LOGIC

Fuzzy logic is multivalued logic, that gives approximations and its truth value ranges in between 0 and 1. In the fuzzy logic, the main benefit is its explicit knowledge representation in making simple IF-THEN rules. In this section, fuzzy expert systems and fuzzy rule base systems are discussed. Zhu et al. [243] present wavelet based fuzzy reasoning approach in which features are extracted by wavelet and on the basis of these features, rule base is generated for fuzzy reasoning for classification of PQ disturbances. The authors propose the fuzzy logic techniques in [244], nine different rules are formed for classification of PQ events. For automatic classification of the PQ disturbances, a fuzzy expert system has been framed and fifteen different rules are created [245]. In [246], hybrid technique of linear Kalman filter and fuzzy expert system is described for PQ disturbances characterization. The rule base is formed on the basis of slope amplitude and harmonics indication of distorted waveform. Biswal et al. [247] present the classification of PQ disturbances using bacterial foraging optimization algorithm (BFOA) based decision tree and chemo-tactic differential evolution based fuzzy clustering (CDEA). The classification accuracy of the proposed approach is increased by fuzzy C-means clustering and bacterial foraging method. In [148], a hybrid fuzzy C-means algorithm and PSO is used, which eliminate trial and error method for choice of cluster centers at starting. In traditional C-means clustering, their is problem of local minima where program can get stuck. Data mining techniques are used by the authors, in this a hybrid approach of fuzzy expert system and particle swarm optimization is used for improving the classification performance of PQ disturbance classification [248]. Detection and classification of single and combined PQ disturbances are discussed in [249] with PSO for improvement of membership function parameters and performance of the fuzzy system. Kapoor and Saini [250], present a PQ event classification based on multiwavelet and FPARR (fuzzy product aggregation reasoning rule). In this work authors use product aggregation assign patterns to a class, where all the features represent a class making classification better. In [251], analysis of PQ events on the basis of fuzzy logic is proposed. In this work, authors use FPARR, FE (fuzzy explicit), FML (fuzzy maximum likelihood) and FK-NN (fuzzy k-nearest neighbor) classifiers and analyzed their performance. For the mitigation of voltage sag and current harmonics, fuzzy logic controller is used in unified power quality conditioner (UPQC). The FL controlled UPQC effectively mitigates the voltage sag and bound harmonics in a acceptable limit in grid connected wind power system [252]. 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. Large number of input to fuzzy system increase correct classification but complexity increase and speed decreases. Parameters of membership function also based on hit and trial which is time consuming. Hence, for analysis of combined PQ problems, it is advantageous to use neuro-fuzzy systems.

D. NEURO-FUZZY SYSTEMS

Neuro-Fuzzy systems are the combinations of ANN and fuzzy logic. These are primarily based on fuzzy systems; the learning algorithm to train these systems uses neural network theory. The main benefit of neuro-fuzzy systems have learning and adaptive quality of NN along with fast learning and generalization capability of fuzzy logic system. In [253], PQD detection and classification is proposed using neuro-fuzzy system. In this work two input and one output system is used, each input feature element in the classifier have three Gaussian membership function. Voltage is converted in three dimensional (3D) space, then principle component analysis (PCA) is used for feature extraction from eigenvalues of each disturbance and after that neuro-fuzzy classifier is used for automatic classification of the PQDs. Adaptive neuro-fuzzy inference system (ANFIS) based representative quality power factor is presented in [254], which is simple, easy to use, flexible and fast. The ANFIS system is applied to displacement power factor, transmission efficiency power factor and oscillation power factor are considered for linear, nonlinear, sinusoidal and non sinusoidal cases with lagging and leading power factors. Negnevitsky and Ringrose [255], presents automatic disturbance recognition based on neuro-fuzzy system. Authors used ANN and fuzzy system, two types of neuro-fuzzy system i.e., fuzzy LVQ and fuzzy MLP are compared. For small training set fuzzy MLP gives better result and for large data fuzzy LVQ gives good results. Noise influenced PQ events with integrated feature extraction and neuro-fuzzy network are suggested in [256]. Here first noise is suppressed from the signal using Parsval's theorem and then twenty two rules are used to PQ event recognition on the basis of spectrum energy. In [257], an adaptive fuzzy self learning technique is presented by authors. Proposed technique monitors the electrical equipment or the system under operation with self learning from the events which leads to system failure. If any past trend repeats a warning signal is given. Data compression techniques are discussed in [258] with adaptive neuro-fuzzy technique with greater accuracy and a small or without loss of information. The proposed ANFIS system uses two membership functions. Islanding detection for grid connected inverter based distributed generation is presented in [259]. In this work the parameters of ANFIS are adjust with gradient descent method and back

