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Review

Power Quality Disturbances Characterization Using Signal Processing and Pattern Recognition Techniques: A Comprehensive Review

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Abstract: Several factors affect existing electric power systems and negatively impact power quality (PQ): the high penetration of renewable and distributed sources that are based on power converters with or without energy storage, non-linear and unbalanced loads, and the deployment of electric vehicles. In addition, the power grid needs more improvement in the performances of real-time PQ monitoring, fault diagnosis, information technology, and advanced control and communication techniques. To overcome these challenges, it is imperative to re-evaluate power quality and requirements to build a smart, self-healing power grid. This will enable early detection of power system disturbances, maximize productivity, and minimize power system downtime. This paper provides an overview of the state-of-the-art signal processing- (SP) and pattern recognition-based power quality disturbances (PQDs) characterization techniques for monitoring purposes.

Keywords: smart grid; power quality monitoring; disturbances characterization; detection; estimation; classification; signal processing methods; pattern recognition methods; information theoretical criteria; phasor measurement unit (PMU)

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1. Introduction

Nowadays, renewable energy sources (RES) are extensively integrated into the power grid in order to meet the energy demand and green energy motive. The high penetration level of renewable energies requires the use of operation and management strategies to maintain and enhance the reliability, efficiency, and safety of the power grid. The power electronic converters are becoming widely used and expanded in this news power grid structure [1,2]. In fact, the power quality (PQ) is significantly impacted by the increased level of RE penetration [3]. Power quality can be defined as the interaction between consumers and the electric grid [4,5]. The first type of PQ is voltage quality, which is presented by a deviation of voltage from its nominal value due to the effect of the power grid on the end-consumers or equipment. The second type of PQ is the current quality which is presented by a deviation of current from its nominal value [1]. Voltage disturbance caused by a producer could have a negative effect on end-user equipment [6,7]. A fault may damage the electric grid and equipment [8,9]. To resume, voltage quality can be explained by the impact of the electric grid on equipment, while current quality is the impact of equipment on the grid. This does not allow us to maintain effectively the balance between consumption and production [10] and could have a negative affect on frequency and voltage [11,12]. In real electric grids, voltage parameters are deviating from the nominal voltages, which correspond to PQ disturbances (PQDs) [8,13]. The deviation is a stationary PQD that is presented by a small deviation (A large or small deviation is reported by IEEE 1159, IEC 61000-4-30 and EN 50160 standards [14–16]) from its nominal value. For example, the frequency and voltage variations are classified as variations. The event can be presented by a high augmentation or diminution in the voltage amplitude compared to its nominal value. The most known events are outage, interruption, sag and swell [17,18]. Within the progressing discussion, the PQDs may cause a huge financial loss and they can degrade system reliability and negatively influence the PQ. To address these challenges, it is important to develop advanced algorithms for PQD characterization that allow for improving the reliability and efficiency of the electric grid according to international standards. Therefore, PQD characterization has become a major issue in PQ monitoring. In this scope, the phasor measurement unit (PMU) becomes an advanced measurement technology used in the electric system and it can be a piece of essential equipment for the state estimation of the power grid. In addition, PMU can validate the performance and the settings of equipment [19]. Standard C37.118.2011 [20] (and its amendment [21]) provides the following criteria: rate of change of frequency (ROCOF), frequency error (FE) and total vector error (TVE). These criteria allow evaluation of the performances of the extraction, selection and detection techniques under stationary and non-stationary conditions associated with RES integration, noise and non-linear loads. Hence, several publications have proposed the use of signal processing (SP) and artificial intelligence (AI) techniques for extracting, selecting and classifying the voltage. Indeed, the techniques-based on SP techniques are widely used to extract and detect the signal's features. For PQDs classification, most used algorithms are based on AI methods. In the last few years, there are few reviews that address various aspects of PQ assessment [22–29]. The paper published in [23], presents a review of soft computing and signal processing techniques for PQ disturbances detection and classification. These papers includes also the issues related to micro-grid applications-based on the distributed generation that uses power electronic technology (PET). This PET leads to an increase the power quality issues. A comprehensive and critical review of PQDs detection and classification for power grid-based RES application is presented in [24]. This paper provided also general software and hardware-based plate-forms for PQ monitoring with renewable energy integration. The paper in [25], provides a review of SP and machine learning techniques for PQDs detection and classification. A review of techniques based on machine learning methods with a focus on control and decision-making performances is proposed in [26]. A critical review of techniques-based on SP, optimization and AI for PQD detection and classification is provided in [27]. This review focuses on PQ issues related to renewable energy in the smart grid context. It gives also attention to the research with experimental and real-time studies. The review provided in [28], presents an overview of the techniques used for PQDs location and cause identification. Ref. [29] provides a thorough overview of the signal processing and soft computing approaches that are used to detect and identify the root causes of PQD. However, there are currently more faster and reliable techniques for PQDs extraction, selection and classification. In this context, the main objective of this paper is to provide an up-to-date and well-organized review of PQDs extraction, selection and classification. These papers presents also the power quality definition, standards, causes and types of disturbances. A discussion is provided of the PMU's requirements and estimation evaluation criteria that are defined by international standards. Moreover, this manuscript gives an overview of the existing SP techniques that are used for extracting, selecting and classifying the disturbance's signal. Regarding the stage of feature extraction, the objective is to estimate the voltage's parameters which are amplitudes and initial phases (phasors) and frequency. For PQ monitoring, frequency is considered as the parameter to control the grid state. In addition, the frequency must be estimated once in order to estimate the phasors. Concerning frequency and phasor estimation, several methods are proposed in the literature that can be classified as non-parametric and parametric. Regarding feature selection, several optimization methods have been published for optimum feature selection [30–32]. For the feature classification stage, the extracted features are used as inputs for the stage techniques. The classification stage provides as output the type or cause of PQD. In the literature, several classical and based-pattern recognition techniques for feature classification have been proposed. For classical techniques, two principal features, which are amplitude or residual voltage and duration, are used to determine the PQD type. Moreover, this paper is interested in PQ issues that need the use of advanced SP, optimization and pattern recognition techniques [3,5,33] and use the advanced techniques of PQD characterization to improve the reliability and efficiency of the electric grids. To this purpose, suitable feature extraction, selection and classification methods become of great importance to developing efficient and reliable algorithms for PQDs characterization. The paper's contributions can be presented as follows:

- Comprehensive review of PQDs and their causes and consequences is presented. A review is also provided of PQ measurement (PMU) and summarizes its main points. The requirements of PMU standards for balanced and unbalanced systems are defined.
- Critical and comprehensive review is presented for PQ disturbances characterization with a focus on extraction, selection and classification techniques.
- A state-of-the-art of feature selection (FS) technique that is based on the optimization algorithms features classification applications is provided.
- In-depth and critical analysis of signal processing, optimization algorithms and pattern recognition techniques are done.
- A discussion on the application of parametric and non-parametric methods is performed.
- A critical analysis and future research of relevant issues that are related to the PQ disturbances characterization is performed.

The organization of the paper is presented as:

- Section 2 presents the PQDs and their origins and consequences. Then the international standard for PQ characterization is provided. In addition, PQ measurement (PMU) is presented.
- Section 3 deals with feature extraction techniques used for frequency and phasor estimation.
- Section 4 is concerned with the problem of feature selection or parameter optimization for classification purposes.
- Section 5 describes power quality disturbances classification with a focus on classical and pattern recognition techniques.
- Sections 6–8 provide comparative analysis, future research, challenges and conclusion.

2. PQ Disturbances Monitoring

PQ issues have received more attention from scientists and engineers. In fact, PQ can have a negative effect on an electric system by impacting its operation conditions, efficiency, and measurements performances [1,11,34,35]. In the following, more reasons that explain the increased interest in PQ issues are presented [9]:

- Sensors: PQD impacts negatively the performance of measurement devices.
- Protective relays: they can lead to mal-function due to PQDs.
- Equipment's lifetime: it can be reduced and equipment can be damaged because of these disturbances.
- Electromagnetic compatibility: PQDs are one of the most important sources of electromagnetic noise [36].

In this paper, the PQ issues that require SP techniques [17,33] and drive the use of advanced algorithms for PQDs characterization are presented. The characterization of the PQDs characterization is considered one of the important PQ monitoring issues. The main steps of PQ characterization are presented in Figure 1, and can be decomposed as follows [17].

- Feature extraction stage: this refers to the voltage estimation (i.e., phasor and frequency) from the acquisition signals that are noise corrupted.
- Feature selection stage.

- Feature detection stage: this presents triggering, i.e., determining the time-points when the event is starting and ending.
- Feature classification stage: this permits the identification of the type of disturbance.

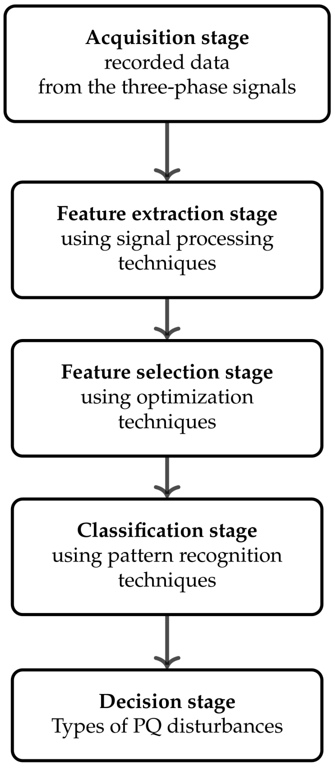

Figure 1. Diagram of main stages characterizing power quality.

2.1. Disturbances

The electric system consists of 3 phases that have a mutual coupling. A balanced power grid has three sinusoidal signals with the same RMS amplitude and same frequency (f) (f = 50 Hz or f = 60 Hz). Moreover, the phase shift between phases = 120° [37,38]. In the case where one of these conditions is not respected, the power grid is unbalanced [13,39]. As mentioned previously, any significant deviation in current or voltage signals from their nominal values is considered as PQDs [17,18]. Table 1 provides the common PQ disturbances, with their causes and consequences.

Table 1. Main disturbances with their causes and impacts [40]. Energies, 2020.

Disturbance	Causes	Impacts
Swell	system fault conditions (such as single line-to-ground (SLG) fault), switching off large loads, capacitor banks	Electronic component's breakdown and damage or other sensitive equipment, insulation failure (induction machine), flicker.
Sag	switching of large loads (such as arc furnaces, motors, etc.), disconnecting capacitors, Lightning.	Flicker, decreasing AC motor speed, switching off of control systems.
Over-voltage	capacitor banks, lighting, resonances, fault condition and circuit breaker opening	damage of equipment and circuit breaker, flicker.

Table 1. *Cont.*

Disturbance	Causes	Impacts
Under-voltage	Low factor of power, overloaded network and transformers, switching off of a large electric generation.	Electromechanical equipment's life reduction, premature failure.
Harmonics	Electronic power converter, non-linear loads, generators and transformers, arc furnaces.	Malfunction of relays and sensitive equipment, degrade of the machine performances, capacitors failures, electromagnetic interference in communication circuits.
Interruptions	Human errors, faults, failures of control-command system, natural causes (high winds, ice on the lines, etc.)	Loss of power, equipment failures, shutdown of computer and sensitive equipment.
Frequency variation	electric generation loss, an un-synchronous between the power system and generator, overloaded of electric system.	Degrade engine performance, inefficient of motors, power failure.
Voltage fluctuation	Electric arc furnaces, start-up of drives, resistance welders, inter-harmonics components in current signal.	Voltages and currents instability of the electronic equipment, flicker.
Flicker	Switching of large load, capacitor banks, electric arc furnace, frequent start-up of AC motors.	Flicker.

2.1.1. Disturbance Variations

1. Frequency and voltage variations:
   As mentioned previously, the real-time frequency value has always a small deviation of ± 1 Hz [16], from the nominal value which is 50 Hz or 60 Hz. Figure 2 presents the measured frequency for several countries. These frequency variations can lead to a variation in motor speed and less power generation in production units.

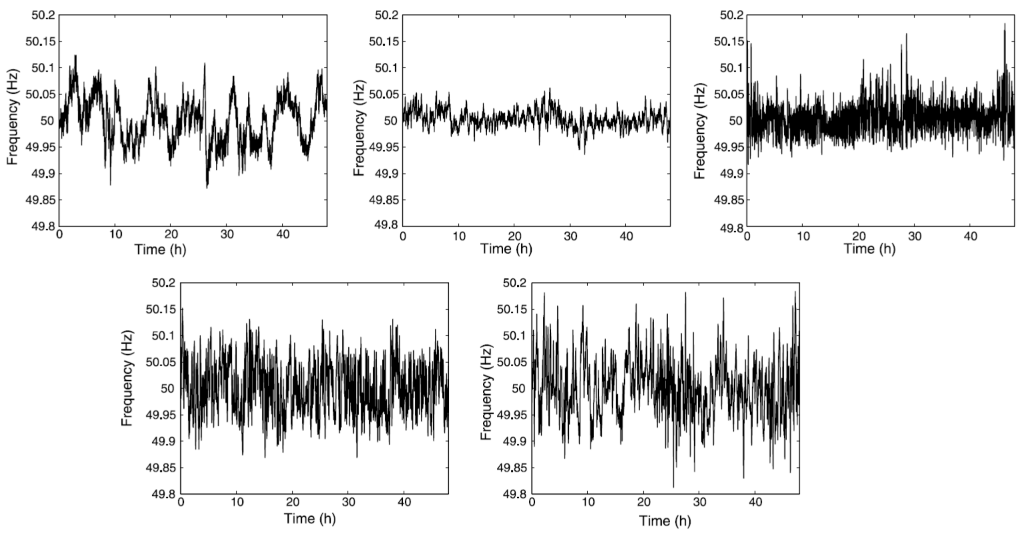

Figure 2. Examples of the variation of frequency in several countries, such as Great Britain (**bottom right**), Singapore (**bottom left**), Chinese east coast (**top right**), Sweden (**top left**) and Spain (**top center**) [8]. IEEE Press, 2006.

The voltage variation is caused by the variation of the end-user loads and distributed generation [13]. These can affect the performance of equipment. They can also cause overheating and reduce the starting torque of electrical motors (induction motors) [6]. For example, over-voltage is a voltage value that arrives at 110–120% of the nominal value over several periods (one minute). An over-voltage is illustrated by Figure 3.

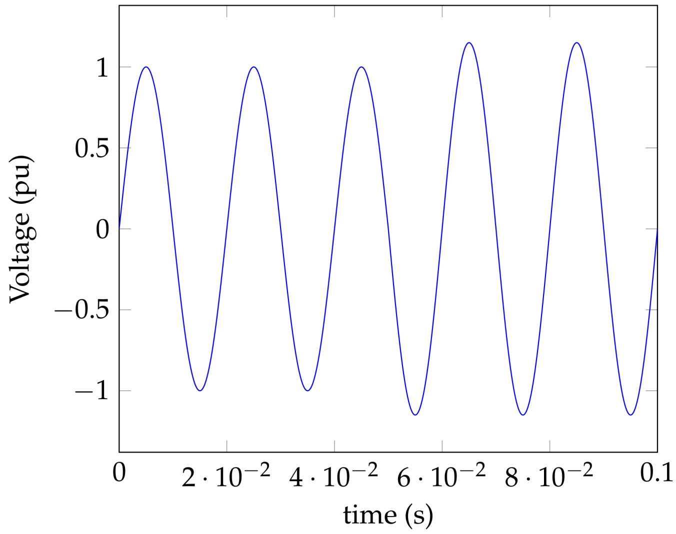

Figure 3. Over-voltage.

2. Harmonic, inter-harmonic, and non-periodic distortions:
   These distortions are a deformation of the current or voltage wave-form from its nominal one. These disturbances can lead to over-heating of power electronic equipment, etc. [41–43]. The harmonics components are more considered by engineers and researchers since they are more dominant in the electric grid than others disturbances [44]. Total harmonic distortion (THD) is a criterion that is used to analyze the number of harmonic components in the signal. THD is defined by the international standard IEC 61000-4-7 [45] as:

$$THD_F(\%) = 100\,\alpha\, \frac{\sqrt[2]{\sum_{h=2}^{\infty} a_{mh}^2}}{a_m}, \tag{1}$$

   where a_m refers to fundamental frequency and a_{mh} corresponds to the amplitude of the hth harmonic component. The parameter $\alpha > 0$ allows controlling THD.

2.1.2. Events

PQ events are represented by large deviations in voltage values from normal ones. The most recurrent events are sags, swells and interruptions [8]. Interruption is defined as a voltage or current with an amplitude that is less than 10% of the nominal voltage [14–16]. These interruptions can be caused by multi-phase disconnection at the power grid, like short-circuits. Figure 4 illustrates an interruption caused by lightning, using recorded data provided by the DOE/EPRI [46].

Voltage sag (Voltage sag is more used in US publications, while the dip is used by the IEC) is one of the severe PQ issues and it is a small diminution of the amplitude that is between 0.1 and 0.9 pu of the nominal voltage over a few periods ($\frac{1}{2}$ period and one minute [14]. Sags can lead to a decrease in the performance of end-user equipment. It is characterized, by the standard IEC 61000-4-30, by its duration and amplitude. Others parameters like phase angle jump and three-phase characteristics are introduced in order to provide more information about sag behavior. Figure 5 presents a sag caused by a two-phases fault for event-code-0284 provided in [46].

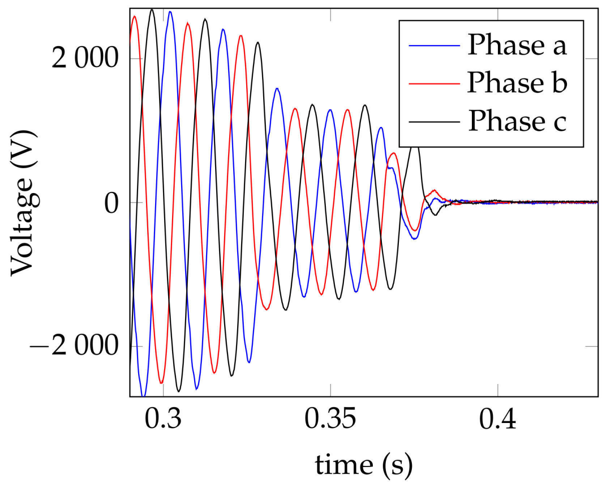

Figure 4. Interruption due to lightning (Event 2857) [46]. DOE EPRI, 2022.

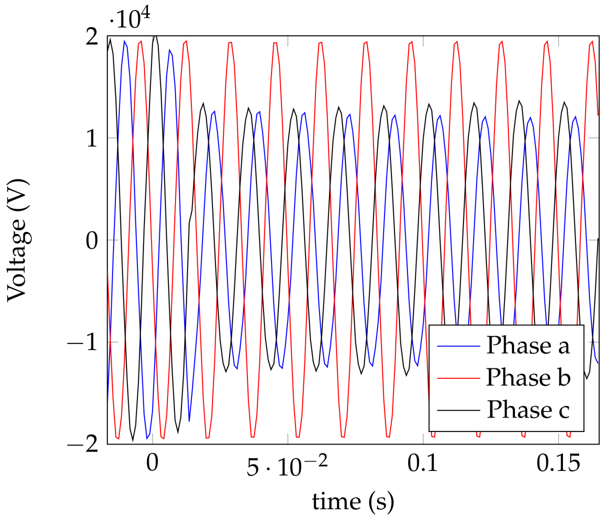

Figure 5. Voltage sag (Event 0284) [46]. DOE EPRI, 2022.

