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Review on Power Quality Disturbances Detection, Classification, Optimization and Mitigation Techniques

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Review on Power Quality Disturbances Detection, Classification, Optimization and Mitigation Techniques

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Abstract: Power quality (PQ) plays an important role in ensuring the smooth operation of power systems. PQ disturbances may cause significant consequences, impacting the reliability and efficiency of power networks. This paper presents a comprehensive review of PQ within smart grids and the integration of renewable energy sources. Methods of detecting, classifying, optimizing, and mitigating PQ events are reviewed with providing a brief theoretical explanation for each technique. Related work done in the past two decades, was conducted, presenting a clear view of the development of research in a chronological order serving as a guide for future investigations in this field of study.

Keywords: power quality; PQ disturbances; detection; classification; SP techniques; neural networks; mitigation; power system; renewable energies; smart grid

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1. Introduction

The quality of power transmitted has received more attention and concern in recent years since it affects electricity producers, consumers, and grid operators. To guarantee the appropriate operation of electrical equipment and the general stability of the power grid, PQ must be monitored and maintained. Depending on one's point of view, power quality can have entirely distinct meanings.[1]. As per Naderi [2] , it can be defined as the ability of the electrical grid to supply customers with dependable, perfect, and non-tolerant electricity. This is achieved by creating a perfect power supply with a pure, noise-free sinusoidal wave shape that is always stable when voltage and frequency are taken into account [3]. According to Biabani [4], another definition of this concept is the range of electrical characteristics' limitations that enable electrical systems to operate as intended without suffering significant performance or safety losses. From an alternative perspective, power quality refers to the idea of powering and grounding electronic devices in a way that is both compatible with the premise wiring system and other linked devices and appropriate for the equipment's intended use.[162]

2. PQ Problems

A Power Quality (PQ) problem can be defined as any variation of the characteristics of voltage and (or) current from the nominal frequency and sinusoidal, symmetrical conditions[1]. PQ issues are often classified into two categories:

- **Issues with voltage** might include harmonics, blackouts, sags, and swells.
- **Issues with current** are radio frequency interference, electromagnetic field, leakage current, and electromagnetic interference.[5]

PQDs are categorized as follows

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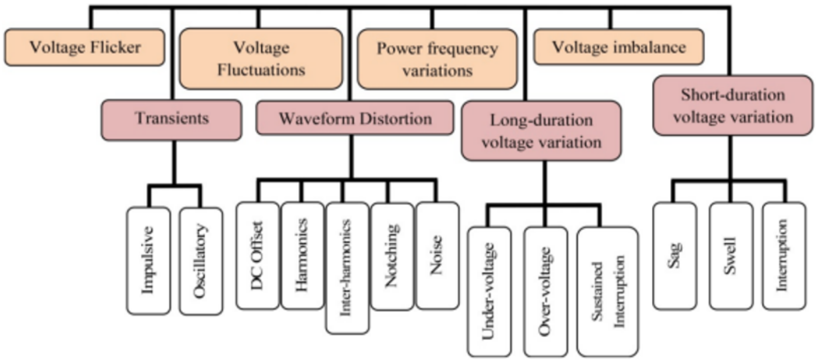

Figure 1. Power Quality problems classification.

1- Transients: A transient, also known as a spike, surge, power pulse, etc. [5] is an undesired brief variation in the load current or voltage supplied [1] that lasts for just a few microseconds. Because of the brief duration, frequency components are much greater than the nominal frequency, and voltages may reach several thousand volts[5]. Transients are generally classified into two categories, *impulsive* and *oscillatory*.[1]

1.a Impulsive transients:

Impulsive transients are unidirectional (either positive or negative) high peak events that occur outside of the power frequency range and increase the voltage and/or current levels. These kinds of occurrences may be further divided into three categories based on their speed: fast, medium, and slow)[5] and their rate of change in voltage or current magnitude, or rise and fall times. Impulsive transients can occur extremely quickly (5 ns rise time from steady state to the impulse peak), last for less than 50 ns, and even at low voltages, reach thousands of volts. A positive polarity impulsive transient that appears in the positive cycle is seen in Figure 2.