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propagation method. Authors describe a two way technique, i.e., recognition of disturbances at distribution level and stability at generating stage [260], using a nural-fuzzy classifier for recognition of PQ and a fuzzy excitation controller with exciter and stabilizer. The proposed technique is very effective in noise influenced signals. Non linear transients' identification is proposed by Franco et al. [261] in a pilot refrigerator plant. For this different neuro-fuzzy models of temperature, condensation, evaporation and refrigeration of fluid are developed to study non-linearity in online and offline mode. In [262], 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 this system is that the combination of these two (ANN and fuzzy logic) overcomes the drawbacks of individual techniques like initial weight setting, number of hidden nodes, over-fitting and parameters of membership function. Nowadays, genetic algorithm is widely used in power system applications for optimizing the performance because it gives best results if fitness function is known and also useful in multi objective optimization problems.

E. MISCELLANEOUS CLASSIFIERS

Classification of fault has been presented using WT and expert rule base [263]. The expert rules classify four types of fault events on the basis of magnitude of the waveform. A simple rule based approach is proposed for detection of voltage event using filter bank and adaptive filters [264]. An expert system (ES) is proposed which contains optimized NN combined with DWT and FL for PQD classification. DWT is used for feature extraction, NN for processing and FL as post processing [265]. 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 ES is proposed in [184]. A hybrid method of Fourier linear combiner and fuzzy ES is presented for transients classification in power system [266]. Adaptive Boosting (AdaBoost) algorithm is proposed in the multi-machine distribution system for the detection of islanding event [267]. Decision tree (DT) is used for classification of single and complex power quality problems with noisy signals [268]. Mathematical Morphology (MM) and HHT are used for PQD detection, where MM is also used for noise suppression [269]. Hidden Markov Model (HMM), based on WT, WPT and vector quantization is presented in [270], [271]. A recursive implementation of MUSIC algorithm is presented in [272], for mitigation of power disturbances due to arc furnace in noisy and noiseless conditions. 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 [273]. A transmission line of 100 km length, voltage sensor and dSPACE 1104 kit with computer are used for practical model. Disturbance classification in a hybrid DG system using modular PNN and SVM is suggested in [154]. Two 9 kVA alternators and a 5 kW load are used for demonstration of wind energy conversion connected to grid. Tran et al. [274] propose an application of transient current in induction motor fault diagnosis, which is based on Fourier-Bessel expansion and fuzzy ARTMAP. Data set is generated using an induction motor, pulleys, shaft and fan with changeable blade pitch angle. Table 6 presents advantages and disadvantages of different classifiers used in PQD classification.

VIII. OPTIMIZATION TECHNIQUES

Optimization techniques are used to maximize the performance of the detection and classification methods. Optimization is a process of finding the best conditions that give the minimum or maximum value of a function, and the function corresponds to the required effort or the desired result. Particle swarm optimization, simulated annealing, Ant-colony optimization, evolutionary algorithms including genetic algorithms and neural network methods represent a class of programming methods for optimization during the last decade [285]. Different modeling techniques are developed in literature to meet the requirement of different type of optimization problems. The applications of optimization techniques are used in PQ analysis. In detection and classification of PQD, optimization can be used in two cases i.e., for selection of most relevant features and for parameter tuning of the classifiers used or for both cases. This results in improved classification performance and computation complexity. Figure 7 shows different optimization techniques.