Swell is by definition an augmentation in the amplitude in the interval that is $[1.1, 1.8]$ of the nominal value.

2.2. Monitoring

The smart grid should address the limitations of the existing one by using PQ monitoring, advanced measurement devices, and self-healing, pervasive system anomalies [1,34,47–50]. Moreover, SG is expected to enhance reliability, efficiency and security through communication technologies and advanced control technologies [12,51–55]. In this scope, PQ monitoring has become the backbone of control strategies that are used in SG applications. In Figure 6, a control strategy (CS) used in SG applications and that uses PMUs is presented. This CS allows for achieving four tasks that are: PMU devices allow extraction of the signals at sub-stations, such as phasors and frequency. Intelligent electronic devices (IEDs) provide data and allow to control and monitor the electric grid for protecting the end-user equipment. The most used IEDs are digital and modern protective relays, infrastructure and energy management systems (EMS) and PMUs. The supervisory control and data acquisition (SCADA) monitors the grid and it is located at the control center.

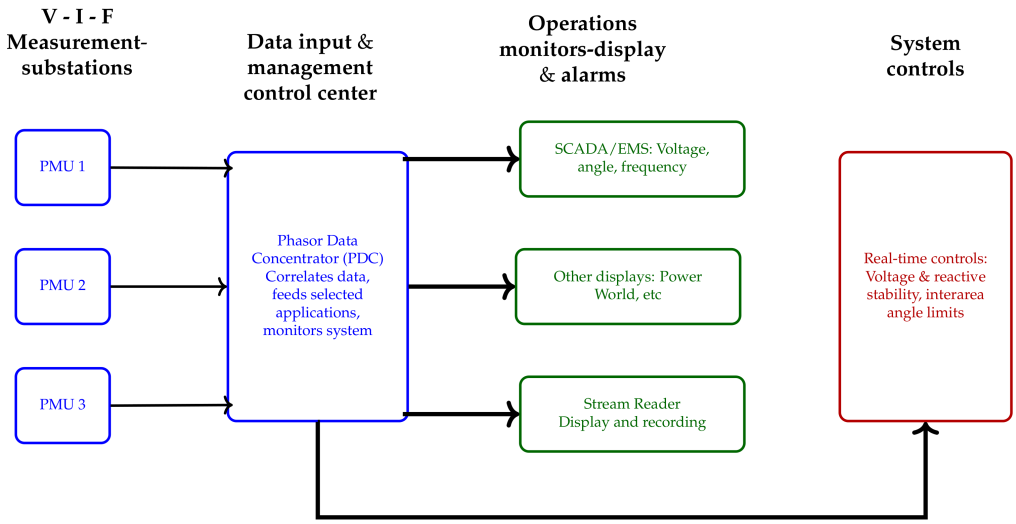

Figure 6. A control strategy based on PMUs applied in electric grid applications.

Figure 7 presents a PQ monitoring system, which allows performing several PQ monitoring tasks.

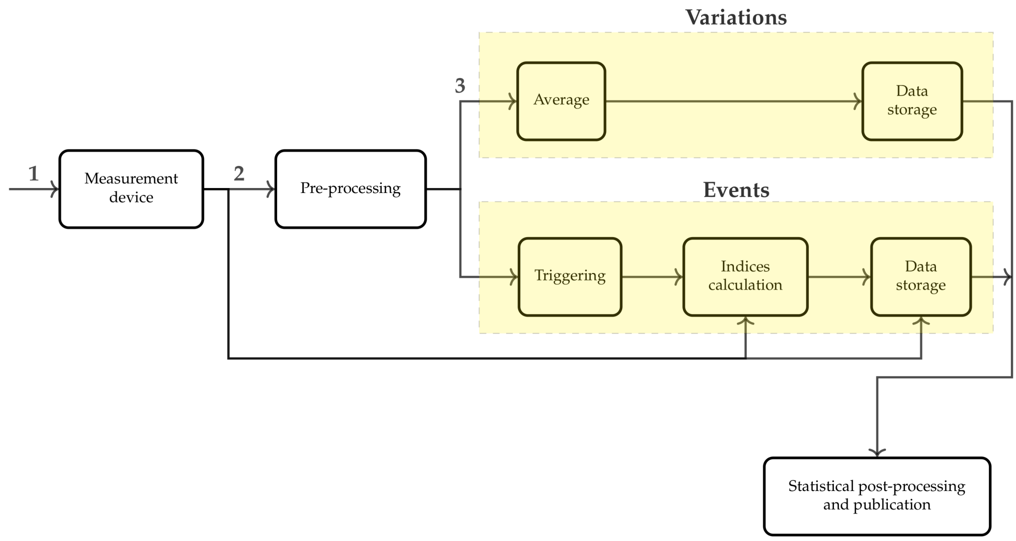

Figure 7. Diagram of a device for PQ measurements with the following blocks: (1) voltage or current input, (2) digitized and sampled voltage or current, (3) others processing.

In Figure 8, an RMS threshold and duration of triggering are given. The vertical axis shows the reference voltage in the percentage of the threshold and the reference is the normal value. The horizontal axis refers to the duration that begins at the time-point when the voltage reaches the threshold. These thresholds are defined in several international standards for characterizing voltage disturbances, such as the IEEE 1159, IEC 61000-4-30, and EN 50160 [14–16].

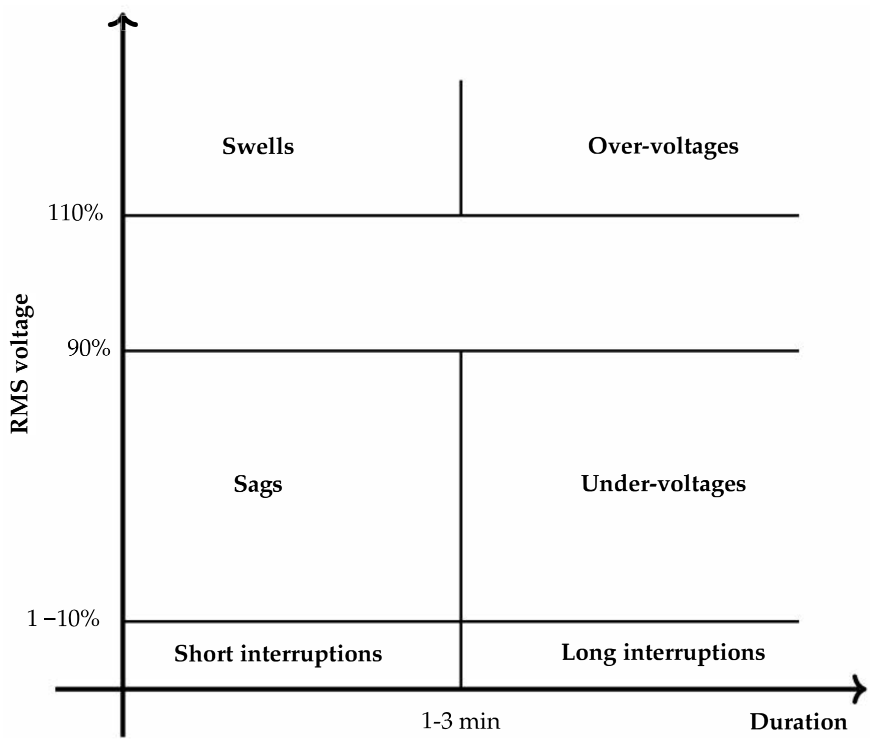

Figure 8. Threshold used for event detection with RMS values triggering.

2.3. Standards

International standards (IS) allow elaborating and defining requirements of PQ in order to satisfy the end-user consumer and to protect the electric grid. IS defines the limits and tolerance variations for different signal parameters, like frequency and voltage. The most known organization for elaborating IS are the Institute of Electrical and Electronics Engineers (IEEE) and the International Electrotechnical Commission (IEC), where EMC describes a description about the equipment and device abilities with its electromagnetic environment [56]. For instance, the international standard IEEE 519 provides the requirements for harmonic components [57]. EN 50160 and IEEE 1159 standards provide a PQDs classification according to duration and RMS thresholds that are shown in Tables 2 and 3. The IEC 61000-4-30 [15] describes the measurement methods of the signal's parameters.

Table 2. classification of PQ disturbances.

PQ Disturbance	Duration	Voltage Values
Sag	>0.5 cycles	0.1 to 0.9 pu
Swell	>0.5 cycles	1.1 to 1.8 pu
Outage	>0.5 cycles	<0.1 pu
Flicker	>0.5 cycles	0.9 to 1.1 pu
Harmonic	-	$THD < 5\%$
Inter-harmonic	-	$THD < 5\%$

Table 3. Definitions of interruption reported in international standards.

Standard	Term	Definition
IEEE 1159	Interruption	Voltage below 10% of nominal
	Sustained interruption	Longer than 3 s
	Momentary interruption	$\frac{1}{2}$ cycle to 3 min
	Temporary interruption	3 s to 1 min

Table 3. *Cont.*

Standard	Term	Definition
IEEE 1250	Instantaneous interruption	Shorter than 30 cycles
	Momentary interruption	$\frac{1}{2}$ to 2 s
	Temporary interruption	2 s to 2 min
	Sustained interruption	longer than 2 min
EN 50160	Short interruption	Shorter than 3 min
	Long interruption	Longer than 3 min
IEEE 1366	Momentary interruption	Shorter than 5 min
	Sustained interruption	Longer than 5 min

2.4. Phasor Measurement Units (PMUs)

Herein, we provide a PQ measurement that is PMU with a presentation of its main points. Then, a discussion is provided about the PMU's requirements that are defined by international standards.

2.4.1. Definition

PMU is an advanced measurement device and is part of PQ monitoring, especially for real-time state estimation. PMU allows for validation of the performance and to control of the settings of end-user equipment [19]. In addition, it can be stand-alone inside another monitoring system, like a protective relay [58]. PMUs allow for providing real-time parameters with respect to global time references, such as frequency, rate of change of frequency (ROCOF), positive sequence and synchro-phasor. A global position system (GPS) is used for generating the time-tags to the PMU device [19]. Figure 9 shows a synchro-phasor system of a sinusoidal signal. The phasor reference is represented by a time-tag ($t = 0$) and it is composed of RMS value (amplitude) and phase angle φ. In the case, where all PMUs are using the same time basis, their estimated parameters can be compared. This presents the main advantage of PMUs over other measurements [20,59].

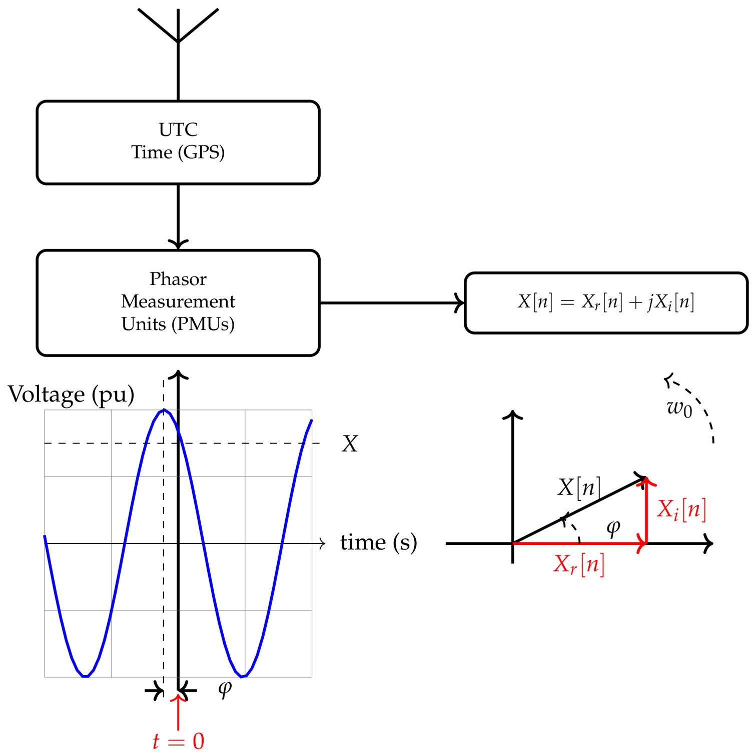

Figure 9. Synchro-phasor representation of a sinusoidal signal.

2.4.2. Standards

In this section, a description of the PMU standard, which is C37.118, is performed. The PMU standard imposes the phasor, frequency, and ROCOF requirements under stationary and non-stationary conditions. It provides the requirements of synchronization and time-tag for the electric grid with an evaluation specification method [20,60,61]. The PMUs standard is enhanced into C37.118 [20,21] to use dynamic synchronized measurement. IEEE standard C37.118 [20,21] provides the following criteria: ROCOF, frequency error (FE) and total vector error (TVE). These criteria allow for evaluating the performances of the phasor and frequency estimates under stationary and non-stationary conditions. C37.118 defines also two classes that are M-class and P-class, the first class requires the highest estimation performances while the second one requires low computation complexity. Under non-stationary conditions, the estimation algorithm must achieve a frequency less or equal to ±5 mHz from the nominal value. Figure 10 illustrates a frequency concept under non-stationary conditions. The signal has a sinusoidal form and is observed over several periods $[0, T_0, 2T_0, \ldots, NT_0]$. $T_0 = \frac{1}{f_0}$ presents the fundamental period, f_0 refers to the fundamental frequency, and $[0, X_0, 2X_0, \ldots, NX_0]$ are the phasors representation. It should be mentioned that the synchrophasor can be variable in terms of time, therefore the PMU device shall provide a real-time estimation over a short time. Figure 11 presents a PMU process that is inspired by the international standard PMU IEEE for power grid applications [20].

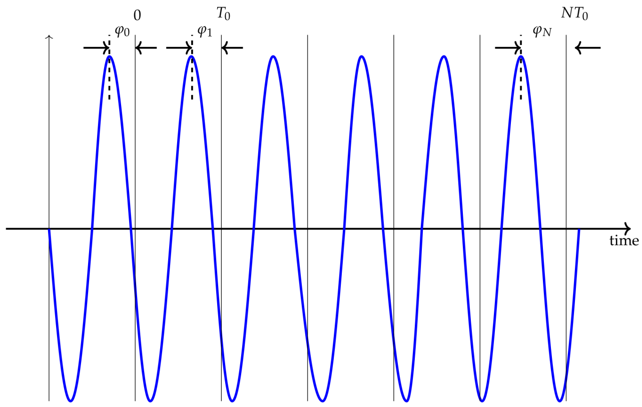

Figure 10. Phase angle change under off-nominal frequency conditions.

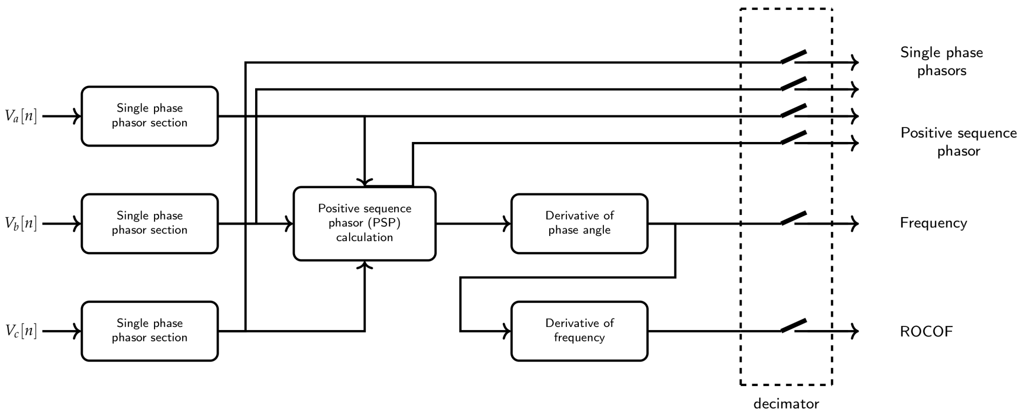

Figure 11. Complete PMU signal processing model [20]. IEEE standard C37.118.1, 2011.

2.4.3. Estimation Evaluation's Criteria

PMU must estimate the signal's parameters with the highest performance under stationary or non-stationary conditions. There are three evaluation criteria that are defined by this standard, which are FE, TVE and ROCOF.

1. Frequency and ROCOF measurement evaluation:
The voltage or current of the three-phase power grid can be expressed by the following model:

$$X_m(t) = a_m \cos(\phi_m(t)), \tag{2}$$

where $m \in \{a, b, c\}$ refers to the phase index, a_m corresponds to the maximum amplitude and $\phi(t)$ is instantaneous phase angle. The frequency expression is given by

$$f(t) = \frac{1}{2\pi}\frac{d\phi(t)}{dt}, \tag{3}$$

and the ROCOF is expressed by

$$ROCOF(t) = \frac{df(t)}{dt}. \tag{4}$$

Both FE and ROCOF error (RFE) are provided by the standard C37.118 for evaluating the estimation performance of the frequency estimator.
The FE is defined as

$$FE(t) = \left| f_0(t) - \widehat{f_0}(t) \right|, \tag{5}$$

and the RFE is expressed as

$$RFE(t) = \left| \frac{df_0(t)}{dt} - \frac{d\widehat{f_0}(t)}{dt} \right|, \tag{6}$$

where f_0 and $\widehat{f_0}$ correspond to the real and estimated frequency.
PMUs must yield high estimation performance in order to meet the requirements specified by the PMU standard. These performances shall meet the requirements of the C37.118 under stationary and non-stationary conditions and for P- and/or M-classes. Table 4 presents the FE and RFE requirements for both classes and under stationary conditions. Under non-stationary conditions, a condition test is also presented that determines the band-width of the synchro-phasor device. In this test, phase modulation and sinusoidal amplitude are used. The model of signals is given by

$$\begin{aligned} X_m(t) &= a_m[1 + k_x cos(wt)] \\ &\times cos[w_0 t + k_a cos(wt - \pi)], \end{aligned}$$

where a_m refers to the input signal amplitude, w_0 and w are, respectively, the nominal and the modulation angular frequencies in $\frac{rad}{s}$. $f_m = \frac{w}{2\pi}$ corresponds to the modulation frequency in Hz, $m \in \{a, b, c\}$ presents the phase index. K_x and K_a correspond, respectively, to the magnitude and the modulation of phase angle. This test must be realized with w, k_x, and k_a over the range of frequency given in Table 5 [21].

Table 4. Steady-state frequency and ROCOF measurement requirements.

Influence Quantity	Reference Condition	Error Requirements for Compliance			
		P-Class		M-Class	
Signal frequency	Frequency $= f_0$ ($f_{nominal}$) Phase angle constant	Range: $f_0 \pm 2.0$		Range: $f_0 \pm 2.0$ Hz for $F_s \leq 10$ $\pm\frac{F_s}{5}$ for $10 \leq F_s < 25$ ± 5.0 Hz for $F_s \geq 25$	
		Max FE	Max RFE	Max FE	Max RFE
		0.005 Hz	0.01 $\frac{Hz}{s}$	0.005 Hz	0.01 $\frac{Hz}{s}$

Table 4. *Cont.*

Influence Quantity	Reference Condition	Error Requirements for Compliance			
		P-Class		M-Class	
Harmonic distortion (same as Table 3 in C37.118-2011) (single harmonic)	<0.2 % THD	1% each harmonic up to 50^{th}		10% each harmonic up to 50^{th}	
		Max Fe	Max RFE	Max Fe	Max RFE
	$F_s > 20$	0.005 Hz	0.01 $\frac{\text{Hz}}{\text{s}}$	0.025 Hz	0.01 $\frac{\text{Hz}}{\text{s}}$
	$F_s \leq 20$	0.005 Hz	0.01 $\frac{\text{Hz}}{\text{s}}$	0.025 Hz	0.01 $\frac{\text{Hz}}{\text{s}}$

Table 5. Frequency and ROCOF performance requirements under modulation tests.