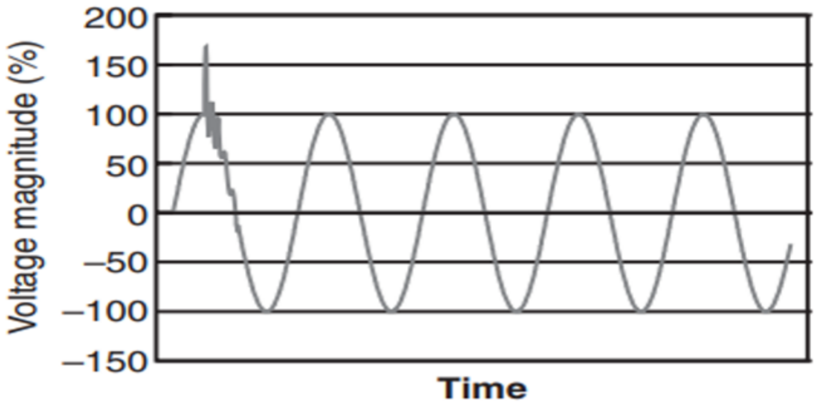

Figure 2. Positive polarity impulsive transient.

1.b Oscillatory transients:

A sudden change in the voltage, current, or both of a signal's steady-state conditions at the positive and negative signal limits, oscillating at the natural system frequency, is known as an oscillatory transient. The transient causes the power signal to alternately swell and then shrink, very rapidly. Low, medium, and high frequency transients can be distinguished from oscillatory transients based on their duration and frequency content.

2- *Waveform distortion*:

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Waveform distortion is defined by IEEE 1159-2019 as a steady-state deviation of a power frequency sine wave from an ideal one, primarily characterized by the deviation's spectral content [5].Waveform distortions include harmonics, noise, and DC offset.

2.a DC offset

A dc offset occurs when a dc voltage or current is present in an ac power system. This can be caused on by an imbalance in electrical power converters or a geomagnetic disturbance.[5]

2.b Harmonics & Interharmonics

Per the definition given by the IEEE guidelines on electrical power systems harmonic control, Harmonics are sinusoidal components of a periodical quantity whose frequency components are integer multiples of the periodical quantity's fundamental frequency; in contrast, interharmonics are non-periodic and have frequency components that are non-integer multiples of the fundamental frequency. Harmonics cause distortion and deviation from sinusoidal waveforms in voltage and current in electrical systems [5].

2.c Noise

Noise is any undesired and external information that interferes with the transmission signal. It is not a component of the original signal and is caused by ignition systems, radio frequency interference, and electromagnetic interference.[5] Figure 3 shows a noisy signal.

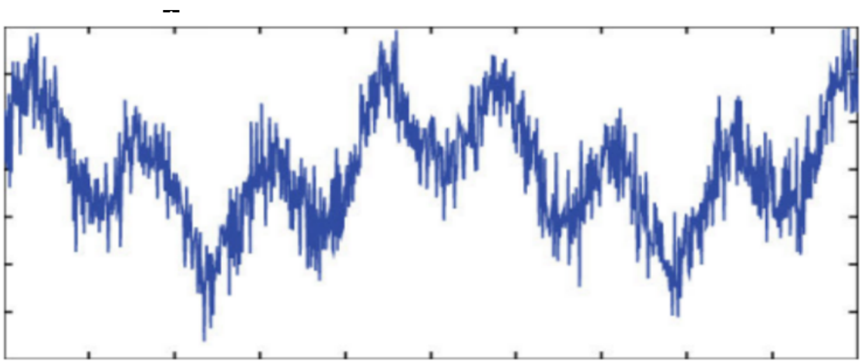

Figure 3. Noisy signal.