A. GENETIC ALGORITHM

Genetic Algorithm (GA) is a search engine based on natural selection. It is mostly used in classification and optimization problems. Multiobjective Genetic Algorithm (GA) and decision tree for PQD's pattern recognition are presented in [280]. GA is used to find feature set with minimum classification error and size of tree. Application of linear vector quantization (LVQ) neural network combined with GA is proposed in [281]. A pattern recognition classifier based on neural network and GA is explained in [282] for automatic detection and classification of PQ disturbances. Breeder GA (BGA) method is used by Yusran in [283] for optimum placement of distributed generation in power system network. Wang and Tseng present an extended GA (EGA) based method for analysis of power quality [286]. Optimum location and number of PQ monitors required for analysis of power quality using GA are given in [287], [288]. For PQ disturbance classification in a wind and PV based DG system, optimum feature selection is performed using GA [155] and effect of noise is also considered for checking the robustness of the proposed method. GA is based on natural selection for optimization problems. GA is used to find the optimized solutions and feature selection [289] and a hybrid approach for GA in [290]. In [291], scaling factor of fuzzy logic

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TABLE 6. Comparison of different AI techniques

Sr. No	Method	Advantage	Disadvantage	Reference
1	ANN	Provides mathematical flexibility and suitable for real-time techniques. Suitability for mixed PQ problems.	The learning process can be affected due to local minima. Noise and network architecture affect convergence speed.	[139], [217], [220], [275] [108], [174], [276]–[278]
2	FL	Suitable for modeling and analysis of complex systems.	Not able to classify new types of disturbances due to fixed training set.	[148], [243]–[245], [251]
3	ES	Gives good performance regardless amount of data.	Normally slow and costly to develop these systems. Results based on the assumptions made.	[184], [246], [248], [265], [266], [279]
4	SVM	Fast learning process, effectively deals with large feature sets. Gives stable solution to quadratic optimization.	Classification accuracy depends on training data.	[230], [232], [235], [236], [240]
5	GA	Suitable for dynamic performance and sub harmonics.	Computation time is large.	[280]–[283]
6	BC	Works well for Gaussian probability density functions.	Knowledge of probability density function in advance. High computational cost, large data set required.	[101], [119], [284]

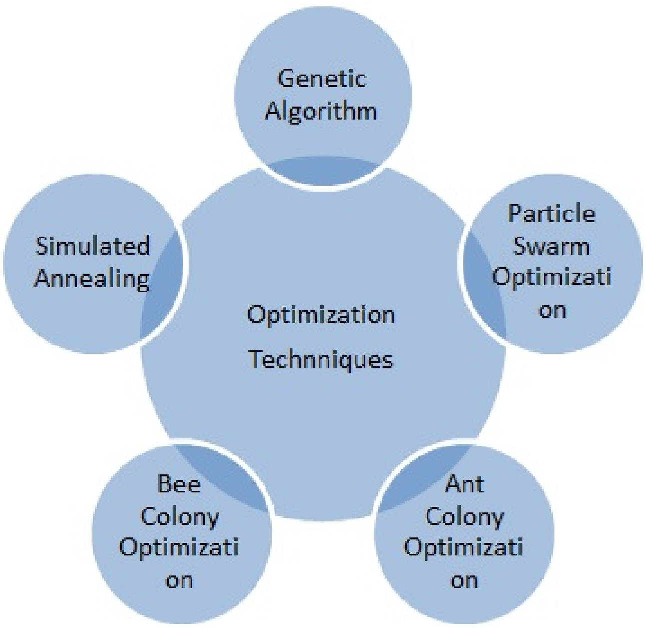

FIGURE 7. Optimization Techniques.

controller is optimized by using GA. GA can be applied to different optimization problems which are not solved by standard method, discontinuous, non-differentiable, stochastic or highly non-linear functions [23]. A GA optimization based demand response control is proposed for grid power balance in peak demand of a building group [292]. Power factor correction (PFC) and distributed feeder reconfiguration (DFR) are optimized through GA in Italian distribution network [293]. GA is used in time constrained and time unconstrained means for minimization of power loss. A multi-objective and hybrid GA is proposed by the Hassan et al. [294], to find the optimal size and the best combination of the different DG systems.

B. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a population based stochastic search process. Chaos synchronization based detector and PNN are used for classification of PQ disturbances and PSO is used for performance optimization [226]. To determine the parameters of the membership functions for the fuzzy/expert system, adaptive PSO is used to improve the performance of fuzzy C-means clustering algorithm [148]. Parameter optimization of a PI controller has been done through PSO in a PV inverter [295]. This technique is a

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TABLE 7. Comparison of different optimization techniques

GA	PSO	ACO	BCO	SA
It is a metaheuristic approach based on population, easily understandable and programmable.	It is an intelligent approach based on particle swarms, easily understandable and programmable.	It is population based approach and on ant colony behavior, complex in programming.	It is population based approach and on bee colony behavior, complex in programming.	It is a metaheuristic approach based on random search, complex in programming.
It provides multiple solutions.	It provides multiple solutions.	It provides accurate solutions.	It provides accurate solutions.	It provides accurate solutions.
Performs well in Combinational problems	Performs well in Mutation problems	Performs well in Distribution computation	Performs well in Multidimensional problems	Performs well in Combinational problems
Issues related to difficulty in variant problems and global optimum.	Issues related to scattering and optimization problems.	Issues related to dependent sequence of random decisions.	Issues related to sequential processing.	Issues of tradeoff between quality of result and time required.

combination of nonlinear optimization with electromagnetic transient simulation and ISE index is used for dynamic response.

C. ANT COLONY OPTIMIZATION

Ant Colony Optimization (ACO) based on real life behavior of ants, is a nature-inspired technique for the solution of complex mathematics and optimization problems. Ant colony optimization is used for optimal feature selection for PQD classification [296]. To improve power quality, ACO based PI control algorithm is proposed to mitigate harmonics using shunt active power filters [297]. Hybrid Ant colony optimization (HACO) algorithm is proposed in [206]. Kabir et al. [298] propose a feature selection and optimization method using hybrid Ant colony optimization algorithm for feature selection (ACOFS). A review on ACO and its variants is presented in [299].

D. BEE COLONY OPTIMIZATION

Bee Colony Optimization is newly introduced algorithm. It is based on intelligence behaviour of honey bee swarm and used for optimization, clustering and classification problems. For classification of PQD, BCO is used for feature selection and parameter optimization of PNN classifier [300]. In this work, authors very nicely explains step by step implementation of BCO and multiple PQD are used for classification. To improve power quality in the distribution, optimal location is find out for distributed energy storage units using artificial bee colony algorithm [301]. A hybrid BCO algorithm is proposed for solving the harmonics estimation problem in [302].

A simulated annealing (SA) immune algorithm is used for optimization of distributed generation reconfiguration in [303], [304] for efficient use of distribution system. An advanced immune algorithm is used in [236] to optimize the clustering performance of TT-SVM pattern classifier. For optimizing automatic classification of PQ events, GA and simulation annealing are presented in [240]. A performance comparison of GA, ACO and Differential Evolution (DE) is presented in [297] for PQ improvement. The performance of PQ disturbance detection and classification system is significantly improved by selecting the proper optimization technique. These optimization techniques used for feature selection as well as parameter tuning of the classifiers. Table 7 presents comparative analysis of different optimization methods.