Modulation Level, Reference Condition, Range (Use the Same Modulation Levels and Ranges under the Reference Conditions Specified in Table 5 in C37.118-2011 Standard)	Error Requirements for Compliance			
	P-Class		M-Class	
	Max FE	Max RFE	Max FE	Max RFE
$F_s > 20$	0.06 Hz	3 $\frac{\text{Hz}}{\text{s}}$	0.3 Hz	30 $\frac{\text{Hz}}{\text{s}}$
$F_s \leq 20$	0.01 Hz	0.2 $\frac{\text{Hz}}{\text{s}}$	0.06 Hz	2 $\frac{\text{Hz}}{\text{s}}$

2. Total vector error evaluation:
The C37.118 standard allows for simplifying the compliance specification by combining the angle phase and amplitude in one evaluation criterion which is TVE, which allows for evaluating the estimation performance of the phasor. TVE is then the difference between the real value and the estimated one of the phasor. Let supposing the following synchrophasor representation $\bar{X} = X_r + jX_i$, the TVE criterion is expressed then as

$$TVE[n] = \sqrt[2]{\left(\frac{\left(\widehat{X}_r[n]-X_r[n]\right)^2+\left(\widehat{X}_i[n]-X_i[n]\right)^2}{X_r^2[n]+X_i^2[n]} \right)}, \tag{7}$$

where $X_r[n]$ and $X_i[n]$ present, respectively, at the instant n, the real and imaginary values of the fundamental phasor. $\widehat{X}_r[n]$ and $\widehat{X}_i[n]$ refer, respectively, at the instant n, to the real and imaginary estimated values of phasor. Both real and estimated values of the phasor are measured at the same time-point. The PMU standard requires that the TVE does not exceed 1%. Figure 12 presents a circle with a radius of 1% which is the allowed error. This concept is inspired by the international standard IEEE C37.118. The signal's parameters are considered to be constant under stationary conditions. However, under non-stationary conditions, these parameters can be time-varying. In this case, it is imperative to use a model of signal that takes into consideration the parameter changes.
Tables 6 shows the requirements of synchrophasor for P- and M-classes under stationary conditions. The modulation tests, under non-stationary conditions, require the TVE requirements given in Table 7.

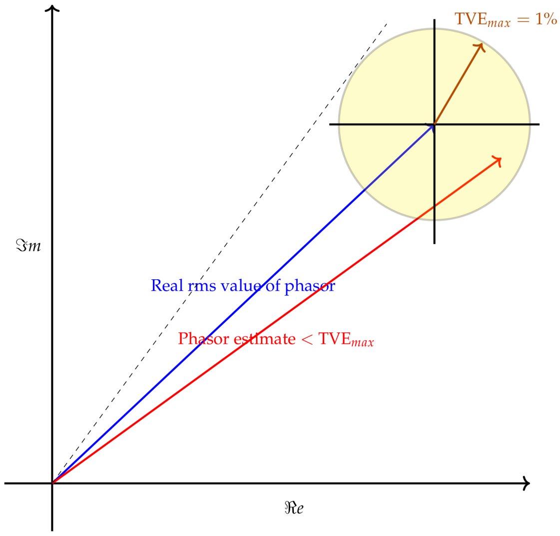

Figure 12. Estimation performance required by PMU standard [21]. IEEE standard C37.118.1a, 2014.

Table 6. Steady-state synchrophasor measurement requirements.

Influence Quantity	**Reference Condition**	**Minimum Range of Influence Quantity over Which PMU Shall Be within Given TVE Limit**			
		P-Class		**M-Class**	
		Range	**Max TVE %**	**Range**	**Max TVE %**
Signal frequency range-f_{dev} (test applied nominal +deviation: $f_0 \pm f_{dev}$)	$F_{nominal}$ (f_0)	$\pm$2.0 Hz	1	$\pm$2.0 Hz for $F_s < 10$ $\pm\frac{F_s}{5}$ for $10 \leq F_s < 25$ $\pm$5.0 Hz for $F_s > 25$	1
The above signal frequency range tests are to be performed over the given ranges and meet the given requirements at three temperatures: T = nominal (23 °C), T = 0 °C, and T = 50 °C					
Signal voltage magnitude	100% rated	80% to 120% rated	1	10% to 120% rated	1
Signal current magnitude	100% rated	10% to 200% rated	1	10% to 200% rated	1
Phase angle with $\lvert f_{in} - f_0 \rvert < 0.25$ Hz	Constant or slowly varying angle	$\pm\pi$	1	$\pm\pi$	1

Table 7. Synchrophasor measurement bandwidth requirements using modulated test signals.

Influence Quantity	**Reference Condition**	**Minimum Range of Influence Quantity over Which PMU Shall Be within Given TVE Limit**			
		P Class		**M Class**	
		Range	**Max TVE (%)**	**Range**	**Max TVE (%)**
$k_x = 0.1$, $k_a = 0.1$	100% rated signal magnitude, $f_{nominal}$	Modulation frequency 0.1 to losser of $\frac{F_s}{10}$ or 2 Hz	3	Modulation frequency 0.1 to losser of $\frac{F_s}{5}$ or 5 Hz	3
$k_x = 0.1$, $k_a = 0$	100% rated signal magnitude, $f_{nominal}$		3		3

The following section presents a review of existing feature extraction techniques for PQ monitoring.

3. Feature Extraction-Spectral Estimation Techniques for Power Quality Monitoring

The studied techniques allow a spectral analysis of the signal and can be classified into parametric and non-parametric methods, where parametric methods are based on a signal model. Moreover, an extension to non-stationary conditions is provided. The analysis of these methods is performed under stationary and non-stationary conditions.

3.1. Non-Parametric Methods

The analysis of these methods can be performed with no assumption about the voltage or current signal.

3.1.1. Zero-Crossing Transform

A simple frequency estimator is proposed by IEC 61000-4-30 standard that is based on the zero-crossing method. This estimator performs a calculation of the time required for the signal shape to change from a positive to a negative value, as shown in Figure 13.

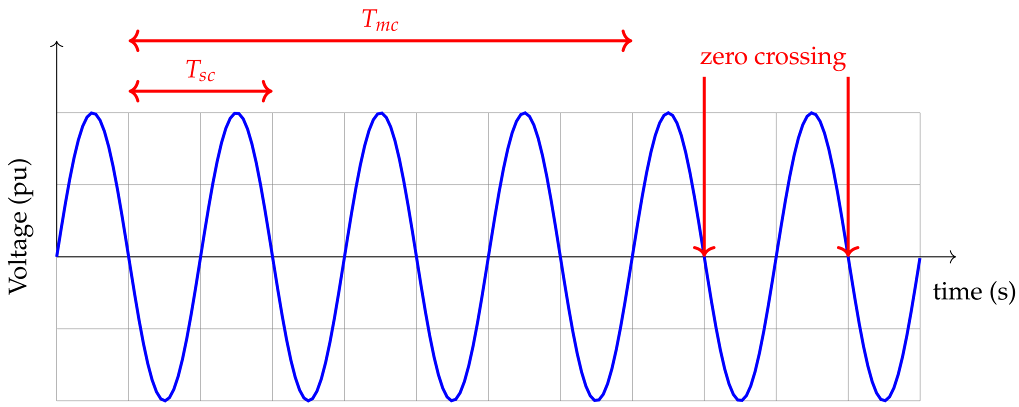

Figure 13. Zero-crossing approach illustration.

The first step is to compute the duration, in the same direction, between two zero-crossings. From Figure 13, the frequency is expressed by

$$\hat{f}_0 = \frac{1}{T_{sc}}, \tag{8}$$

where T_{sc} presents the duration of 2 consecutive zero-crossings. In the case of N_{zc} zero crossings, the frequency can be estimated by

$$\hat{f}_0 = \frac{N_{zc}}{T_{mc}}, \tag{9}$$

where T_{mc} presents the duration of N_{zc} zero crossing. However, this approach achieves low performance under noisy environments and for harmonics, inter-harmonics and distorted signals [33].

3.1.2. Root Mean Square and Peak Voltage Techniques

Different techniques can estimate the signal's magnitude, such as the RMS and PV techniques. The concept of the former one is based on the computation of the RMS value of voltage over several half-periods. The RMS value could then be calculated as a function of $V(t)$ over the period T.

$$V_{rms} = \sqrt{\frac{1}{T}\int_0^T V^2(t)dt}, \tag{10}$$

The peak voltage estimates the signal's amplitude as a function of time. It is given by

$$V_{peak} = \max_{0<\tau<T} |v(t-\tau)| \tag{11}$$

PQ monitoring devices estimate the rms voltage once every period, which can give an over-estimation of the PQD duration like sag [13].

Both techniques are simple and proven approaches. Nevertheless, they cannot estimate the phase angle and they lead to poor estimation in a noisy environment. In order to improve the estimation performance, several techniques based on the Fourier transform (FT) are proposed in the literature.

3.1.3. Fourier Transform and Its Extensions

FT is one of the most used estimation methods for stationary signals for extracting spectra at specific frequencies. Fourier transform models the studied signal as a sum of sinusoids where each sinusoid has a specific frequency. These frequencies are estimated without any information about the time the frequency appeared. Several references and books are devoted to the FT [62,63].

The continuous FT of a time signal $x(t)$ is expressed as follows [62,64]

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi f t}dt, \tag{12}$$

The discrete-time Fourier transform (DTFT) is widely used for sampled data systems and is implemented using the fast Fourier transform (FFT) with a short sliding window. First, the input signal of FFT is sampled in the time domain, then the FFT is performed in the frequency domain in discrete steps. The length of the signal contains N samples that are recorded over equal interval t_n

$$t_n = n\Delta t = \frac{nT_w}{N}, \tag{13}$$

where n presents an integer number ($n = 0, 1, \ldots, N-1$). N refers to the samples number within the window T_w. The phasor estimation by DTFT is provided by

$$\widehat{V} = \frac{1}{N}\sum_{n=0}^{N-1} x[n]e^{-j\widehat{w}n}, \tag{14}$$

where the estimator of angular frequency, w, is expressed as follows

$$\widehat{w} = \arg\max_{w} \frac{1}{N}\left|\sum_{n=0}^{N-1} x[n]e^{-j\omega n}\right|^2. \tag{15}$$

In fact, the DTFT is used over a multiple half-period of signal and can be interpreted as multiplying a rectangular window function with an infinitely continuous signal that is given by

$$w[n] = \begin{cases} 1 & \text{if } |n| \le \frac{1}{2}T_w. \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

As mentioned previously, the discrete Fourier transform uses a window with truncation of the sampled data, which leads to an estimation error. This phenomenon is the leakage effect. The most used window in electric grid applications is a rectangular windowing function because of its simplicity.

DTFT presents several advantages such as its low computational complexity, simple implementation, accuracy, and immunity to harmonic components under stationary conditions. Indeed, DTFT achieves high estimation performance if the fundamental frequency has a very small deviation from the nominal value. However, its performance critically degrades under off-nominal frequency and for amplitude and/or phase variations [65]. Table 8 provides a fair comparison of the Fourier transform and its extension techniques that are reported in this subsection, comprising their advantages and drawbacks.

Table 8. Advantages and drawbacks of Fourier-based techniques.

Method	Ref	Advantages	Drawbacks
Discrete Fourier transform (DFT)	[66]	DFT is the most used computation algorithms for PQDs analysis. In most cases, DFT is used to analysis three-phase signals under stationary conditions.	In real power systems, the three-phase signals are affected by small and large variations (events). In such conditions, the signal parameters are time-varying that affect the performance of DFT.
Fast Fourier transform (FFT)	[67]	FFT is commonly used for harmonic analysis and it has lower computation time compared to one DFT.	Due to aliasing and leakage effects, the FFT yields inaccurate results.
Short time Fourier transform (STFT)	[68]	STFT is a technique that performs the DFT on the time-dependent length using a "sliding window".	STFT yields inaccurate results under non-stationary conditions.
Wavelet transform (WT)	[69–71]	Compared to FT, WT allows obtaining the time and frequency information of the power system signals.	The performance of this technique is affected by the leakage effect and noisy environment. Moreover, using a short sliding window yield to high computation time.

3.2. Harmonic Decomposition-Based Methods

3.2.1. Pisarenko Method

Pisarenko Harmonic Decomposition (PHD) is based on eigenanalysis [33]. PHD is a parametric method that is used for harmonic estimation in the power systems field [72]. The signal $x(n)$ is assumed to consist of a sum of N sinusoids $s(n)$ and an additive white noise $b(n)$.

$$x(n) = s(n) + b(n) \tag{17}$$

It is possible also to write:

$$s(n) = -\sum_{m=1}^{2N} a_m s(n-m) \tag{18}$$

where,

$$x(n) = -\sum_{m=1}^{2N} a_m s(n-m) + b(n)$$

By replacing $s(n-m)$ by $x(n-m) - b(n-m)$, we find

$$\sum_{m=0}^{2N} a_m x(n-m) = \sum_{m=0}^{2N} a_m b(n-m) \tag{19}$$

Using matrix notations, the signal model can be written as follows:

$$\mathbf{x}(n)^T \mathbf{a} = \mathbf{b}(n)^T \mathbf{a} \tag{20}$$

where $(.)^T$ denotes the matrix transpose. with,

$$\mathbf{x}(n)^T = [x(n), x(n-1), \ldots, x(n-2N)]^T$$

$$\mathbf{b}(n)^T = [b(n), b(n-1), \ldots, b(n-2N)]^T$$

and

$$\mathbf{a} = [a_0, a_1, \ldots, a_{2N}]^T$$

The vector **a** is therefore the eigenvector associated with the variance of the white noise with the constraint a_0 = 1.

To analyze a signal according to the Pisarenko method, it is necessary to:

- Observe N values of the signal $x(nT_e)$.
- Compute the auto-correlation matrix and decompose it into eigenelements.
- Detect variance (σ^2 and deduce the number of sinusoids).
- Extract the roots of a complex polynomial of degree $2N$.

In [73], the authors proposed a technique based on Pisarenko's harmonic method. This technique allows for determining the corresponding eigenvector and the minimum eigenvalue of the covariance matrix in order to estimate the frequency. Pisarenko allows for achieving higher resolution compared to FFT. However, the Pisarenko method needs exact information on the model order and it gives inaccuracy estimation because of the statistical auto-correlation lag estimation.

3.2.2. Prony Method

This method is used for estimating inter-harmonic, harmonic and damping components. In this method, the signal is, as in Pisarenko's method, assumed to consist of a sum of N sinusoids but the noise is replaced by damping on the latter. The starting hypothesis therefore reads:

$$x(n) = \sum_{m=1}^{N} b_m Z_m^n \tag{21}$$

with,

$$Z_m = e^{\alpha_m} e^{j2\pi f_m}$$

We can then construct the polynomial:

$$\Psi(Z) = \sum_{i=0}^{N} a_i Z^{N-i} \tag{22}$$

with $a_0 = 1$

$$x(n) = -\sum_{m=1}^{N} a_m x^{n-m} \tag{23}$$

The coefficients a_m can therefore be obtained by solving the following linear system of dimension N:

$$\begin{bmatrix} x(N+1) \\ \vdots \\ x(2N) \end{bmatrix} = \begin{bmatrix} x(N+1) & \ldots & x(1) \\ \vdots & \vdots & \vdots \\ x(2N) & \ldots & x(N) \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_N \end{bmatrix} \tag{24}$$

From the N coefficients a_m, it is possible to form the following polynomial:

$$\Psi(Z) = \sum_{m=0}^{N} a_m Z^{m-i} \tag{25}$$

with,

$$a_0 = 1$$

The moduli of these roots give the attenuation α_m while those phases give the frequencies f_m. The amplitudes b_m of the different sinusoids can finally be obtained by solving the following system:

$$\begin{bmatrix} 1 & \dots & 1 \\ \vdots & \vdots & \vdots \\ Z_1^{N-1} & \dots & Z_N^{N-1} \end{bmatrix} \begin{bmatrix} b_1 \\ \vdots \\ b_N \end{bmatrix} = \begin{bmatrix} x_0 \\ \vdots \\ x_{N-1} \end{bmatrix} \tag{26}$$

For the Prony method, it is needed to:

- Observe $2N$ values of the signal $x(nT_e)$.
- Solve a complex N-dimensional linear system.
- Extract the roots of a complex polynomial of N degree.
- In order to determine the amplitudes, it is necessary to solve a complex linear system of N dimension.

An approach based on the Prony method is proposed in [74]. This approach allows minimizing the mean square for computing the harmonic and inter-harmonic sub-groups. Authors have proposed in [69–71], an approach based on the wavelet and Prony methods. However, the wavelet method requires appropriate windowing in order to obtain an accurate estimate. The Prony method has lower complexity compared to the Pisarenko method [75]. Furthermore, it leads to the highest performance compared to FT [76]. However, this method is still sensible to noise and it depends on the system's parameters [77–80].

3.2.3. Least Square Prony Method

It is imperative to increase the data points in order to improve Prony's method performance. In this context, the least square method uses data points for generating the desired coefficients.

$$x(n) + \sum_{m=1}^{N} a(m)x(n-m) = \epsilon(n) \tag{27}$$

for

$$p + 1 \leq n \leq N$$

This equation presents the linear predictor filter and $\epsilon(n)$ refers to the error of prediction and the predictor filter is referred to by the summation. The coefficient of the linear predictor filter can be optimized by the minimization of the following cost-function:

$$\mathcal{J}(\mathbf{a}) = \sum_{n=p+1}^{N} |\epsilon(n)|^2 \tag{28}$$

3.2.4. Modified Least Square Prony Method

In the case where a number of frequencies are known, it is recommended to use the Prony method. In such conditions, it has low computation complexity than conventional methods [81].

$$y[n] = \sum_{m=0}^{N} c[m]x(n-m). \tag{29}$$

The $y[n]$ can be obtained by filtering the signal $x[n]$. $c[m]$ is an impulse response of the filter.

A modified least squares Prony method is proposed in [82]. This approach allows estimating the frequency and phasor for electric power systems. The LS Prony method leads to high estimation performances compared to those of the Prony method. Other methods that lead to high performances under specific conditions are proposed in [83–85]. The Prony method allows for estimating inter-harmonics, harmonics and damping components. Their performance depends on the number of samples, model order and *SNR* [74]. Compared to the Fourier transforms, the Prony method has lower computation cost and it leads to high estimation performance. However, the Prony method is still sensible to noise.

3.3. Parametric Methods

The parametric methods require a knowledge of the signal model and they include auto-regressive-moving average (ARMA) and sinusoidal models. They are also known as model-based methods where a signal model with a known form is assumed. The matching between the real and proposed signal should follow this process:

- A good knowledge and hypothesis of generated process.
- Using models that are validated by good experimental results.

The signal's parameters can be estimated when a good signal model is chosen. If there is a good matching between the used and real models, then these methods yield the highest estimation performances over short signal lengths. The limitation of parametric methods is how to find a good matching between the real and theoretical signal models. There are two categories of methods: (1) parametric methods for discrete spectra, and (2) parametric methods for rational spectra.