3- Voltage disturbances

Having any disturbance in voltage can lead to poor power quality, there are different types of disturbances related to voltage, in the below sections these disturbances are explained.

3.a Voltage fluctuation and Flicker

Voltage fluctuations are random voltage changes or systemic variations of the voltage envelope that, in most cases, do not exceed determined voltage ranges (0.9 to 1.1 pu, according to ANSI C84.1-1982, for example). The term "flicker" describes the rapid and continuous changes in voltage caused by variations in load current magnitude. These fluctuations affect lamps, creating a perceived flickering effect to the human eye. Arc furnaces are a prevalent cause of voltage fluctuations in utility transmission and distribution systems.

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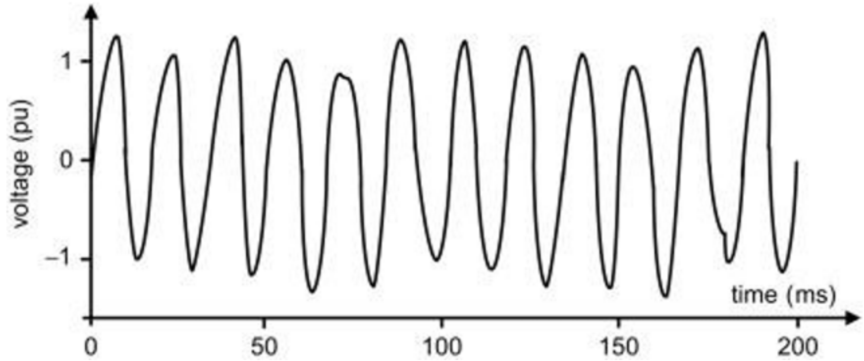

Figure 4. Flicker phenomena.

3.b Voltage Fluctuations

There are two types of voltage fluctuations: long-duration and short-duration changes.

3.b.1 Long duration Voltage fluctuations

Root-mean-square (rms) deviations at power frequencies for periods longer than one minute are included in long-duration fluctuations. The table below enumerates the various forms of long duration voltage variation:

Table 1. Long duration voltage variation .

Type	Duration	Voltage magnitude
Undervoltage	>1 min	0.8 - 0.9 pu
Overvoltage	>1 min	1.1 - 1.2 pu
Sustained interruption	>1 min	0.0 pu
Current overload	>1 min	-

3.b.1.1 Overvoltage is a rise in the RMS ac voltage that lasts longer than one minute and is more than 110% at the power frequency [5]. Causes may include the shutdown of a significant load, the charging of capacitor banks, or improper transformer tap configuration.

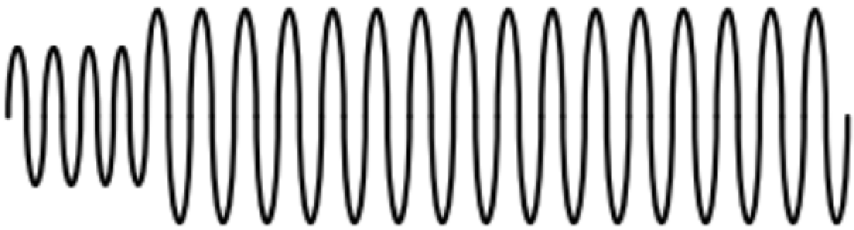

Figure 5. Overvoltage

3.b.1.2 Undervoltage is a drop in the RMS AC voltage of less than 90% at the power frequency that lasts more than a minute. Causes: Overloaded circuits; a load turning on; a capacitor bank turning off.