IX. COMPARATIVE ANALYSIS

A number of signal processing techniques and artificial intelligence methods are propounded in the field of PQ signal analysis. Table 8 enlists some noteworthy works from literature on PQ disturbance detection and classification methods. In this table, comparison is made on the basis of different criteria like type of feature extraction technique used, classifier used, whether feature selection method used or not, any additional algorithm or optimization technique used for improving performance, type of input signal i.e., synthetic or real (with or without noise). Classification efficiency is also compared under noiseless or noisy environment. From this table it is also observed that very less researchers used feature selection and real/experimental data.

A. DISCUSSION

- Section 1 enlighten the importance of PQ analysis in present era.
- Basic terms and techniques used in PQ analysis including International Standards is presented in section 2. This will help to understand different steps used in PQ analysis.
- Power quality issues faced in distributed generation, penetration of renewable energy resources and smart grid is considered in section 3. The applications of IoT and 5G is also presented. This gives clear understating to the readers about PQ issues.
- Section 4, discuss the methodology and importance of pre-processing of input signal. This gives an idea about process of normalization, segmentation and noise filtration.
- Various signal processing techniques used for feature extraction are discussed in section 5. Their advantages and disadvantages are presented in Table 5. On the basis of these, one can understand that which type of feature

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TABLE 8. Comprehensive comparison of reported articles

Sr. No.	Author/ Reference	Feature Extraction	Classifier	Feature Selection	Algo/ Optimization	Input Signal	Classification Efficiency
1	Huang et al. [305]	WT	FSCL*+LVQ	No	No	Real (Noiseless)	93.76
2	Zhu et al. [243]	WT	Fuzzy	No	No	Real (Noisy)	95.31
3	Reaz et al. [265]	WT	NN+Fuzzy	No	No	Real (Noiseless)	98.19
4	Hu et al. [306]	WT	SVM	No	No	Synthetic (Noiseless)	98.5
5	Eristi and Demir [41]	WT	SVM	No	No	Synthetic (Noisy, Noiseless)	Noisy 95.81 Noiseless 99.71
6	Meher and Pradhan [251]	WT	Fuzzy	No	No	Synthetic (Noisy, Noiseless)	Noisy 96.87 Noiseless 98.95
7	Masoum et al. [95]	WT	NN	No	No	Real (Noisy)	98.18
8	Eristi et al. [93]	WT	LS-SVM	Yes	k-means based Apriori	Real (Noisy)	98.88
9	Dehghani et al. [94]	WT	HMM	No	Dampster-Shafer Algo.	Real (Noisy)	99.46
10	Alshahrani et al. [307]	WT	ANN	No	No	Synthetic (noiseless)	90
11	Uyar et al. [96]	ST	NN	No	No	Synthetic (Noisy)	99.56
12	Salem et al. [308]	ST	ES	No	No	Real (Noiseless)	99.44
13	Behera et al. [248]	ST	ES	No	PSO	Synthetic (Noisy)	Noisy 99.00
14	Jayasree et al. [309]	HT	RBF	No	No	Synthetic (Noisy, Noiseless)	Noisy 94.00 Noiseless 97.00
15	Perez et al. [310]	HOS	–	No	No	Real (Noiseless)	83.00
16	Biswal et al. [311]	WPT	LVQ	No	No	Synthetic (Noiseless)	99.14
17	Khokhar et al. [312]	DWT	MPNN	No	No	Synthetic (Noisy, Noiseless), Real	Noisy 88.75 Noiseless 97.68 Real time 94.93
18	Ferreira et al. [192]	HOS	NN	No	Fisher's discriminant ratio	Synthetic (Noiseless)	100
19	Zhang et al. [313]	Modified-ST	ELM	Yes	MST and ELM Algo	Synthetic (Noisy, Noiseless)	Noisy 96.85 Noiseless 99.99
20	Hajian el al. [116]	DWT+HST	SVM+NN	Yes	PSO	Synthetic (noiseless)	Online 99.38 Offline 99.68
21	Hooshmand and Enshaee [249]	FT+WT	Fuzzy	No	PSO	Synthetic (Noisy)	96.00
22	Lee and Shen [314]	ST+TT	MLP	Yes	PNN based FS	Synthetic (Noisy, Noiseless)	Noisy 97.20 Noiseless 98.10
23	Abdoos et al. [315]	VMD*+ST	SVM	Yes	Wrapper based methods	Synthetic (Noisy, Noiseless)	Noisy 98.11 Noiseless 99.66
24	Abdoos et al. [316]	ST+WT	PNN	Yes	No	Synthetic (Noisy, Noiseless)	Noisy 97.44 Noiseless 99.22