3.3.1. Discrete Spectra

For these techniques, the estimation problem can be reduced to the frequency (f_0) estimation from the recorded data, which is the most difficult task. Then, estimate phasors by reformulating this estimation problem as a linear regression problem. The most known methods are high-resolution or sub-space techniques such as multiple signal classification (MUSIC) and estimation of signal parameters via rotational invariance approaches (ESPRIT). MUSIC-based on a sinusoidal model gives an estimation of the frequency components and it is considered a noise sub-space technique. Nevertheless, this technique presents several drawbacks such as it can not provide an estimation for closely spaced signals under a low noise environment and it is highly computationally complex. ESPRIT technique based on a sinusoidal model allows also estimating the frequency components and it is considered as a signal sub-space technique. Both techniques can be used for the analysis of harmonic and inter-harmonics components [8]. In addition, MUSIC and ESPRIT can estimate the frequency of events, such as transient voltages and currents [8]. Nevertheless, these techniques require knowledge of the order of the signal model. Moreover, under highly noisy environments, they achieve low estimation performances.

3.3.2. Continuous Spectra

The mentioned discrete spectra technique in the previous section allows for characterizing PQDs such as harmonic and inter-harmonics components. Otherwise, other PQDs are characterized by a continuous spectrum, in particular when the harmonic and inter-harmonics number is unlimited. For example, active rectifiers and arc furnaces generate high-frequency components. However, the limited knowledge of the causes of these high components is still the main barrier in electric grids [33] and their interpretation is not easy. The continuous spectra methods include auto-regressive (AR) models, where ARMA models are still general rational models. More details about this class of techniques can be found in [86]. The continuous spectra include also linear prediction methods such as Prony ones. These techniques don't estimate the parameters from the data, but they allow modeling the data as the output of a linear system corrupted by noise. After that, the estimation of parameters can be obtained using the ARMA model. Knowing that the Prony method achieves the same performance as the ESPRIT and MUSIC techniques [33]. The theoretical considerations are given in [86,87]. However, several PQ disturbances possess discrete spectra with components at discrete frequencies.

3.4. Extension to Non-Stationary Conditions

As mentioned previously, most PQ disturbances are non-stationary signals. Under these conditions, FT-based techniques can not perfectly analyze these disturbances. Therefore, PQ estimation is realized by using non-stationary approaches, such as time-frequency or time-scale representation [88–92]. These methods include Hilbert–Huang transform (HHT), continuous wavelet transform (CWT) and Kalman filters (KF) [8,88,93–95].

3.4.1. Hilbert–Huang Transform (HHT)

HHT is a recent advance in SP techniques to analysis the non-stationary signals [96–99]. HHT is based on Hilbert transform (HT) and Empirical Mode Decomposition (EMD) techniques [100].

EMD is an analysis based on the time-frequency domain, which allows decomposing of a signal into intrinsic mode functions (IMFs) [101]. After that, the HT estimates the frequency, phases and amplitudes at each instant with an analysis of the IMFs. The advantage of using HT is its using of one phase signal for feature extraction.

An HHT algorithm was proposed in [102] for PQDs classification with a focus on the swell, sag, harmonics, transient, etc. The proposed probabilistic neural network approach allows us to identify the corresponding event. In [103], a PQD classification technique for distorted signals was proposed with a comparison between S-transform and the proposal. The results seem to achieve a good PQD classification for the different disturbances. The separation between frequency components, in particular under non-stationary conditions, becomes an essential task. To achieve this objective, HT and EMD are combined for detecting sag cause [104] and the PNN-based classifier allows for determining the sag type.

However, HT could lead to false information and it suffers from the effects of the border. In addition, it is not easy to interpret when there is no satisfaction of the Bedrosian condition, while the EMD could achieve wrong IMF decomposition, mode mixing and border effect.

3.4.2. Kalman Filters

Kalman filter (KF) is a special type of filter. KF solutions are based on a set of state-space equations. These filters are widely used in power quality applications, such as real-time tracking harmonics [105–108], signal parameters estimation of transients [109,110]. The Kalman filter is a linear filter that can be applied to a linear system. However, most of the systems are ultimately nonlinear [111].

A technique for PQ disturbances classification was proposed in [112]. This classifier can be applied for short-duration of disturbances. This technique is based on the Stockholm transform (ST) and extended KF (EKF), where ST allows for detecting the signal and EKF is used to estimate the harmonic components and frequency, amplitude, and phase variations. The authors proposed in [113] a PQ disturbances classifier that uses Unscented KF (UKF) and modified Particle Swarm Optimization (PSO) algorithms. The frequency, amplitude, and phase can be tracked at low signal-to-noise ratio (SNR) values. A phasor and frequency estimator based on a dynamic model is proposed in [114]. In [112], the authors proposed a PQ disturbances classifier based on discrete wavelet transform and Kalman filter with a fuzzy expert system. In [115], an approach based on Taylor EKF is proposed. This approach uses a dynamic model, which reduces the state space and takes into consideration harmonic components.

3.4.3. Maximum Likelihood Estimator

Under high noise and off-nominal conditions, the performance of the previously mentioned techniques critically degrades. To overcome these limitations, the maximum likelihood estimator (MLE) yields to highest performances of estimation over a short signal length compared to non-parametric methods. MLE is an asymptotically optimal estimator [116] that leads to the highest estimation performances compared to traditional techniques. The estimation problem can be solved as follows: (1) first, from recorded data, MLE can estimate the frequency (f_0). (2) The estimate of amplitude and initial phases can be obtained by resolving a problem in linear regression. The w can be estimated ($\widehat{w}$) by the following maximization

$$\{\widehat{w}_0, \widehat{\mathbf{S}}\} = \arg\max_{w,\mathbf{S}} \mathcal{L}(\mathbf{X}; w, \mathbf{S}) = \text{argmin}_{w,\mathbf{S}} \|\mathbf{X} - \mathbf{G}(w)\mathbf{S}\|_F^2, \tag{30}$$

where $\widehat{\mathbf{S}}$ refers to the $\mathbf{S}$ estimate and $\mathcal{L}(\mathbf{X}; w, \mathbf{S}) = log(p(\mathbf{X}; w, \mathbf{S}))$ is the log-likelihood function of $\mathbf{X}$. $\|.\|_F^2$ is the Frobenius norm.

- $\mathbf{X}$ is $N \times 3$ matrix containing the recorded. This matrix is expressed as

$$\mathbf{X} = \begin{bmatrix} x_a[0] & x_b[0] & x_c[0] \\ \vdots & \vdots & \vdots \\ x_a[N-1] & x_b[N-1] & x_c[N-1] \end{bmatrix}, \tag{31}$$

- $\mathbf{G}(w)$ is a $N \times 2$ matrix containing the fundamental frequency $w = 2\pi f$. This matrix is given by

$$\mathbf{G}(w) = \begin{bmatrix} 1 & 0 \\ cos(w) & sin(w) \\ . & . \\ . & . \\ . & . \\ cos(w(N-1)) & sin(w(N-1)) \end{bmatrix}. \tag{32}$$

- $\mathbf{S}$ is a 2×3 real-valued matrix containing the amplitudes and initial phases of the three-phase voltage system. This matrix is expressed by

$$\mathbf{S} = \begin{bmatrix} a_a cos(\phi_a) & a_b cos(\phi_b) & a_c cos(\phi_c) \\ -a_a sin(\phi_a) & -a_b sin(\phi_b) & -a_c sin(\phi_c) \end{bmatrix}. \tag{33}$$

A technique proposed in [117,118], presents an estimator of the fundamental frequency and phasor. This technique is based on the ML method and it uses three-phase information. The signal parameters are time-varying and the analysis is realized on a short sliding window. This estimator-based ML technique needs to maximize the 1-dimensional cost function. For such an objective, an algorithm of optimization that uses the Newton–Raphson approach is proposed. ML-based Newton–Raphson technique has lower computational complexity than classical techniques and enhances the estimation performance.

3.5. Discussion

The most used extraction techniques for signal features, i.e., frequency and phasor, are the non-parametric methods. Indeed, these techniques need a long signal length in order to achieve a good performance. For instance, for FT-based techniques, the window may lead to a leakage effect. It should be mentioned that in a real electrical grid, the recorded data are limited, which represents the main limitation of these methods [33].

Parametric methods require knowledge of real signals to achieve good resolution. When there is a good match between theoretical and real signal models, these methods can achieve the best estimation performance on short-length signals compared to non-parametric methods. Nevertheless, the performance of parametric-methods depends on the choice of the theoretical signal model.

The features of several PQDs are time-variant, therefore FT-based techniques can not be used to analyze these non-stationary disturbances. To overcome this challenge, other non-stationary methods are used to perform this task with good performance. For example, time-frequency or time-scale representation are non-parametric methods that are applied for time-variant disturbances [64,119–127]. In addition, high-resolution and ML techniques are parametric methods [8,117,118]. These techniques are based on the concept of using a short sliding window that allows handling the non-stationarity problem. This sliding window decomposed the signal into several stationary blocks. Then, time-varying parameters can be estimated over each short window.

Advanced feature extraction techniques are proposed to estimate the PQD's features under non-stationary conditions. HHT is an advanced SP technique that is based on HT and EMD techniques [100]. EMD decomposes the signal into IMFs and it is a time-frequency analysis method [101]. Then, the EMD estimates the instantaneous frequency, amplitude, and phase by analysis these IMFs. The main advantage of HT is its requirement of one phase signal in order to extract the IF and IA. The HT could detect the disturbance; however, it could lead to false information and it suffers from the effects of the border. The main drawbacks of EMD are the wrong intrinsic mode functions, border effect and mode mixing. Finally, an estimator based on the ML technique was proposed for the analysis of the time-varying disturbances. This estimator uses a Newton–Raphson optimization algorithm for maximizing a one-dimensional cost function. This estimator has lower computational complexity than classical techniques and enhances the estimation performance. Table 9 reports an analysis of the feature extraction techniques mentioned in this section.

Table 9. Advantages and drawbacks of feature extraction techniques.

Method	Advantages	Drawbacks
Zero-crossing transform [33]	Low Computationally complexity.	It has low performance under noisy environments and for distorted wave-forms, harmonics, and inter-harmonics.
RMS and peak voltage techniques [13]	They are well-proven and simple techniques.	They can not estimate other signal parameters, such as phase angle. Moreover, they achieve low performance in noisy environments.
Fourier transform and its extensions [65,119]	They have a simple implementation, low computation complexity, accuracy, and immunity against harmonic components under stationary conditions.	Their estimation performance is limited under off-nominal conditions.
Pisarenko [33,72,73]	It has low computation complexity.	Pisarenko method needs exact information on the model order and it gives inaccuracy estimation because of the statistical auto-correlation lag estimation. It suffers also under low noisy environments.
Prony method and its extension [69,70,76–80]	They have low computation complexity and high estimation performance compared to those of the Pisarenko method.	These techniques are still sensible to noise and they depend on the system's parameters.
Music approach [8]	It has high resolution than Prony techniques and achieves asymptotically unbiased estimation of signal parameters.	It can not resolve a problem with closely spaced signals under a low SNR environment and its high computational burden.
ESPRIT approach [8]	It has a lower computational burden compared to MUSIC. It achieves the highest performance for inter-harmonic estimation.	It needs to know the order of the signal model and it achieves low performance under high noisy environment.
Hilbert–Huang transform [96–99]	It achieves good performance under a non-stationary environment and for non-linear signals.	Its drawbacks are end effects and mode mixing during the process of empirical mode decomposition (EMD).
Kalman filters [105–108,111]	It achieves the highest performance for linear systems.	It leads to poor estimation for non-linear systems.
Maximum likelihood [8,116]	It allows achieving the highest performance and it is an asymptotically optimal estimator.	The signal model is required. Moreover, its resolution is near to this of Fourier-based techniques for low SNR.

4. Feature Selection Techniques

Herein, a study of the problem of feature selection or parameters optimization, i.e., finding the most unique and optimum feature, is provided. The classification stage needs as input the extracted feature that should achieve a high recognition rate. In the literature, proposed optimization algorithms used in the feature selection stage include particle swarm algorithm (PSA), ant colony optimization (ACO), genetic algorithm (GA), genetic k-means algorithm (KMA), Newton–Raphson method and downhill simplex. The genetic algorithm is based on the evolutionary of natural selection [30] and is an iterative heuristic algorithm. It can be used as an optimization algorithm for obtaining the optimum solution(s) [128]. A GA uses chromosomes that are binary digits. By modifying the individual population, it is possible to make a decision based on probabilistic rules. A GA chooses a random individual, which is a parent, from the actual population and for the next generation, it provides children. The GA-based competitive selection allows for eliminating the poor solution. GA's main advantage is its capability to obtain the optimum solution(s) over successive generations [120,129–131]. KMA is widely used for feature selection for classification applications [132,133]. This algorithm is iterative and allows minimizing SE measure [132,134]. The main drawback of this optimization method is how to choose the first guess. It could give as result a local maximum or minimum in the case where the initial guess is not suitable. In [132], a classifier using two approaches, which are GA and fuzzy k-nearest neighbor (FKNN), was proposed. The solution or optimum feature is selected by a GA with improved performance. The classification performance is also improved by using 16 features from 96 features. The authors proposed in [135] a classification approach based on GA and SVM algorithms for PQDs. In [136], a classifier that uses a combination between extension theory (EXT) and GA was proposed. Indeed, GA gives the optimum solution over a large space while EXT allows providing a means for distance measurement.

PSO is an iteration algorithm that allows obtaining the optimum solution according to a given measure [137–144]. This algorithm is based on the social sharing concept, where the particle refers to the individual and the swarm represents the population. The main objective of PSO is to find the particle that gives the optimum solution of the cost-function. The authors proposed in [139] a PQ disturbances classifier that uses PSO for feature selection under a noisy environment. In [140], an SVM classifier for online and offline monitoring was proposed. This classifier is based on the PSO algorithm for optimizing the classifier's parameters. A combination between artificial bee colony (ABC) and PSO for PQD classification is proposed in [142], and it is used for selecting the algorithm's features. ACO is a computation intelligence approach introduced by M. Dorigo, A. Colorni and V. Maniezzo [145]. ACO is an iterative algorithm that is based on ants' behaviors. The solution is obtained by heuristic information given by memory containing experience in the previous iteration that is provided by the ants as well as the problem instance. In [146], the authors proposed an ACO to improve classification performance and reduce computational time. The ACO is used for minimizing the set size of the feature and classification error. The downhill simplex optimization (DSO) method is a heuristic search method that is used for non-linear problems for optimizing 1- or multi-dimensional cost-functions. This method allows for finding the maximum or minimum of the objective function [147]. DSO does not always lead to an optimal solution [148,149]. MATLAB® environment provides an optimization algorithm that is called *fminsearch* based on the Nelder–Mead technique. However, this technique is highly computationally complex to find the feature with the highest performance. To overcome this limitation, the Newton–Raphson algorithm (NRA) was proposed in [117]. It is an iterative algorithm allowing the maximization of the objective-function to find the optimum solution. This algorithm uses the tangent knowledge of the curve that is close to the root. The main advantage of the Newton–Raphson method is its capability to find the optimum feature in a few iterations reducing then the computation time [150]. The newton-Raphson method can be applied to the analysis, detection and classification of short transients and disturbances. In [117], a parametric spectral estimation technique for PQ monitoring application was proposed. This technique allows for reducing the computation time compared to classical techniques. Table 10 presents the advantages and drawbacks of the main selection techniques.

Table 10. Main optimization techniques with their advantages and drawbacks.

Technique	Advantages	Drawbacks
GA	It is the heuristic method that can provide multiple solutions for several search and optimization problems. GA design is simple and easy to understand. GA can obtain a solution for difficult problems over traditional methods and it requires less amount of information.	The main drawbacks of GA are the hyper-parameter tuning, time-consuming, and the need for special definitions. Its implementation is still a difficult task.
PSA	PSA design is based on particle swarm and it is adapted with mutation computation. PSA requires a few parameters to tune and it can provide fast and multiple solutions.	PSA leads a low performance for complex and large numbers of dimensions and data-sets. IT requires software knowledge and theoretical analysis is still a difficult step.
ACO	ACO design is based on ant colony and it may be continuously used and can instantly adjust to changes. It can provide a good solution compared to other methods.	It is complex and the theoretical analysis is still difficult with a random decision. It requires a pre-knowledge of factors and software languages.
ABC	Its concept is based on a bee colony and it has the ability to convert to local solutions with good speed. It needs fewer steps for optimization. It adapted to optimization problems that have multi-dimensions.	ABC requires pre-knowledge of factors and software languages.
Downhill simplex	This method is a heuristic search that is used for non-linear problems for optimizing 1- or multi-dimensional cost-functions. This method allows for finding the maximum or minimum of the objective function.	However, this technique is highly computationally complex to find the feature with the highest performance.
Newtho-Raphson	It is an iterative algorithm and it uses the tangent knowledge of the curve that is close to the root. The main advantage of the Newton–Raphson method is its capability to find the optimum feature in a few iterations.	This technique has two main drawbacks that are: (1) it requires an initial guess that must be close to the searched-for zero in order to obtain a good solution. (2) The computation of the inverse of the derivative is still a difficult task.

5. PQ Disturbances Classification Techniques

The PQDs classification stage requires as input the extracted or estimated feature, whose output is the type of disturbance. As mentioned previously, advanced SP techniques have become essential to extract the feature with the highest performance. Regarding PQ monitoring, feature classification has become a great important part. Among the variety of classification techniques, the most known and common techniques are presented in this section that is classified into three classes: (1) classical techniques, (2) techniques based on signal processing methods and (3) pattern recognition techniques [151,152]. More PQDs classification techniques are presented in [153–162].

5.1. Classical Techniques

For this class, two parameters are used to classify the PQ disturbances that are duration and phasor (amplitude) without using the phase angle [8]. Indeed, classical techniques exploit the information of single-phase to classify the corresponding disturbance; however, the power grid is a three-phase system. The most common classical techniques are discussed in the following sections.

5.1.1. ABC Classifier

For unbalanced voltage sags, the ABC classifier permits to find the corresponding sag. The voltage sags consist of 7 sag signatures that are denoted from *A* to *G* [163]. Figure 14 illustrates the phasor representation of each sag, where the balanced three-phase is presented by dashed arrows and the sag phasor is presented by the solid ones. For example, symmetrical faults in the power grid result in three-phase symmetrical sags that are referred to as type A. Regarding phase a, the sag value differs from the pre-fault E and a value in faulted phase V [163]. ABC classification has a simple design to classify the sag voltage. Nevertheless, The ABC classifier can not select other sag parameters.

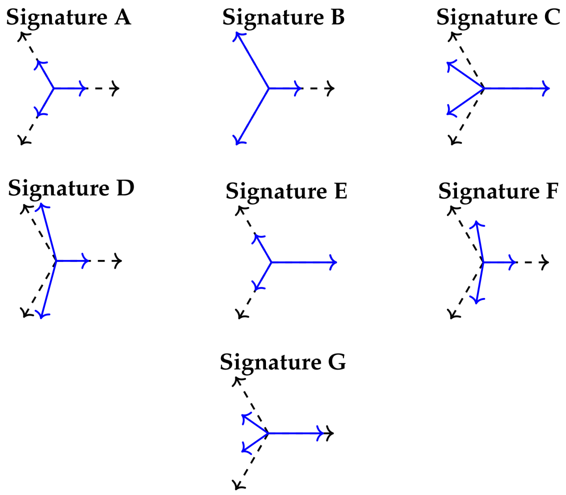

Figure 14. Phasor representation of sag signatures proposed by ABC classification.