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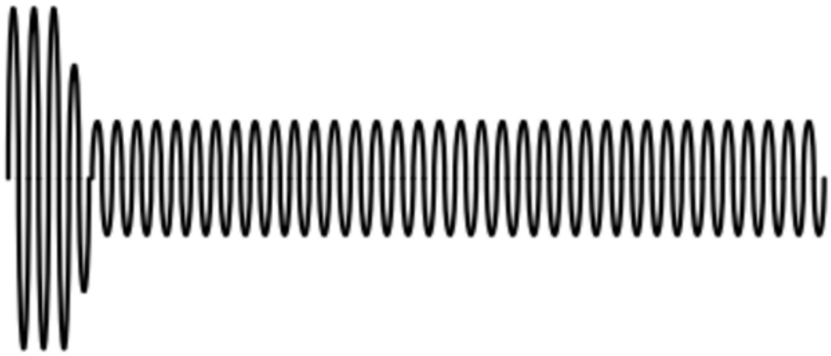

Figure 6. Undervoltage

3.b.1.3 Sustained interruptions is defined as the absence of supply voltage for one minute or more. These disruptions are frequently irreversible, and fixing the system will need human assistance.[5]

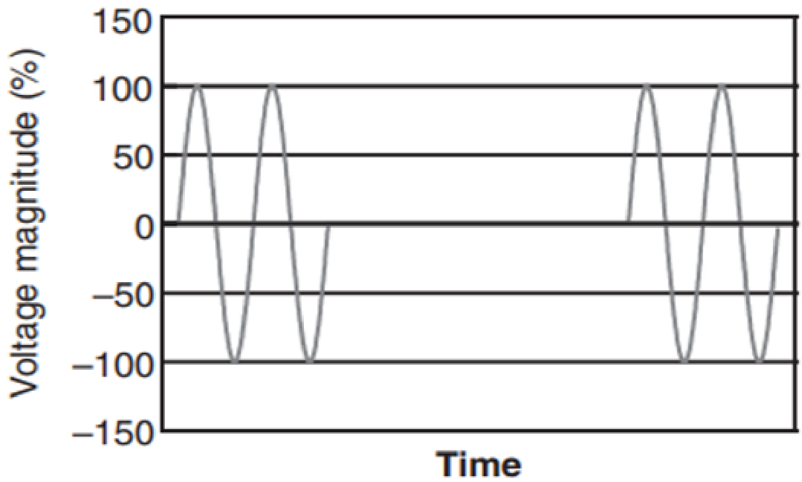

Figure 7. Sustained interruptions

3.b.2 Short duration Voltage variations

IEEE 1159-2019 defines short duration RMS fluctuations as variations in RMS voltage that last from 0.5 cycles to less than or equal to one minute. Three categories—immediate, momentary, and temporary—can be used to categorize short-duration voltage variations based on how long they lasted as summarized in Table 2.

Table 2. Classification of short duration voltage variations.

Voltage fluctuations	Immediate		Momentary		Temporary	
	Duration	V amplitude	Duration	V amplitude	Duration	V magnitude
Sag	0.5-30 cycles	0.1-0.9 pu	30cycles-3s	0.1-0.9 pu	>3s-1 min	0.1 - 0.9 pu
Swell	0.5-30 cycles	1.1-1.8 pu	30cycles-3s	1.1-1.4 pu	>3s-1 min	1.1 - 1.2 pu
Interruption	-	-	0.5 cycles-3s	<0.1 pu	>3s-1 min	<0.1 pu

Sag: is a drop in RMS voltage that lasts from half of a main cycle to less than a minute. It typically occurs at a rate of 0.1 to 0.9 per unit. Also referred to as a "dip," it happens as a result of malfunctions, a spike in demand for energy, and changes like starting large motors...