*Frequency sensitive competitive learning (FSCL); Variational mode decomposition (VMD) extraction technique is good for analysis of stationary or non-stationary signals.

- Section 6 indicates importance of feature selection methods. This shows that the signal processing techniques and AI classification methods give better classification accuracy with the selected features.
- Artificial intelligence based classifiers are presented in section 7. Their respective pros and cons are listed in Table 6, which will helps in selection of classifier.
- Section 8 covers the optimization techniques and their comparison in Table 7. Optimization techniques are used for feature selection as well as parameter tuning of the classifiers. This results in improved performance and execution time.
- In some earlier reported articles, single events are focused whereas recent researches are done on the multiple events rather than single events.
- In power system we are dealing with three phase system but their is very less work has been carried out on three phase systems.
- Hybrid methods for the feature extraction and classification give comparatively better results than individual techniques.
- The results claimed by researchers are based on selected PQ events and the classification performance is significantly high.
- The classification performance also depends on type of signal i.e., Synthetic or Real. Classification rate is generally high in case of synthetic signals compared to real signals.
- Presence of noise affect classification performance. If signal to noise ratio is less then efficiency also be lesser.
- Many algorithms are formulated by various authors to attain fast response and to get rid of noise effects.
- Most of the research is based on simulation studies, a very few researchers used hardware framework.

X. CONCLUSION AND FUTURE SCOPE

The paper presents comprehensive and critical review of the techniques used in PQ analysis. This survey paper facilitates the researchers to select the appropriate method to carry forward the research work in the concerned area. Smart grid evolution and distributed generation further increase its relevance. The applications based on Iot and the 5G network support brings a revolution in smart grid domain. An incisive critic is provided for the PQ event detection techniques. Researchers characterize the different PQ events by feature extraction from various techniques followed by the feature selection and then classification. Here it can be concluded that numerous feature extraction or signal processing methods, namely Fourier transform, S-transform, Hilbert-Huang transform and wavelet transform are discussed in detail. To analyze the various disturbances through the extracted features, the classifiers play an important role. Thus, various classification/artificial intelligence techniques such as neural networks, fuzzy logic, support vector machines and neuro-fuzzy are investigated. Also, the effect of noise and optimization on the classification performance is investigated. Various research works, that incorporate algorithms for PQ analysis using PQ indices have been listed in tabular form (Table 8). The advantages and limitations of different types of approaches are compared in tabular form for easy understanding of the reader. So this paper will helps in for adopting of particular method for special type of application. In this manuscript, more than 300 papers are critically reviewed but there is no such technique in literature which is equally applicable to each type of PQ disturbance.

On the basis of critical review of power quality detection and classification techniques presented in literature, some remarks that may be helpful in future research are:

- The challenge in PQ analysis is to focus on characterization of PQ disturbances by means of PQ Indices.
- In literature, a plenty of work has been carried out on offline mode and synthetic data. The online detection and classification approach with real applications are still required.
- The researches still lacks in proposing efficient methodologies that are robust to noise.
- Techniques required for high classification performance in case of single and multiple events.
- To develop one method that gives the high classification performance when the different sets of PQ events are given as input. There is also need to perform these studies on the basis of three phase systems.
- Computational cost and the complexity of the techniques play an important role specially in online applications, so fast algorithms are required.
- Further, there is a need to explore advance hardware, that is fast enough and compatible with real-time classification.
- Issues and challenges with technological change and security issues in IoT, 5G technology and smart grids.

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