5.1.2. Symmetrical Component Classifier (SCC)

This classifier is proposed to identify the corresponding sag among sag types C & D [164]. Concerning sags sub-types, Figure 15 illustrates the 6 sag sub-types among C & D types. The angle between positive- (V_1) and negative-sequence voltages (V_2) [164] is used for selecting the corresponding sag. This angle is expressed as

$$T = \frac{1}{60^\circ} \arg\left(\frac{V_2}{1 - V_1}\right), \tag{34}$$

where T is the integer close to the obtained result. The sag sub-type can be obtained as follows:

$$\begin{aligned} T &= 0 \quad \text{Type } C_a \\ T &= 1 \quad \text{Type } D_c \\ T &= 2 \quad \text{Type } C_b \\ T &= 4 \quad \text{Type } D_a \\ T &= 5 \quad \text{Type } C_c \\ T &= 6 \quad \text{Type } D_b \end{aligned} \tag{35}$$

These techniques achieve low performance for high amplitude or phase angle variations. Moreover, they lead to frequency errors that can provide a false type of sag. Under these conditions, it is become essential to utilize an improved technique for PQDs classification.

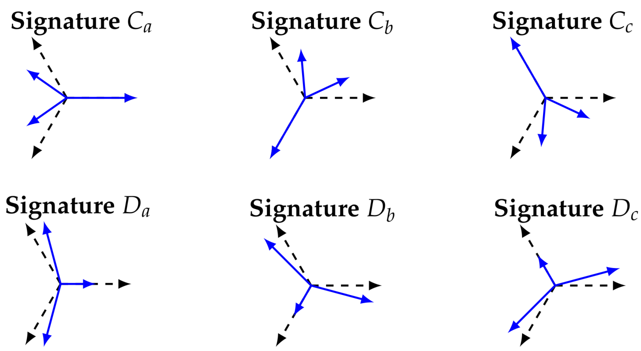

Figure 15. Six sub-types of sags.

5.2. Techniques-Based on Signal Processing Methods

5.2.1. PQDs Classification Based on Information Theoretic Criteria

A technique for PQDs classification uses the Model Order Selection proposed by the authors in [162]. This technique studies the signatures of the sag and swell voltages illustrated by Figure 16. These 9 signatures, provided in Figure 16, can be pre-classified into 4 classes as depicted in Table 11. It should be noted that each class depends on a symmetrical component number that is equal to zero. The task of obtaining the corresponding class is reformulated as a problem of pure model order selection [165]. Once the corresponding class is selected, the estimated value of the symmetrical component allows for determining the corresponding signature. Authors proposed in [162] two approaches that are based on Information Theoretical Criteria (ITC) for selecting the corresponding class. The first approach achieves the highest classification performance, while the second approach reduces the computation time. The obtained results prove the efficiency of these classifiers to identify the correct sag and swell voltage.

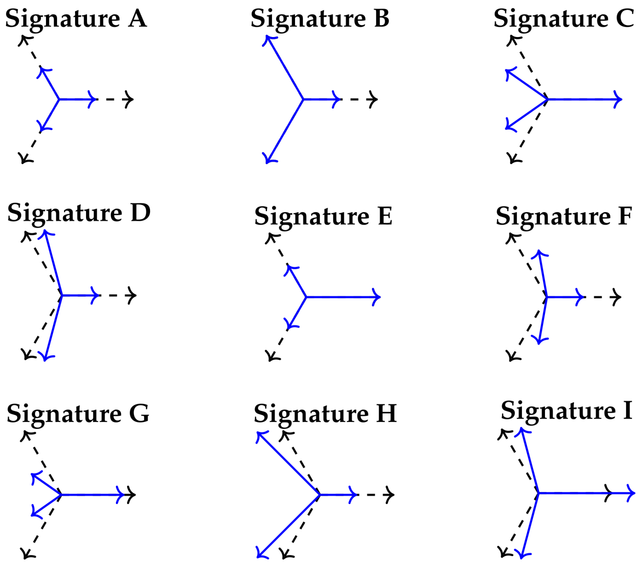

Figure 16. Phasor representation of sag and swell signatures [166]. IEEE, 2009.

Table 11. Pre-classification of sag/swell signatures into 4 classes.

Type	z_0	z_1	z_2	Class
Balanced	0	E	0	$\mathcal{C}_1$
A	0	V	0	
C	0	$\frac{V+E}{2}$	$\frac{E-V}{2}$	$\mathcal{C}_2$
D	0	$\frac{V+E}{2}$	$\frac{V-E}{2}$	
F	0	$\frac{2V+E}{3}$	$\frac{V-E}{3}$	
G	0	$\frac{2V+E}{3}$	$\frac{E-V}{3}$	
H	$V-E$	E	0	$\mathcal{C}_3$
I	$\frac{3(E-V)}{2}$	E	0	
B	$\frac{V-E}{3}$	$\frac{V+2E}{3}$	$\frac{V-E}{3}$	$\mathcal{C}_4$
E	$\frac{E-V}{3}$	$\frac{2V+E}{3}$	$\frac{E-V}{3}$	

5.2.2. PQDs Classification Based on Space Vector Method

A classification technique based on space vector transformation and zero sequence voltage is proposed in [166]. Under nominal conditions, and in the complex plane, the result is a circle that has a radius equal to the voltage nominal value. For balanced sags, the circle's radius is inferior to the nominal value. Under unbalanced conditions, for sags, the result is an ellipse that depends on amplitude, phase(s) and phase angle shift. For swells, the sequence voltage allows for analysis of the swells. Finally, the zero sequence and space vector changes allow for determining the time occurrence of the sag and swell.

5.3. Pattern Recognition (PR) Techniques

Artificial intelligence-based techniques use the data and take action based on the pattern category. These techniques perform tasks to mimic human behavior, such as learning from experiences, speech recognition, decision-making, etc. In PQ monitoring, these techniques have become of great important. The PR techniques used for disturbance classification include artificial neural network (ANN), support vector machine (SVM) and fuzzy expert system (FES) [167–171]. These techniques have the ability to generalization and learn from examples.

5.3.1. Artificial Neural Networks

ANNs are used to identify the PQ disturbance and can achieve high classification performance. The commonly used structure of ANN is the multilayer perceptron (MLP). An ANN with an MLP is illustrated by Figure 17. Each layer consists of several neurons, whereas the first and last layers consist of the inputs and outputs data, respectively. Indeed, the input data are transformed in a non-linear manner into a new space by the hidden layers. After that, the PR classes are separated in this space [172]. ANNs can self-learn the PR of several systems. Several classifiers based on ANNs are used for disturbances analysis and harmonics sources classification.

Several techniques-based on ANNs are proposed and they deal with disturbances classification in PQ monitoring [173–183]. In [184], a classification technique based on a hybrid approach for PQ disturbances was proposed. This technique combines a convolutional neural network (CNN) and Wigner–Ville distribution (WVS). WVD Allows transferring a 1-dimensional disturbance into a two-dimension image file. Then, the CNN allows for achieving the task of image classification. In [178], a classification technique using an MLP neural network with 3 layers and WT was proposed. In [179], an adaptive linear network (ADALINE) with FFNN is used to identify the corresponding disturbances. ADALINE estimates the harmonic component or inter-harmonic component in order to compute the rms value and THD, then, the FFNN allows selecting the corresponding disturbance.

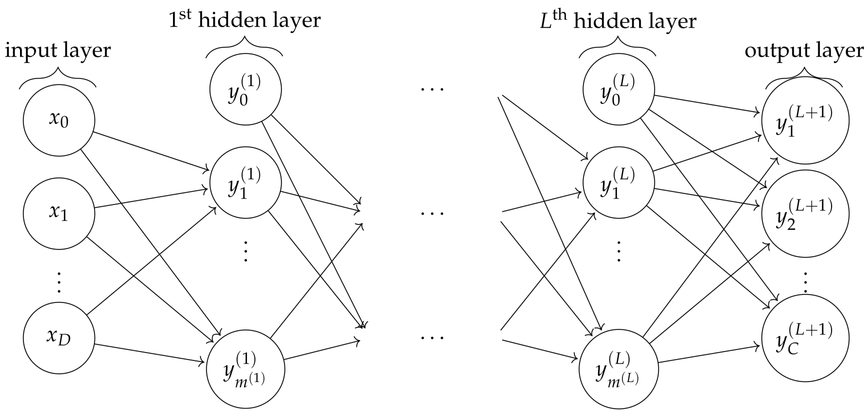

Figure 17. Network graph of a $(L+1)$-layer perceptron with $(D+1)$ input units and C output units. The l^{th} hidden layer contains $(m^{(l)+1)}$ hidden units.

5.3.2. Support Vector Machine

SVM was introduced by Vapnik in the late 1970s and it uses the learning theory for classification [185,186], such as intelligent machines and forecasting. The main phases of SVM are: (1) the input data are linearly transformed into multi-dimensional space. (2) The input is classified by an optimal hyper-plane determination in high or infinitedimensional space. A learning stage is also required by a support vector machine such as ANN. In the literature, several techniques-based on SVM were proposed for PQDs classification [187–199]. In [191], the authors proposed a classifier based on DWT and SVM to classify several disturbances in a power grid. Authors in [192], proposed two SVM classifiers that are the One-Versus-One (OVO) and the One-Versus- Rest (OVR), which are suitable tools for solving class problems. However, their performances depend on the network size and the stage of data preparation. In [193], a disturbances-Versus-Normal (DVN) approach was proposed. It is suitable for solving multi-class problems. A technique-based on DWT and multi-class SVM was proposed in [200].

5.3.3. Fuzzy Expert Systems

FESs allows for generalizing the binary logic under uncertainty and it is inspired by the reasoning of humans. A mapping of the objects to their member values using a function is performed into a concern domain. The most common functions are the triangular and trapezoidal ones. Indeed, the expert system is a specific application of AI that is used in module diagnostic [201]. For reasoning about data, a fuzzy rule base (FRB) and fuzzy sets (FS) are used by FES instead of Boolean sets. To classify the PQ disturbances, the ES needs to extract information from computers and learn from human experts. However, this information is heuristic which makes it difficult to be used by the computer. The rule-based expert system is the typical ES structure and it is illustrated in Figure 18. It includes a user interface that shows how the information is sent to the system, i.e., the output of PQ monitoring. The classification results present the outputs of the system. Reasoning between rules and information is performed by the interface engine. An explanation system allows for defining the reasoning to the user. The knowledge base editor allows updating the knowledge base and rules. Finally, the user can stock all data that has additional information in case-specific data.

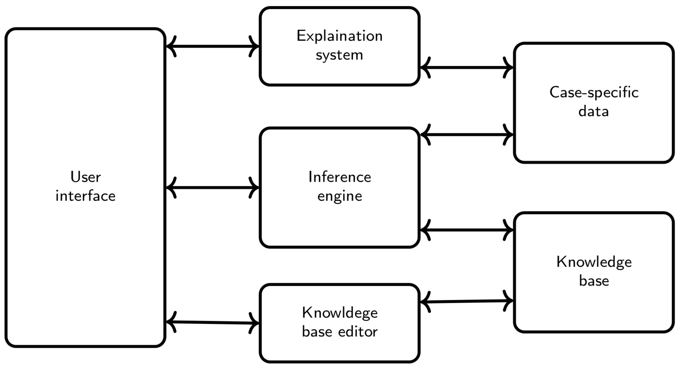

Figure 18. Architecture of rule-based expert system.

Figure 19 illustrates a rule-based ES for disturbances classification. Based on the input recorded data, its architecture has the ability to classify the corresponding disturbance. From the knowledge base, the ES classifier provides the corresponding disturbance.

In the literature, several classifiers-based on expert systems to classify the PQ disturbances were proposed [126,137,155,202–211]. In [202], the authors proposed an events classification technique during the RES integration in the power system. This technique is based on the data mining tool and the expert system. The authors proposed in [203] a techniques-based on neuro-fuzzy classifier and principle component analysis (PCA). The authors proposed in [204], a classifier uses the neuro-fuzzy and theorem of Parseval for PQ disturbances recognition systems. This technique was tested for several disturbances using noise-riding signals. An algorithm-based fuzzy decision tree for the classification of various disturbances was proposed in [205].

However, the above-presented techniques require a good knowledge of the disturbances or training database and their performance depends on the learning stage. Database size must be large to cover all types of PQ disturbances which is a difficult task in practice. Moreover, their performance also depends on that of the extraction stage. In addition, the learning step results in a high computational time to perform the task.

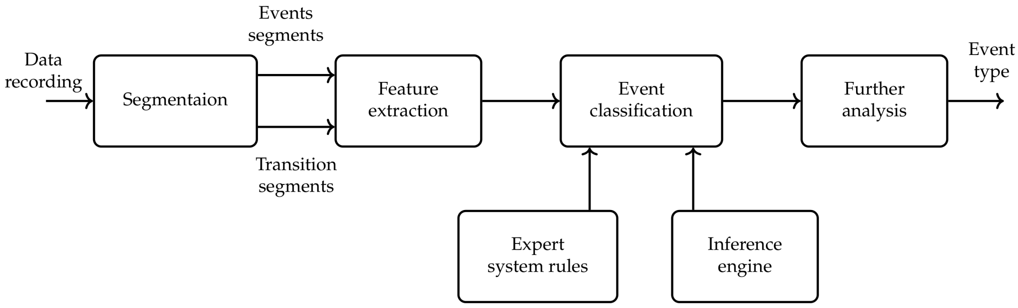

Figure 19. Illustration of rule-based expert system for event classification of PQ disturbance.

5.3.4. Machine Learning-Based Techniques

In recent years, the research on Deep Learning (DL) algorithms has attracted the attention of scientists in several domains, such as signal and image processing, speech recognition and human face recognition. DL is a type of machine learning and AI that consists essentially of a NN with several layers. The DL algorithms have the ability to automatically learn the best features from the original input signal without being specifically coded [212,213]. A neural network with more hidden layers allows for improving accuracy compared to the NN with only one layer. DL-based techniques have been used to solve certain PQ issues, for instance, the architecture-based convolutional neural network (CNN) is mostly employed in PQ extraction, detection and classification applications. In addition, DL architectures include deep belief and neural networks, identity RNN (I-RNN), and recurrent neural networks (RNN). However, these deep learning techniques are highly complex and they rely on training sets.

In previous works, some authors have applied DL techniques to analysis, detect and classify the power quality disturbances in the power grid [214–217]. The authors proposed in [212] a technique based on deep CNN for PQDs detection and classification. This technique uses a one-dimension convolutional, pooling and batch-normalization layers for reducing over-fitting and capturing multi-scale features. In [218], a technique-based on machine learning for PQ disturbances classification is proposed. The stage of feature extraction of this technique uses an algorithm-based on un-decimated WT that allows reducing the over-fitting under noisy conditions. A technique based on CWT and CNN for PQDs classification is proposed in [219]. The CWT allows for generating a 2-D representation that incorporates frequency and time from the disturbance's signal.

Decision Trees-based learning (DT) is a supervised learning method used in different fields, such as machine learning and data mining. This approach can be used as a classification and predictive model that allows taking conclusions about observation data. In a decision tree structure, the leaves refer to the classes and the branches are the characteristics that lead to the corresponding classes. In [220], a PQDs classification algorithm-based on a time-frequency and DT was proposed. Compared to the S-transform, the proposed technique requires limited feature statistics. Moreover, the DT classifier allows the training of these features in order to improve automatic classification. A classifier-based on multi-resolution S transform and DT was proposed in [221]. This classifier uses adjustment factors that allow for improving accuracy and their performances are evaluated under a noisy environment. Ref. [222] proposed an approach for detecting and classifying the PQ disturbances. This technique is based on the Stockwell transform and DT method. ST permits to detection of 5 statistical features, such as the oscillatory's high frequency, voltage oscillation and harmonics. A DT algorithm-based on rules set is used for classifying the PQ disturbances. Table 12 presents the benefits and drawbacks of the main PQDs classification Techniques.

Table 12. Benefits and Drawbacks of PQ Disturbances Classification Techniques.

Techniques	Benefits	Drawbacks
ABC	ABC has a simple design to classify the sag voltage.	Nevertheless, The ABC classifier can not select other sag parameters.
Symmetrical component classifier	This classifier is used to identify the corresponding sag among sag types C & D [164].	SCC achieves low-performance classification under noisy environments.
Classifier-based on ITC	It yields to highest classification performance with a lower computation time.	It requires a signal model.
ANN	It can self-learn the PR of several systems.	It requires sufficient layers and a good knowledge of neurons. Moreover, the learning step results in a high computation time.
SVM	has a high ability of learning and it achieves high performance for large dimensional spaces.	SVM has low performance under noisy environments and its training and testing data requires a huge computation time.
FES-based classifier	This classifier achieves good accuracy for several PQDs and it can be used to analyze complex systems.	It requires a good knowledge about the disturbances or training database and its performance depends on the learning stage.
Machine learning	DL algorithms do not require having specifically coded to automatically learn the best features.	These techniques are highly complex and they rely on the training stage.

6. Comparative Analysis and Discussion

This work provided a review of the international standards used in PQ monitoring. The main objective of these standards is to ensure good compatibility between end-user consumers and the electric grid. In addition, they define and impose requirements of frequency and phasor with recommendations and guide-lines. IEEE and IEC organizations develop international standards and are the most known standards in PQ filed. Concerning PQ monitoring, PMUs allow extracting frequency and phasor in order to solve the problems of PQDs. In this scope, the IEEE organization provides a PMU standard that is refereed by C37.118, where several estimation requirements of frequency and phasor are imposed. These requirements must be tested and validated under stationary and non-stationary conditions. Power systems utility requires a high level of power quality due to the complexity of the power system and RES integration. A comprehensive review of the characterization techniques of PQ disturbances, with a focus on feature extraction, feature selection and PQDS classification techniques is provided. Table 13 provides a detailed comparison of the above-mentioned techniques. This comparison takes into consideration the accuracy and environment of each technique. In fact, the techniques-based on signal processing (SP) techniques are widely used to extract and detect the signal's features, whereas the most used algorithms for PQDs classification are based on artificial intelligence (AI) methods. The combination of SP and AI techniques allows for improving accuracy, especially with a high sample rate. However, the above-published estimation techniques are sub-optimal and most of these techniques do not use the information of the three-phase signals. Moreover, their performances lead to low performance under off-nominal conditions. Regarding the classification stage, the extracted feature is used as input for the PQDs classifier. Pattern recognition-based techniques (i.e., ANN, SVM, etc.) require a good knowledge of disturbances, and a large training database and their performance critically rely upon the extraction, selection and learning stages. Moreover, these techniques have a high computation complexity. To overcome these limitations, the development of advanced SP algorithms has become essential. It is still necessary to develop robust and reliable techniques under noisy and off-nominal environments and for short-length signals.

Table 13. Comparative Study of Feature Extraction, Selection and PQ Disturbances Classification Techniques.

Ref-Year	Feature Extraction	Feature Selection	Feature Classification	System Employed	Non-Noisy Environment	Noisy Environment
[223], 2012	DWT	-	-	Synthetic and single data	98.03	-
[208], 2011	DWT	-	HHM	Synthetic and multi-phase data	99.66	-
[224], 2013	DWT	-	LS-SVM-kMA	Synthetic and multi-phase data	98.88	98.14
[225], 2014	DWT and FFT	-	Threshold	Synthetic and multi-phase data	90.04	-
[141], 2015	DWT	PSO	ELM	Synthetic and multi-phase data	97.60	–
[226], 2011	WPT	GA-SA	SVM	Synthetic data	98.33	-
[227], 2012	WPT	-	MSVM	Synthetic data	97.7	92.25
[228], 2013	WPT	-	-	Synthetic and single data in real-time	-	–
[27], 2021	HT-DWT	-	ANN-SVM	Synthetic and single-phase data	98.11	-
[218], 2022	un-decimated WT	-	Stochastic Gradient Boosting Trees (SGBT)	Synthetic, simulation and multi-phase data	-	99.29–99.50
[229], 2013	ST	-	DT	Real time and multi-phase data	99.27	94.36–97.91
[230], 2012	ST	-	Hidden Markov model	Synthetic and multi-phase data	98.14	91.86–95.04
[231], 2017	ST	-	Fuzzy C-means clustering	Synthetic and single-phase data	99.20	98.50
[232], 2017	ST	-	Fuzzy C-means	Real data	-	<90
[233], 2018	ST	-	RF	Synthetic and multi-phase data	99.85	99.61
[234], 2020	ST	-	Fuzzy C-means	Real data	-	<90
[235], 2010	HT	-	ANN	single-phase data in real-time	96.75	-
[123], 2014	HHT	-	PNN–SVM	Synthetic and multi-phase data	100	-
[236], 2014	HHT	-	FES	Synthetic and multi-phase data	98	87.22–91.55
[237], 2020	EMD-HT	-	SVM	Real data	-	<90
[238], 2018	Orthogonal EMD	-	-	Real data	-	<90
[239], 2018	VMD	-	DT	Real-time and single-phase data	98.56	96.73
[240], 2015	VMD	-	DT	Real-time and multi-phase data	99.50	93.80
[241], 2018	LMS	-	MLP-NN	Synthetic and single-phase data	96.71	-
[117], 2017	ML	Newton–Raphson	-	Synthetic and multi-phase data	100	-
[118], 2015	ML	Nelder–Mead (fminsearch)	-	Synthetic and multi-phase data	100	-
[161], 2016	ML	-	ITC	Synthetic and single data	100	100
[162], 2017	ML	-	ITC	Synthetic and single data	100	100

7. Prospects and Challenges

A smart grid covers a large-scale system from generation until end-consumers. SG shall overcome the limitations of the existing system by spreading automated control and modern communication technologies through every power system's parts. SG allows providing real-time estimation and classification that satisfies the PQ standards requirements. Moreover, it is needed to enhance reliability, safety and efficiency for controlling and monitoring the power system. In this context, the main challenge we face is to involve real-time PQ disturbance characterization algorithms with high performance even under off-nominal conditions. Future research should evaluate the real-time characterization algorithms that require low computational complexity, high accuracy and low false alarm rate under balanced or unbalanced conditions. For distribution networks, it is important to take into consideration forecasting schemes. Finally, these algorithms must exploit the three-phases nature of the power system to achieve high performances over a short signal length.

8. Conclusions

This paper provided a comprehensive review of the characterization of PQ disturbances. In particular, several feature extraction, selection, and classification techniques for PQ monitoring were presented. A comparative study of the existing techniques was also highlighted with useful comments and remarks, which can be used for future development on PQDs characterization. An overview of international standards for PQ was also provided, where these standards define and provide extraction performance of frequency and phasor with recommendations and guidelines. An in-depth analysis related to the application of signal processing, optimization and pattern recognition techniques was highlighted. However, most of the previously published estimation techniques are sub-optimal, since they only use single-phase information. In addition, the mentioned techniques achieve low estimation performance under high noisy and off-nominal conditions. Furthermore, they require a long signal length to achieve high estimation performance, where various fast disturbances occur. For the classification stage, the studied classical techniques achieve low performance under highly noisy environments and for high variations in frequency. In addition, these techniques are not able to classify all sag and swell types. Pattern recognition-based techniques require a good knowledge of disturbances, a large training database and their performance critically relies on the extraction, selection and learning stages. The disturbances extraction based on SP tools is required and is considered of great importance to accelerate the evolution of future electric grids. Under off-nominal conditions, the use of suitable feature extraction and selection techniques over short data acquisition time is still a difficult task to perform. Moreover, PQ disturbances monitoring needs to improve feature extraction, optimal selection and classification algorithms for identifying disturbance causes. Finally, to improve PQ disturbance monitoring, further research should offer great scope on the use of communication and computing technologies, e.g., future 5G wireless networks, edge computing, three-phase system, and real-time data.

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References

1. Farhangi, H. The path of the smart grid. *IEEE Power Energy Mag.* **2010**, *8*, 18–28. [CrossRef]
2. Sauer, P.W.; Pai, M.A.; Chow, J.H. *Power System Dynamics and Stability: With Synchrophasor Measurement and Power System Toolbox*; John Wiley & Sons: Hoboken, NJ, USA, 2017.
3. Wasiak, I.; Pawelek, R.; Mienski, R. Energy storage application in low-voltage microgrids for energy management and power quality improvement. *IET Gener. Transm. Distrib.* **2014**, *8*, 463–472. [CrossRef]
4. Bollen, M.H. Understanding power quality problems. In *Voltage Sags and Interruptions*; IEEE Press: Piscataway, NJ, USA, 2000.
5. Bollen, M. What is power quality? *Electr. Power Syst. Res.* **2003**, *66*, 5–14. [CrossRef]
6. Bollen, M.H.J.; Hassan, F. *Integration of Distributed Generation in the Power System*; John Wiley & Sons: Hoboken, NJ, USA, 2011; Volume 80.
7. Baggini, A. *Handbook of Power Quality*; John Wiley & Sons: Hoboken, NJ, USA, 2008.
8. Bollen, M.; Gu, I. *Signal Processing of Power-Quality Disturbances*; IEEE Press: New York, NY, USA, 2006.
9. Kusko, A.; Thompson, M.T. *Power Quality in Electrical Systems*; McGraw-Hill: New York, NY, USA, 2007.
10. Mohd, A.; Ortjohann, E.; Schmelter, A.; Hamsic, N.; Morton, D. Challenges in integrating distributed energy storage systems into future smart grid. In Proceedings of IEEE 2008 International Symposium on Industrial Electronics, Cambridge, UK, 30 June–2 July 2008; pp. 1627–1632.
11. Fang, X.; Misra, S.; Xue, G.; Yang, D. Smart grid the new and improved power grid: A survey. *IEEE Commun. Surv. Tutor.* **2012**, *14*, 944–980. [CrossRef]
12. *IEEE P2030.2/D9.0*; IEEE Approved Draft Guide for the Interoperability of Energy Storage Systems Integrated with the Electric Power Infrastructure. IEEE: New York, NY, USA, 2015; pp. 1–136.
13. Bollen, M.H.J. *Understanding Power Quality Problems*; IEEE Press: New York, NY, USA, 1999; Volume 3.
14. *IEEE Std 1159-2009*; IEEE Recommended Practice for Monitoring Electric Power Quality; (Revision of IEEE Std 1159-1995). IEEE: New York, NY, USA, 2009; pp. 1–81.
15. *IEC 61000-4-30*; Testing and Measurement Techniques–Power Quality Measurement Methods. International Electrotechnical Commission Standard: Geneva, Switzerland, 2015.
16. *EN Std. 50160*; Voltage Characteristics of Electricity Supplied by Public Distribution Systems. British Standard: London, UK, 2002.
17. Bollen, M.H.; Gu, I.Y.; Santoso, S.; McGranaghan, M.F.; Crossley, P.A.; Ribeiro, M.V.; Ribeiro, P.F. Bridging the gap between signal and power. *IEEE Signal Process. Mag.* **2009**, *26*, 12–31. [CrossRef]
18. Gu, Y.H.; Bollen, M.H.J. Time-frequency and time-scale domain analysis of voltage disturbances. *IEEE Trans. Power Deliv.* **2000**, *15*, 1279–1284. [CrossRef]
19. Phadke, A.G.; Thorp, J.S. *Synchronized Phasor Measurements and Their Applications*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2008.
20. *IEEE Standard C37.118.1-2011*; IEEE Standard for Synchrophasor Measurements for Power Systems; Revision of IEEE Standard C37.118-2005. IEEE: New York, NY, USA, 2011.
21. *IEEE Standard C37.118.1a-2014*; IEEE Standard for Synchrophasor Measurements for Power Systems Amendment 1: Modification of Selected Performance Requirements; Amendment to IEEE Standard C37.118.1-2011. IEEE: New York, NY, USA, 2014.
22. Liang, X. Emerging power quality challenges due to integration of renewable energy sources. *IEEE Trans. Ind. Appl.* **2017**, *53*, 855–866. [CrossRef]
23. Mishra, M. Power quality disturbance detection and classification using signal processing and soft computing techniques: A comprehensive review. *Int. Trans. Electr. Energy Syst.* **2019**, *29*, e12008. [CrossRef]
24. Chawda, G.S.; Shaik, A.G.; Shaik, M.; Padmanaban, S.; Holm-Nielsen, J.B.; Mahela, O.P.; Kaliannan, P. Comprehensive review on detection and classification of power quality disturbances in utility grid with renewable energy penetration. *IEEE Access* **2020**, *8*, 146807–146830. [CrossRef]
25. Khetarpal, P.; Tripathi, M.M. A critical and comprehensive review on power quality disturbance detection and classification. *Sustain. Comput. Inform. Syst.* **2020**, *28*, 100417. [CrossRef]
26. Alimi, O.A.; Ouahada, K.; Abu-Mahfouz, A.M. A review of machine learning approaches to power system security and stability. *IEEE Access* **2020**, *8*, 113512–113531. [CrossRef]
27. Beniwal, R.K.; Saini, M.K.; Nayyar, A.; Qureshi, B.; Aggarwal, A. A critical analysis of methodologies for detection and classification of power quality events in smart grid. *IEEE Access* **2021**, *9*, 83507–83534. [CrossRef]
28. Martinez, R.; Castro, P.; Arroyo, A.; Manana, M.; Galan, N.; Moreno, F.S.; Laso, A. Techniques to Locate the Origin of Power Quality Disturbances in a Power System: A Review. *Sustainability* **2022**, *14*, 7428. [CrossRef]
29. Bonde, G.N.; Paraskar, S.R.; et Jadhao, S.S. Review on detection and classification of underlying causes of power quality disturbances using signal processing and soft computing technique. *Mater. Today Proc.* **2022**, *58*, 509–515. [CrossRef]
30. Back, T. *Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic Algorithms*; Oxford University Press: Oxford, UK, 1996.
31. Celli, G.; Ghiani, E.; Mocci, S.; Pilo, F. A multiobjective evolutionary algorithm for the sizing and siting of distributed generation. *IEEE Trans. Power Syst.* **2005**, *20*, 750–757. [CrossRef]
32. Gunal, S.; Gerek, O.N.; Ece, D.G.; Edizkan, R. The search for optimal feature set in power quality event classification. *Expert Syst. Appl.* **2009**, *36*, 10266–10273. [CrossRef]

33. Ribeiro, P.F.; Duque, C.A.; Ribeiro, P.M.; Cerqueira, A.S. *Power Systems Signal Processing for Smart Grids*; John Wiley & Sons: Hoboken, NJ, USA, 2013.
34. Hu, J.; Zhu, J.; Platt, G. Smart grid the next generation electricity grid with power flow optimization and high power quality. In Proceedings of the 2011 IEEE International Conference on Electrical Machines and Systems, Beijing, China, 20–23 August 2011; pp. 1–6.
35. Dugan, R.C.; McGranaghan, M.F.; Beaty, H.W. *Electrical Power Systems Quality*; McGraw-Hill: New York, NY, USA, 1996.
36. Chung, H.; Hui, S.; Tse, K. Reduction of power converter emi emission using soft-switching technique. *IEEE Trans. Electromagn. Compat.* **1998**, *40*, 282–287. [CrossRef]
37. Morsi, W.G.; El-Hawary, M. Power quality evaluation in smart grids considering modern distortion in electric power systems. *Electr. Power Syst. Res.* **2011**, *81*, 1117–1123. [CrossRef]
38. Jaramillo, S.H.; Heydt, G.; O'Neill-Carrillo, E. Power quality indices for aperiodic voltages and currents. *IEEE Trans. Power Deliv.* **2000**, *15*, 784–790. [CrossRef]
39. Laughton, M. Analysis of Unbalanced Polyphase Networks by the Method of Phase Co-ordinates. Part 2: Fault Analysis. In Proceedings of the Institution of Electrical Engineers, London, UK, 6–8 May 1969; Volume 116, pp. 857–865.
40. Kaleybar, H.J.; Brenna, M.; Foiadelli, F.; Fazel, S.S.; Zaninelli, D. Power Quality Phenomena in Electric Railway Power Supply Systems: An Exhaustive Framework and Classification. *Energies* **2020**, *13*, 6662. [CrossRef]
41. Heydt, G.T. *Electric Power Quality*; Stars in a Circle Publications: Lafayette, IN, USA, 1991.
42. Arrillaga, J.; Watson, N.R. *Power System Harmonics*; John Wiley & Sons: Hoboken, NJ, USA, 2004.
43. Arrillaga, J. *Power System Harmonic Analysis*; John Wiley & Sons: Hoboken, NJ, USA, 1997.
44. Wagner, V.; Balda, J.C.; Griffith, D.; McEachern, A.; Barnes, T.; Hartmann, D.; Phileggi, D.; Emannuel, A.; Horton, W.F.; Reid, W.E.; et al. Effects of harmonics on equipment. *IEEE Trans. Power Deliv.* **1993**, *8*, 672–680. [CrossRef]
45. *IEC Std. 61000-4-7*; Electromagnetic Compatibility (EMC) Part 4–7: Testing and Measurement Techniques—General Guide on Harmonics and Interharmonics Measurements and Instrumentation, for Power Supply Systems and Equipment Connected Thereto. International Electrotechnical Commission: Geneva, Switzerland, 2002.
46. DOE EPRI National Database Repository of Power System Events. Available online: http://pqmon.epri.com/disturbance_library (accessed on 1 August 2022).
47. Zeng, Z.; Yang, H.; Zhao, R.; Cheng, C. Topologies and control strategies of multi-functional grid-connected inverters for power quality enhancement: A comprehensive review. *Renew. Sustain. Energy Rev.* **2013**, *24*, 223–270. [CrossRef]
48. Ipakchi, A.; Albuyeh, F. Grid of the future. *IEEE Power Energy Mag.* **2009**, *7*, 52–62. [CrossRef]
49. Bollen, M.H.J.; Ribeiro, P.; Gu, I.Y.; Duque, C.A. Trends, challenges and opportunities in power quality research. *Eur. Trans. Electr. Power* **2010**, *20*, 3–18. [CrossRef]
50. Chattopadhyay, S.; Mitra, M.; Sengupta, S. *Electric Power Quality*; Springer: Dordrecht, The Netherlands, 2011.
51. Bergen, A.R. *Power Systems Analysis*; Pearson Education: Bengaluru, India, 2000.
52. McBee, K.D.; Simoes, M.G. Utilizing a smart grid monitoring system to improve voltage quality of customers. *IEEE Trans. Smart Grid* **2012**, *3*, 738–743. [CrossRef]
53. Amin, S.; Wollenberg, B. Toward a smart grid: Power delivery for the 21st century. *IEEE Power Energy Mag.* **2005**, *3*, 34–41. [CrossRef]
54. Granjon, P.; Phua, G.S.L. Estimation of geometric properties of threecomponent signals for system monitoring. *Mech. Syst. Signal Process.* **2017**, *97*, 95–111. [CrossRef]
55. Cablea, G.; Granjon, P.; Bérenguer, C. Three-phase electrical signals analysis for mechanical faults monitoring in rotating machine systems. *Mech. Syst. Signal Process.* **2017**, *92*, 278–292. [CrossRef]
56. *IEC Standard 61000-1-1.1*; Electromagnetic Compatibility (EMC), Part 1: General, Section 1: Application and Interpretation of Fundamental Definitions and Terms. International Electrotechnical Commission: Geneva, Switzerland, 2011.
57. *IEEE Standard 519*; Recommended Practices and Requirements for Harmonic Control in Electrical Power Systems; ANSI IEEE Std. 519 to 992. IEEE: New York, NY, USA, 1993.
58. Narendra, K.; Gurusinghe, D.R.; Rajapakse, A.D. Dynamic performance evaluation and testing of phasor measurement unit (PMU) as per IEEE c37.118.1 standard. In Proceedings of the Doble Client Committee Meetings International Protection Testing Users Group, Chicago, IL, USA, 6–10 August 2012.
59. Zhang, Q.; Chakhchoukh, Y.; Vittal, V.; Heydt, N.; Logic, G.T.; Sturgill, S. Impact of PMU measurement buffer length on state estimation and its optimization. *IEEE Trans. Power Syst.* **2013**, *28*, 1657–1665. [CrossRef]
60. *IEEE Standard C37.118.2005*; IEEE Standard for Synchrophasor Measurements for Power Systems; Revision of IEEE Std. 1344–1995. IEEE: New York, NY, USA, 2005.
61. Depablos, J.; Centeno, V.; Phadke, A.G.; Ingram, M. Comparative testing of synchronized phasor measurement units. In Proceedings of the Power Engineering Society General Meeting, Denver, CO, USA, 6–10 June 2004; pp. 948–954.
62. Papoulis, A.; Maradudin, A. *The Fourier Integral and Its Applications*; McGraw Hill: New York, NY, USA, 1963.
63. Brigham, E.O.; Morrow, R. The fast Fourier transform. *IEEE Spectr.* **1967**, *4*, 63–70.
64. Robertson, D.C.; Camps, O.I.; Mayer, J.S.; Gish, W.B. Wavelets and electromagnetic power system transients. *IEEE Trans. Power Deliv.* **1996**, *11*, 1050–1058. [CrossRef]

65. Barchi, G.; Macii, D.; Petri, D. Accuracy of one-cycle dft-based synchrophasor estimators in steady-state and dynamic conditions. In Proceedings of the Instrumentation and Measurement Technology Conference (I2MTC), Ottawa, ON, Canada, 16–19 May 2022; pp. 1529–1534.
66. Chaitanya, M.N.; Rao, G.S.K. Performance Evaluation of Recursive DFT as Phasor Estimator in PMUs under Power Quality Disturbances. *Int. J. Eng. Res. Technol.* **2015**, *4*, 315–325.
67. Pinto, L.S.; Assunção, M.V.; Ribeiro, D.A.; Ferreira, D.D.; Huallpa, B.N.; Silva, L.R.; Duque, C.A. Compression method of power quality disturbances based on independent component analysis and fast fourier transform. *Electr. Power Syst. Res.* **2020**, *187*, 106428. [CrossRef]
68. Jayasree, D.D. Classification of power quality disturbance signals using FFT, STFT, wavelet transforms and neural networks—A comparative analysis. In Proceedings of the International Conference on Computational Intelligence and Multimedia Applications (ICCIMA 2007), Sivakasi, India, 13–15 December 2007; pp. 335–340.
69. Barros, J.; Diego, R.I.; Apraiz, M.D. Applications of wavelets in electric power quality: Voltage events. *Electr. Power Syst. Res.* **2012**, *88*, 130–136. [CrossRef]
70. Labos, T.; Rezmer, J.; Janik, P.; Amaris, H.; Alonso, M.; Alvarez, C. Application of wavelets and prony method for disturbance detection in fixed speed wind farms. *Int. J. Electr. Power Energy Syst.* **2009**, *31*, 429–436. [CrossRef]
71. Hauer, J. Initial results in prony analysis of power system response signals. *IEEE Trans. Power Syst.* **1990**, *5*, 80–89. [CrossRef]
72. Pisarenko, V.F. The retrieval of harmonics from a covariance function. *Geophys. J. Int.* **1973**, *33*, 347–366. [CrossRef]
73. Reddy, V.; Egardt, B.; Kailath, T. Least squares type algorithm for adaptive implementation of Pisarenko's harmonic retrieval method. *IEEE Trans. Acoust. Speech Signal Process.* **1982**, *30*, 399–405. [CrossRef]
74. Bracale, A.; Caramia, P.; Carpinelli, G. Adaptive Prony method for waveform distortion detection in power systems. *Int. J. Electr. Power Energy Syst.* **2007**, *29*, 371–379. [CrossRef]
75. Marple, L. Spectral line analysis by Pisarenko and Prony methods. In Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP'79), Washington, DC, USA, 2–4 April 1979; Volume 4, pp. 159–161.
76. Lobos, T.; Leonowicz, Z.; Rezmer, J.; Schegner, P. High-resolution spectrum-estimation methods for signal analysis in power systems. *IEEE Trans. Instrum. Meas.* **2006**, *55*, 219–225. [CrossRef]
77. Zygarlicki, J.; Zygarlicka, M.; Mroczka, J.; Latawiec, K. A reduced Prony's method in power quality analysis – parameters selection. *IEEE Trans. Power Deliv.* **2010**, *25*, 979–986. [CrossRef]
78. Zygarlicki, J.; Mroczka, J. Short time algorithm of power waveforms fundamental harmonic estimations with Prony's methods use. *Metrol. Meas. Syst.* **2011**, *18*, 33–38. [CrossRef]
79. Zygarlicki, J.; Zygarlicka, M.; Mroczka, J. Prony's metod in power quality analysis. *Energy Spectr.* **2009**, *4*, 26–30.
80. Zygarlicki, J.; Mroczka, J. Data compression using Prony's method and wavelet transform in power quality monitoring systems. *Metrol. Meas. Syst.* **2006**, *13*, 237–251.
81. Marple, S.L. *Digital Spectral Analysis with Applications*; Prentice Hall: Upper Saddle River, NJ, USA, 1987.
82. Zygarlicki, J.; Mroczka, J. Variable-frequency Prony method in the analysis of electrical power quality. *Metrol. Meas. Syst.* **2012**, *19*, 39–48. [CrossRef]
83. Del Rio, J.E.F.; Sarkar, T.K. Comparison between the Matrix Pencil Method and the Fourier Transform Technique for High-Resolution Spectral Estimation. *Digit. Signal Process.* **1996**, *11*, 108–125. [CrossRef]
84. Markovsky, I.; Van Huffel, S. Overview of total least squares methods. *Signal Process.* **2007**, *87*, 2283–2302. [CrossRef]
85. Robenack, K.; Einschke, K. On generalized inverses of singular matrix pencils. *Int. J. Appl. Math. Comput. Sci.* **2011**, *21*, 161–172. [CrossRef]
86. Stoica, P.; Moses, R.L. *Introduction to Spectral Analysis*; Prentice Hall: Upper Saddle River, NJ, USA, 1997; Volume 1.
87. Kay, S.M.; Marple, S.L. Spectrum analysis—A modern perspective. *Proc. IEEE* **1981**, *69*, 1380–1419. [CrossRef]
88. Flandrin, P. *Time-Frequency/Time-Scale Analysis*; Academic Press: Oxford, UK, 1998; Volume 10.
89. Duda, K.; Zieliński, T.P. P class and M class compliant PMU based on discrete-time frequency-gain transducer. *IEEE Trans. Power Deliv.* **2021**, *37*, 1058–1067. [CrossRef]
90. Sahu, B.; Dhar, S.; Dash, P.K. Frequency-scaled optimized time-frequency transform for harmonic estimation in photovoltaic-based microgrid. *Int. Trans. Electr. Energy Syst.* **2020**, *30*, e12169. [CrossRef]
91. Reddy, M.V.; Sodhi, R. An open-loop fundamental and harmonic phasor estimator for single-phase voltage signals. *IEEE Trans. Ind. Inform.* **2019**, *16*, 4535–4546. [CrossRef]
92. Hosseini, H.S.; Koochaki, A.; Hosseinian, S.H. A novel scheme for current only directional overcurrent protection based on post-fault current phasor estimation. *J. Electr. Eng. Technol.* **2019**, *14*, 1517–1527. [CrossRef]
93. Rivas, A.E.L.; da Silva, N.; Abrão, T. Adaptive current harmonic estimation under fault conditions for smart grid systems. *Electr. Power Syst. Res.* **2020**, *183*, 106276. [CrossRef]
94. Auger, F.; Flandrin, P.; Goncalves, P.; Lemoine, O. Time-Frequency Toolbox, for Use with Matlab; Technical Report; CNRS, GDR ISIS: 1995–1996. Available online: http://tftb.nongnu.org/refguide.pdf (accessed on 8 August 2021).
95. Jopri, M.; Abdullah, A.; Manap, M.; Yusoff, M.; Sutikno, T.; Habban, M. An improved detection and classification technique of harmonic signals in power distribution by utilizing spectrogram. *Int. J. Electr. Comput. Eng.* **2017**, *7*, 12. [CrossRef]
96. Dehghani, M.; Ghiasi, M.; Niknam, T.; Kavousi-Fard, A.; Padmanaban, S. False data injection attack detection based on Hilbert-huang transform in AC smart islands. *IEEE Access* **2020**, *8*, 179002–179017. [CrossRef]

97. Baayeh, A.G.; Bayati, N. Adaptive overhead transmission lines auto-reclosing based on Hilbert–Huang transform. *Energies* **2020**, *13*, 5416. [CrossRef]
98. Munir, B.S.; Trisetyarso, A.; Reza, M.; Abbas, B.S. Feature Extraction of Low Frequency Oscillation in Power System Using Hilbert–Huang Transform. *TEM J.* **2019**, *8*, 12.
99. Munir, B.S.; Reza, M.; Trisetyarso, A.; Abbas, B.S. Feature extraction using Hilbert–Huang transform for power system oscillation measurements. In Proceedings of the 2017 4th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), Semarang, Indonesia, 18–19 October 2017.
100. Biswal, B.; Biswal, M.; Mishra, S.; Jalaja, R. Automatic classification of power quality events using balanced neural tree. *IEEE Trans. Ind. Electron.* **2014**, *61*, 521–530. [CrossRef]
101. Huang, N.E.; Shen, Z.; Long, S.R.; Wu, M.C.; Shih, H.H.; Zheng, Q.; Yen, N.-C.; Tung, C.C.; Liu, H.H. The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc. R. Soc. Lond. A Math. Phys. Eng. Sci.* **1998**, *454*, 903–995. [CrossRef]
102. Kumar, R.; Singh, B.; Shahani, D.T. Recognition of single-stage and multiple power quality events using hilbert–huang transform and probabilistic neural network. *Electr. Power Compon. Syst.* **2015**, *43*, 607–619. [CrossRef]
103. Shukla, S.; Mishra, S.; Singh, B. Empirical-mode decomposition with hilbert transform for power-quality assessment. *IEEE Trans. Power Deliv.* **2009**, *24*, 2159–2165. [CrossRef]
104. Manjula, M.; Mishra, S.; Sarma, A. Empirical mode decomposition with hilbert transform for classification of voltage sag causes using probabilistic neural network. *Int. J. Electr. Power Energy Syst.* **2013**, *44*, 597–603. [CrossRef]
105. Saiz, V.M.; Guadalupe, J.B. Application of kalman filtering for continuous real-time tracking of power system harmonics. *IEEE Proc.-Gener. Transm. Distrib.* **1997**, *144*, 13–20. [CrossRef]
106. Kamwa, I.; Grondin, R.; McNabb, D. On-line tracking of changing harmonics in stressed power systems: Application to hydro-quebec network. *IEEE Trans. Power Deliv.* **1996**, *11*, 2020–2027. [CrossRef]
107. Ferrero, R.; Pegoraro, P.A.; Toscani, S. Dynamic synchrophasor estimation by extended Kalman filter. *IEEE Trans. Instrum. Meas.* **2019**, *69*, 4818–4826. [CrossRef]
108. De Apráiz, M.; Diego, R.I.; Barros, J. An extended Kalman filter approach for accurate instantaneous dynamic phasor estimation. *Energies* **2018**, *11*, 2918. [CrossRef]
109. Girgis, A.A.; Qiu, J. Measurement of the parameters of slowly time varying high frequency transients. *IEEE Trans. Instrum. Meas.* **1989**, *38*, 1057–1063. [CrossRef]
110. Bashian, A.; Macii, D.; Fontanelli, D.; Petri, D. A Tuned Whitening-Based Taylor-Kalman Filter for P Class Phasor Measurement Units. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 1–13. [CrossRef]
111. Mishra, C.; Vanfretti, L.; Jones, K.D. Synchrophasor phase angle data unwrapping using an unscented Kalman filter. *IEEE Trans. Power Syst.* **2021**, *36*, 4868–4871. [CrossRef]
112. Dash, P.K.; Chilukuri, M.V. Hybrid s-transform and kalman filtering approach for detection and measurement of short duration disturbances in power networks. *IEEE Trans. Instrum. Meas.* **2004**, *53*, 588–596. [CrossRef]
113. Reddy, J.; Dash, P.K.; Samantaray, R.; Moharana, A.K. Fast tracking of power quality disturbance signals using an optimized unscented filter. *IEEE Trans. Instrum. Meas.* **2009**, *58*, 3943–3952. [CrossRef]
114. Ferrero, R.; Pegoraro, P.A.; Toscani, S. Synchrophasor estimation for three-phase systems based on Taylor extended Kalman filtering. *IEEE Trans. Instrum. Meas.* **2020**, *69*, 6723–6730. [CrossRef]
115. Ferrero, R.; Pegoraro, P.A.; Toscani, S. Dynamic fundamental and harmonic synchrophasor estimation by Extended Kalman filter. In Proceedings of the 2016 IEEE International Workshop on Applied Measurements for Power Systems (AMPS), Aachen, Germany, 28–30 September 2016.
116. Kay, S.M. *Fundamentals of Statistical Signal Processing: Estimation Theory*; Prentice Hall: Upper Saddle River, NJ, USA, 1993; Volume 1.
117. Oubrahim, Z.; Choqueuse, V.; Amirat, Y.; Benbouzid, M.E.H. Maximum-likelihood frequency and phasor estimations for electric power grid monitoring. *IEEE Trans. Ind. Inform.* **2017**, *14*, 167–177. [CrossRef]
118. Oubrahim, Z.; Choqueuse, V.; Amirat, Y.; Benbouzid, M. An improved algorithm for power system fault type classification based on least square phasor estimation. In Proceedings of the IECON 2015-41st Annual Conference of the IEEE Industrial Electronics Society, Yokohama, Japan, 9–12 November 2015.
119. Kay, S.M. *Modern Spectral Estimation*; Pearson Education: Bengaluru, India, 1988.
120. Ibrahim, W.A.; Morcos, M.M. Artificial intelligence and advanced mathematical tools for power quality applications: A survey. *IEEE Trans. Power Deliv.* **2002**, *17*, 668–673. [CrossRef]
121. Nath, S.; Sinha, P.; Goswami, S.K. A wavelet based novel method for the detection of harmonic sources in power systems. *Int. J. Electr. Power Energy Syst.* **2012**, *40*, 54–61. [CrossRef]
122. Ozgonenel, O.; Yalcin, T.; Guney, I.; Kurt, U. A new classification for power quality events in distribution systems. *Electr. Power Syst. Res.* **2013**, *95*, 192–199. [CrossRef]
123. Saxena, D.; Singh, S.; Verma, K.; Singh, S.K. HHT-based classification of composite power quality events. *Int. J. Energy Sect. Manag.* **2014**, *8*, 146–159. [CrossRef]
124. Haykin, S.S. *Kalman Filtering and Neural Networks*; Wiley Online Library: Hoboken, NJ, USA, 2001.
125. Moon, T.K.; Stirling, W.C. *Mathematical Methods and Algorithms for Signal Processing*; Prentice Hall: Hoboken, NJ, USA, 2000.

126. Abdelsalam, A.A.; Eldesouky, A.A.; Sallam, A.A. Classification of power system disturbances using linear kalman filter and fuzzy-expert system. *Int. J. Electr. Power Energy Syst.* **2012**, *43*, 688–695. [CrossRef]
127. Amirat, Y.; Oubrahim, Z.; Benbouzid, M.E.H. On phasor estimation for voltage sags detection in a smart grid context. In Proceedings of the 2015 IEEE International Symposium on Industrial Electronics, Rio de Janiero, Brazil, 3–5 June 2015; pp. 1351–1356.
128. Bakirtzis, A.G.; Biskas, P.N.; Zoumas, C.E.; Petridis, V. Optimal power flow by enhanced genetic algorithm. *IEEE Trans. Power Syst.* **2002**, *17*, 229–236. [CrossRef]
129. Sen, O.; Song, Z.; Wang, J.; Chen, D. Application of lvq neural networks combined with genetic algorithm in power quality signals classification. In Proceedings of the 2002 IEEE International Conference on Power System Technology, Kunming, China, 13–17 October 2002; Volume 1, pp. 491–495.
130. Al-Hasawi, W.M.; El-Naggar, K.M. A genetic based algorithm for voltage flicker measurement. *Int. J. Electr. Power Energy Syst.* **2004**, *26*, 593–596. [CrossRef]
131. Juang, C.-F. A hybrid of genetic algorithm and particle swarm optimization for recurrent network design. *IEEE Trans. Syst. Man Cybern. Part (Cybern.)* **2004**, *34*, 997–1006. [CrossRef] [PubMed]
132. Panigrahi, B.K.; Pandi, V.R. Optimal feature selection for classification of power quality disturbances using wavelet packet-based fuzzy k-nearest neighbour algorithm. *IET Gener. Transm. Distrib.* **2009**, *3*, 296–306. [CrossRef]
133. Priyadarshini, L.; Prasad, E.N.; Dash, P.K. Diagnosis of PQ Disturbances using Local mean decomposition based SVD entropy and modified K-means clustering. In Proceedings of the 2021 International Conference in Advances in Power, Signal, and Information Technology (APSIT), Bhubaneswar, India, 8–10 October 2021.
134. Krishna, K.; Narasimha Murty, M. Genetic K-means algorithm. *IEEE Trans. Syst. Man Cybern. Part (Cybern.)* **1999**, *29*, 433–439. [CrossRef]
135. Manimala, K.; Selvi, K.; Ahila, R. Hybrid soft computing techniques for feature selection and parameter optimization in power quality data mining. *Appl. Soft Comput.* **2011**, *11*, 5485–5497. [CrossRef]
136. Wang, M.-H.; Tseng, Y.-F. A novel analytic method of power quality using extension genetic algorithm and wavelet transform. *Expert Syst. Appl.* **2011**, *38*, 12491–12496. [CrossRef]
137. Biswal, B.; Dash, P.K.; Panigrahi, B.K. Power quality disturbance classification using fuzzy C-means algorithm and adaptive particle swarm optimization. *IEEE Trans Ind Electron.* **2009**, *56*, 212–220. [CrossRef]
138. Rodriguez-Guerrero, M.A.; Jaen-Cuellar, A.Y.; Carranza-Lopez-Padilla, R.D.; Osornio-Rios, R.A.; Herrera-Ruiz, G.; Romero-Troncoso, R.D.J. Hybrid approach based on GA and PSO for parameter estimation of a full power quality disturbance parameterized model. *IEEE Trans. Ind. Inform.* **2017**, *14*, 1016–1028. [CrossRef]
139. Hajian, M.; Akbari Foroud, A. A new hybrid pattern recognition scheme for automatic discrimination of power quality disturbances. *Measurement* **2014**, *51*, 265–280. [CrossRef]
140. Hajian, M.; Akbari Foroud, A.; Abdoos, A.A. New automated power quality recognition system for online/offline monitoring. *Neurocomputing* **2014**, *128*, 389–406. [CrossRef]
141. Ahila, R.; Sadasivam, V.; Manimala, K. An integrated PSO for parameter determination and feature selection of ELM and its application in classification of power system disturbances. *Appl. Soft Comput.* **2015**, *32*, 23–37. [CrossRef]
142. Chamchuen, S.; Siritaratiwat, A.; Fuangfoo, P.; Suthisopapan, P.; Khunkitti, P. High-Accuracy power quality disturbance classification using the adaptive ABC-PSO as optimal feature selection algorithm. *Energies* **2021**, *14*, 1238. [CrossRef]
143. Chen, J.-F.; Do, Q.H.; Hsieh, H.-N. Training artificial neural networks by a hybrid PSO-CS algorithm. *Algorithms* **2015**, *8*, 292–308. [CrossRef]
144. Huang, N.; Zhang, S.; Cai, G.; Xu, D. Power quality disturbances recognition based on a multiresolution generalized S-transform and a PSO-improved decision tree. *Energies* **2015**, *8*, 549–572. [CrossRef]
145. Dorigo, M.; Birattari, M.; Stitzle, T. Ant Colony Optimization: Arificial Ants as a Computational Intelligence Technique. *IEEE Comput. Intell. Mag.* **2006**, *1*, 28–39. [CrossRef]
146. Singh, U.; Singh, S.N. A new optimal feature selection scheme for classification of power quality disturbances based on ant colony framework. *Appl. Soft Comput.* **2019**, *74*, 216–225. [CrossRef]
147. Lagarias, J.C.; Reeds, J.A.; Wright, M.H.; Wright, P.E. Convergence properties of the nelder–mead simplex method in low dimensions. *SIAM J. Optim.* **1998**, *9*, 112–147. [CrossRef]
148. Brent, R.P. *Algorithms for Minimization without Derivatives*; Courier Corporation: Chelmsford, MA, USA, 2013.
149. Forsythe, G.E.; Moler, C.B.; Malcolm, M.A. *Computer Methods for Mathematical Computations*; Prentice-Hall: Hoboken, NJ, USA, 1977.
150. Kay, S.M. *Fundamentals of Statistical Signal Processing*; PTR Prentice-Hall: Englewood Cliffs, NJ, USA, 1993.
151. Khokhar, S.; Zin, A.A.B.M.; Mokhtar, A.S.B.; Pesaran, M. A comprehensive overview on signal processing and artificial intelligence techniques applications in classification of power quality disturbances. *Renew. Sustain. Energy Rev.* **2015**, *51*, 1650–1663. [CrossRef]
152. Saini, M.K.; Kapoor, R. Classification of power quality events—A review. *Int. J. Electr. Power Energy Syst.* **2012**, *43*, 11–19. [CrossRef]
153. Duda, R.O.; Hart, P.E.; Stork, D.G. *Pattern Classification*; Wiley: New York, NY, USA, 1973; Volume 2.
154. Devroye, L.; Györfi, L.; Lugosi, G. *A Probabilistic Theory of Pattern Recognition*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2013; Volume 31.

155. Huang, J.; Negnevitsky, M.; Nguyen, D.T. A neural-fuzzy classifier for recognition of power quality disturbances. *IEEE Trans. Power Deliv.* **2002**, *17*, 609–616. [CrossRef]
156. Fausett, L.V. *Fundamentals of Neural Networks*; Prentice-Hall: Hoboken, NJ, USA, 1994.
157. Jackson, P. *Introduction to Expert Systems*; Addison-Wesley Publishing Company: Reading, MA, USA, 1986.
158. Biswal, B.; Dash, P.K.; Panigrahi, B.K. Non-stationary power signal processing for pattern recognition using hs-transform. *Appl. Soft Comput.* **2009**, *9*, 107–117. [CrossRef]
159. Biswal, B.; Dash, P.K.; Panigrahi, B.K.; Reddy, J. Power signal classification using dynamic wavelet network. *Appl. Soft Comput.* **2009**, *9*, 118–125. [CrossRef]
160. Morsi, W.G.; El-Hawary, M. Novel power quality indices based on wavelet packet transform for non-stationary sinusoidal and non-sinusoidal disturbances. *Electr. Power Syst. Res.* **2010**, *80*, 753–759. [CrossRef]
161. Oubrahim, Z.; Choqueuse, V.; Amirat, Y.; Benbouzid, M.E.H. Classification of three-phase power disturbances based on model order selection in smart grid applications. In Proceedings of the 42nd Annual Conference of the IEEE Industrial Electronics Society (IECON), Florence, Italy, 23–26 October 2016; pp. 5143–5148.
162. Oubrahim, Z.; Choqueuse, V.; Amirat, Y.; Benbouzid, M.E.H. Disturbances classification based on a model order selection method for power quality monitoring. *IEEE Trans. Ind. Electron.* **2017**, *64*, 9421–9432. [CrossRef]
163. Bollen, M.H.J.; Zhang, L. Different methods for classification of three-phase unbalanced voltage dips due to faults. *Electr. Power Syst. Res.* **2003**, *66*, 59–69. [CrossRef]
164. Bollen, M.H.J. Algorithms for characterizing measured three-phase unbalanced voltage dips. *IEEE Trans. Power Deliv.* **2003**, *18*, 937–944. [CrossRef]
165. Stoica, P.; Selen, Y. Model-order selection: A review of information criterion rules. *IEEE Signal Process. Mag.* **2004**, *21*, 36–47. [CrossRef]
166. Ignatova, V.; Granjon, P.; Bacha, S. Space vector method for voltage dips and swells analysis. *IEEE Trans. Power Deliv.* **2009**, *24*, 2054–2061. [CrossRef]
167. Bishop, C.M. *Pattern Recognition and Machine Learning*; Springer: Berlin/Heidelberg, Germany, 2006.
168. Fukunaga, K. *Introduction to Statistical Pattern Recognition*; Academic Press: Cambridge, MA, USA, 2013.
169. Kamwa, I.; Grondin, R.; Sood, V.; Gagnon, C.; Mereb, J. Recurrent neural networks for phasor detection and adaptive identification in power system control and protection. *IEEE Trans. Instrum. Meas.* **1996**, *45*, 657–664. [CrossRef]
170. Cerqueira, A.S.; Ferreira, D.D.; Ribeiro, M.V.; Duque, C.A. Power quality events recognition using a svm-based method. *Electr. Power Syst. Res.* **2008**, *78*, 1546–1552. [CrossRef]
171. Ma, L.; Lee, K.Y. Fuzzy neural network approach for fault diagnosis of power plant thermal system under different operating points. In Proceedings of the 2008 IEEE Power and Energy Society General Meeting, Pittsburgh, PA, USA, 20–24 July 2008; pp. 1–7.
172. Haykin, S.S.; Haykin, S.S.; Haykin, S.S.; Haykin, S.S. *Neural Networks and Learning Machines*; Pearson: Hoboken, NJ, USA, 2009; Volume 3.
173. Sahani, M.; Dash, P.K. Automatic power quality events recognition based on Hilbert Huang transform and weighted bidirectional extreme learning machine. *IEEE Trans. Ind. Inform.* **2018**, *14*, 3849–3858. [CrossRef]
174. Sahani, M.; Dash, P.; Samal, D. A real-time power quality events recognition using variational mode decomposition and online-sequential extreme learning machine. *Measurement* **2020**, *157*, 107597. [CrossRef]
175. Zhao, C.; Li, K.; Li, Y.; Wang, L.; Luo, Y.; Xu, X.; Ding, X.; Meng, Q. Novel method based on variational mode decomposition and a random discriminative projection extreme learning machine for multiple power quality disturbance recognition. *IEEE Trans. Ind. Inform.* **2018**, *15*, 2915–2926. [CrossRef]
176. Liu, S.; Yang, D. Identification and detection algorithm of electric energy disturbance in microgrid based on wavelet analysis and neural network. *EURASIP J. Wirel. Commun. Netw.* **2021**, 27. [CrossRef]
177. Lee, C.; Nam, S. Efficient feature vector extraction for automatic classification of power quality disturbances. *Electron. Lett.* **1998**, *34*, 1059–1061. [CrossRef]
178. Monedero, I.; Leon, C.; Ropero, J.; Garcia, A.; Elena, J.M.; Montano, J.C. Classification of electrical disturbances in real time using neural networks. *IEEE Trans. Power Deliv.* **2007**, *22*, 1288–1296. [CrossRef]
179. Valtierra-Rodriguez, M.; de Jesus Romero-Troncoso, R.; Osornio-Rios, R.A.; Garcia-Perez, A. Detection and classification of single and combined power quality disturbances using neural networks. *IEEE Trans. Ind. Electron.* **2014**, *61*, 2473–2482. [CrossRef]
180. Bhende, C.; Mishra, S.; Panigrahi, B. Detection and classification of power quality disturbances using s-transform and modular neural network. *Electr. Power Syst. Res.* **2008**, *78*, 122–128. [CrossRef]
181. Uyar, M.; Yildirim, S.; Gencoglu, M.T. An effective wavelet-based feature extraction method for classification of power quality disturbance signals. *Electr. Power Syst. Res.* **2008**, *78*, 1747–1755. [CrossRef]
182. Negnevitsky, M.; Faybisovich, V.; Santoso, S.; Powers, E.; Grady, W.; Parsons, A. Discussion of "power quality disturbance waveform recognition using waveletbased neural classifier-part 1: Theoretical foundation" [closure to discussion]. *IEEE Trans. Power Deliv.* **2000**, *15*, 1347–1348. [CrossRef]
183. Kanitpanyacharoean, W.; Premrudeepreechacharn, S. Power quality problem classification using wavelet transformation and artificial neural networks. In Proceedings of the 2004 PES General Meeting, New York, NY, USA, 10–13 October 2004; pp. 1496–1501.
184. Cai, K.; Cao, W.; Aarniovuori, L.; Pang, H.; Lin, Y.; Li, G. Classification of power quality disturbances using Wigner–Ville distribution and deep convolutional neural networks. *IEEE Access* **2019**, *7*, 119099–119109. [CrossRef]
185. Vapnik, V.N.; Kotz, S. *Estimation of Dependences Based on Empirical Data*; Springer: New York, NY, USA, 1982; Volume 40.

186. Vapnik, V.N.; Vapnik, V. *Statistical Learning Theory*; Wiley: New York, NY, USA, 1998; Volume 1.
187. Choudhary, B. An Advanced Genetic Algorithm with Improved Support Vector Machine for Multi-Class Classification of Real Power Quality Events. *Electr. Power Syst. Res.* **2021**, *191*, 106879.
188. Karasu, S.; Saraç, Z. Investigation of power quality disturbances by using 2D discrete orthonormal S-transform, machine learning and multi-objective evolutionary algorithms. *Swarm Evol. Comput.* **2019**, *44*, 1060–1072. [CrossRef]
189. Motlagh, S.Z.; Foroud, A.A. Power quality disturbances recognition using adaptive chirp mode pursuit and grasshopper optimized support vector machines. *Measurement* **2021**, *168*, 108461. [CrossRef]
190. Nagata, E.A.; Ferreira, D.D.; Bollen, M.H.; Barbosa, B.H.; Ribeiro, E.G.; Duque, C.A.; Ribeiro, P.F. Real-time voltage sag detection and classification for power quality diagnostics. *Measurement* **2020**, *164*, 108097. [CrossRef]
191. Ekici, S. Classification of power system disturbances using support vector machines. *Expert Syst. Appl.* **2009**, *36*, 9859–9868. [CrossRef]
192. Janik, P.; Lobos, T. Automated classification of power-quality disturbances using svm and rbf networks. *IEEE Trans. Power Deliv.* **2006**, *21*, 1663–1669. [CrossRef]
193. Lin, W.-M.; Wu, C.-H.; Lin, C.-H.; Cheng, F.-S. Detection and classification of multiple power-quality disturbances with wavelet multiclass svm. *IEEE Trans. Power Deliv.* **2008**, *23*, 2575–2582. [CrossRef]
194. Liu, Z.; Cui, Y.; Li, W. A classification method for complex power quality disturbances using EEMD and rank wavelet SVM. *IEEE Trans. Smart Grid* **2015**, *6*, 1678–1685. [CrossRef]
195. Axelberg, P.G.; Gu, I.Y.-H.; Bollen, M.H.J. Support vector machine for classification of voltage disturbances. *IEEE Trans. Power Deliv.* **2007**, *22*, 1297–1303. [CrossRef]
196. Eristi, H.; Uçar, A.; Demir, Y. Wavelet-based feature extraction and selection for classification of power system disturbances using support vector machines. *Electr. Power Syst. Res.* **2010**, *80*, 743–752. [CrossRef]
197. Zhan, Y.; Cheng, H.Z.; Ding, Y.F.; Lü, G.Y.; Sun, Y.-B. S-transform-based classification of power quality disturbance signals by support vector machines. *Proc. CSEE* **2005**, *4*, 9.
198. Hu, G.-S.; Xie, J.; Zhu, F.-F. Classification of power quality disturbances using wavelet and fuzzy support vector machines. In Proceedings of the 2005 International Conference on Machine Learning and Cybernetics, Guangzhou, China, 18–21 August 2005; Volume 7, pp. 3981–3984.
199. Hu, G.-S.;Zhu, F.-F.; Ren, Z. Power quality disturbance identification using wavelet packet energy entropy and weighted support vector machines. *Expert Syst. Appl.* **2008**, *35*, 143–149. [CrossRef]
200. De Yong, D.; Bhowmik, S.; Magnago, F. An effective power quality classifier using wavelet transform and support vector machines. *Expert Syst. Appl.* **2015**, *42*, 6075–6081. [CrossRef]
201. Dash, P.; Mishra, S.; Salama, M.; Liew, A. Classification of power system disturbances using a fuzzy expert system and a fourier linear combiner. *IEEE Trans. Power Deliv.* **2000**, *15*, 472–477. [CrossRef]
202. Rajeshbabu, S.; Manikandan, B.V. Detection and classification of power quality events by expert system using analytic hierarchy method. *Cogn. Syst. Res.* **2018**, *52*, 729–740. [CrossRef]
203. Pires, V.F.; Amaral, T.G.; Martins, J. Power quality disturbances classification using the 3-d space representation and pca based neuro-fuzzy approach. *Expert Syst. Appl.* **2011**, *38*, 11911–11917. [CrossRef]
204. Liao, C.-C.; Yang, H.-T. Recognizing noise-influenced power quality events with integrated feature extraction and neuro-fuzzy network. *IEEE Trans. Power Deliv.* **2009**, *24*, 2132–2141. [CrossRef]
205. Biswal, M.; Dash, P.K. Measurement and classification of simultaneous power signal patterns with an s-transform variant and fuzzy decision tree. *IEEE Trans. Ind. Inform.* **2013**, *9*, 1819–1827. [CrossRef]
206. Saikia, L.; Borah, S.; Pait, S. Detection and classification of power quality disturbances using wavelet transform, fuzzy logic and neural network. In Proceedings of the 2006 IEEE INDICON, Kolkata, India, 15–17 September 2006; pp. 1–5.
207. Meher, S.K.; Pradhan, A.K. Fuzzy classifiers for power quality events analysis. *Electr. Power Syst. Res.* **2010**, *80*, 71–76. [CrossRef]
208. Decanini, J.G.; Tonelli-Neto, M.S.; Malange, F.C.; Minussi, C.R. Detection and classification of voltage disturbances using a fuzzy-artmap-wavelet network. *Electr. Power Syst. Res.* **2011**, *81*, 2057–2065. [CrossRef]
209. Bizjak, B.; Planinšic, P. Classification of power disturbances using fuzzy logic. In Proceedings of the 2006 IEEE EPE-12th International Power Electronics and Motion Control Conference, Portoroz, Slovenia, 30 August–1 September 2006; pp. 1356–1360.
210. Eristi, H.; Demir, Y. A new algorithm for automatic classification of power quality events based on wavelet transform and SVM. *Expert Syst. Appl.* **2010**, *37*, 4094–4102. [CrossRef]
211. Chilukuri, M.; Dash, P. Multiresolution s-transform-based fuzzy recognition system for power quality events. *IEEE Trans. Power Deliv.* **2004**, *19*, 323–330. [CrossRef]
212. Wang, S.; Chen, H. A novel deep learning method for the classification of power quality disturbances using deep convolutional neural network. *Appl. Energy* **2019**, *235*, 1126–1140. [CrossRef]
213. Eristi, B.; Eristi, H. A new deep learning method for the classification of power quality disturbances in hybrid power system. *Electr. Eng.* **2022**, *104*, 3753–3768. [CrossRef]
214. Shen, Y.; Abubakar, M.; Liu, H.; Hussain, F. Power quality disturbance monitoring and classification based on improved PCA and convolution neural network for wind-grid distribution systems. *Energies* **2019**, *12*, 1280. [CrossRef]
215. Sindi, H.; Nour, M.; Rawa, M.; Öztürk, Ş.; Polat, K. A novel hybrid deep learning approach including combination of 1D power signals and 2D signal images for power quality disturbance classification. *Expert Syst. Appl.* **2021**, *174*, 114785. [CrossRef]

216. Wang, J.; Zhang, D.; Zhou, Y. Ensemble deep learning for automated classification of power quality disturbances signals. *Electr. Power Syst. Res.* **2022**, *213*, 108695. [CrossRef]
217. Sindi, H.; Nour, M.; Rawa, M.; Öztürk, Ş.; Polat, K. An adaptive deep learning framework to classify unknown composite power quality event using known single power quality events. *Expert Syst. Appl.* **2021**, *178*, 115023. [CrossRef]
218. Yılmaz, A.; Küçüker, A.; Bayrak, G. Automated classification of power quality disturbances in a SOFC-PV-based distributed generator using a hybrid machine learning method with high noise immunity. *Int. J. Hydrogen Energy* **2022**, *47*, 19797–19809. [CrossRef]
219. Salles, R.S.; Ribeiro, P.F. The use of deep learning and 2-D wavelet scalograms for power quality disturbances classification. *Electr. Power Syst. Res.* **2023**, *214*, 108834. [CrossRef]
220. Zhong, T.; Zhang, S.; Cai, G.; Huang, N. Power-quality disturbance recognition based on time-frequency analysis and decision tree. *IET Gener. Transm. Distrib.* **2018**, *12*, 4153–4162. [CrossRef]
221. Zhong, T.; Zhang, S.; Cai, G.; Li, Y.; Yang, B.; Chen, Y. Power quality disturbance recognition based on multiresolution S-transform and decision tree. *IEEE Access* **2019**, *7*, 88380–88392. [CrossRef]
222. Minh Khoa, N.; Van Dai, L. Detection and classification of power quality disturbances in power system using modified-combination between the Stockwell transform and decision tree methods. *Energies* **2020**, *13*, 3623. [CrossRef]
223. Shareef, H.; Mohamed, A.; Ibrahim, A.A. An image processing based method for power quality event identification. *Int. J. Elect. Power Energy Syst.* **2013**, *46*, 184–197. [CrossRef]
224. Erişti, H.; Yıldırım, Ö.; Erişti, B.; Demir, Y. Optimal feature selection for classification of the power quality events using wavelet transform and least squares support vector machines. *Int. J. Electr. Power Energy Syst.* **2013**, *49*, 95–103. [CrossRef]
225. Deokar, S.A.; Waghmare, L.M. Integrated DWT–FFT approach for detection and classification of power quality disturbances. *Int. J. Electr. Power Energy Syst.* **2014**, *61*, 594–605. [CrossRef]
226. Manimala, K.; Selvi, K.; Ahila, R. Optimization techniques for improving power quality data mining using wavelet packet based support vector machine. *Neurocomputing* **2012**, *77*, 36–47. [CrossRef]
227. Zhang, M.; Li, K.; Hu, Y. Classification of power quality disturbances using wavelet packet energy and multiclass support vector machine. *COMPEL-Int. J. Comput. Math. Electr. Electron. Eng.* **2012**, *31*, 424–442. [CrossRef]
228. Barik, A.K.; Tripathy, D.; Mohanty, A.K. Detection & mitigation of power quality disturbances using WPT & FACTS technology. *Int. J. Sci. Eng. Technol. Res.* **2013**, *2*, 336–343.
229. He, S.; Li, K.; Zhang, M. A real-time power quality disturbances classification using hybrid method based on S-transform and dynamics. *IEEE Trans. Instrum. Meas.* **2013**, *62*, 2465–2475. [CrossRef]
230. Hasheminejad, S.; Esmaeili, S.; Jazebi, S. Power quality disturbance classification using S-transform and hidden Markov model. *Electr. Power Compon. Syst.* **2012**, *40*, 1160–1182. [CrossRef]
231. Mahela, O.P.; Shaik, A.G. Recognition of power quality disturbances using S-transform based ruled decision tree and fuzzy C-means clustering classifiers. *Appl Soft Comput.* **2017**, *59*, 243–257. [CrossRef]
232. Mahela, O.P.; Shaik, A.G. Power quality recognition in distribution system with solar energy penetration using S-transform and fuzzy C-means clustering. *Renew. Energy* **2017**, *106*, 37–51. [CrossRef]
233. Reddy, M.V.; Sodhi, R. A modified S-transform and random forests-based power quality assessment framework. *IEEE Trans. Instrum. Meas.* **2018**, *67*, 78–89. [CrossRef]
234. Mahela, O.P.; Khan, B.; Alhelou, H.H.; Siano, P. Power quality assessment and event detection in distribution network with wind energy penetration using stockwell transform and fuzzy clustering. *IEEE Trans. Ind. Inform.* **2020**, *16*, 6922–6932. [CrossRef]
235. Jayasree, T.; Devaraj, D.; Sukanesh, R. Power quality disturbance classification using Hilbert transform and RBF networks. *Neurocomputing* **2010**, *73*, 1451–1456. [CrossRef]
236. Shukla, S.; Mishra, S.; Singh, B. Power quality event classification under noisy conditions using EMD-based de-noising techniques. *IEEE Trans. Ind. Inf.* **2014**, *10*, 1044–1054. [CrossRef]
237. Prakash, S.; Purwar, S.; Mohanty, S.R. Adaptive detection of islanding and power quality disturbances in a grid-integrated photovoltaic system. *Arab. J. Sci. Eng.* **2020**, *45*, 6297–6310. [CrossRef]
238. Singh, H.R.; Mohanty, S.R.; Kishor, N.; Thakur, K.A. Realtime implementation of signal processing techniques for disturbances detection. *IEEE Trans. Ind. Electron.* **2019**, *66*, 3550–3560. [CrossRef]
239. Achlerkar, P.D.; Samantaray, S.R.; Manikandan, M.S. Variational mode decomposition and decision tree based detection and classification of power quality disturbances in grid-connected distributed generation system. *IEEE Trans. Smart Grid* **2018**, *9*, 3122–3132. [CrossRef]
240. Soman, K.P.; Poornachandran, P.; Athira, S.; Harikumar, K. Recursive variational mode decomposition algorithm for real time power signal decomposition. *Procedia Technol.* **2015**, *21*, 540–546. [CrossRef]
241. Muthusamy, T.A.; Ramanathan, N. An expert system based on least mean square and neural network for classification of power system disturbances. *Int. J. Future Revolut. Comput. Sci. Commun.* **2018**, *1*, 308–313.