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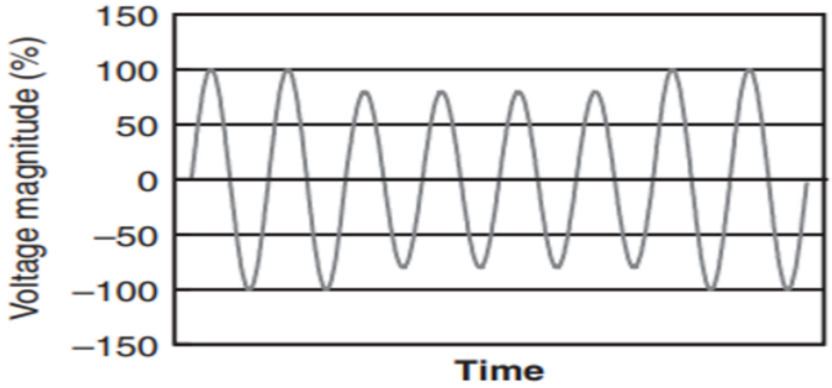

Figure 8. Voltage sag.

Swell: is the RMS voltage rising between 1.1 and 1.8 p.u. during a period longer than half of a main cycle yet shorter than one minute. caused by load switching, capacitor switching, and system errors.

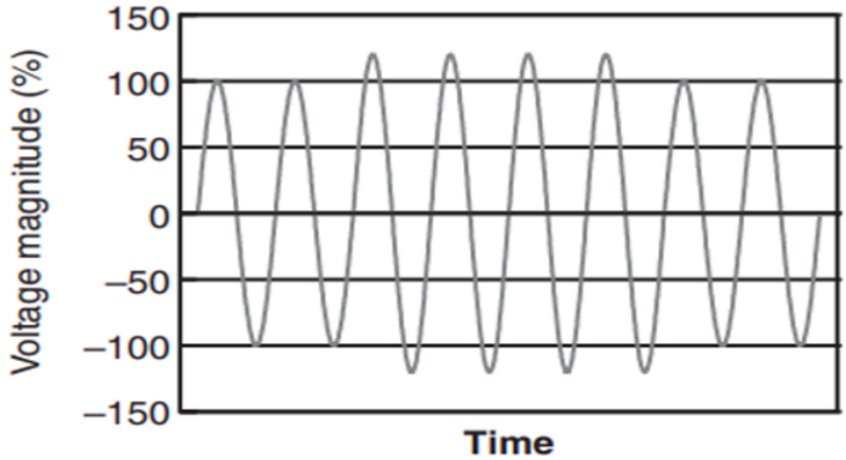

Figure 9. Voltage swell.

Short Interruption If the load current or supply voltage drops to less than 0.1 p.u. for less than a minute, it is referred to as an interruption. System faults, failures of equipments, or problems with control and protection might all be the reason.

3.c Voltage Imbalance : occurs when there are differences in magnitude or phase among the phases in a three-phase power supply. This is often seen in rural areas, where some phases may carry heavier loads. It's measured as a percentage relative to the positive phase sequence.

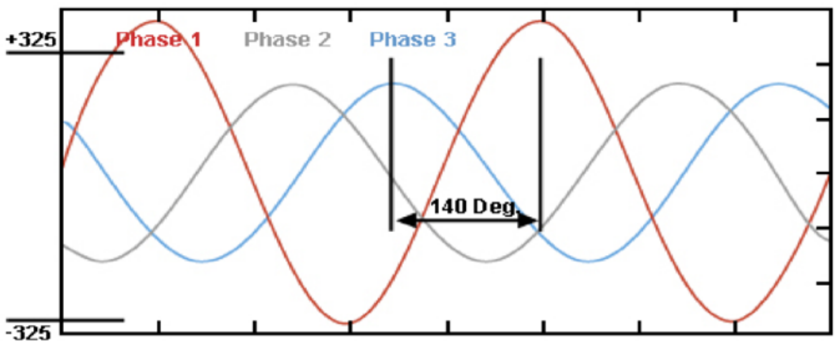

Figure 10. Voltage imbalance.

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4- Power frequency variation

Variations in Power frequency are deviations from the *standard frequency* (e.g., 50 or 60 Hz) in a power system. The speed of this system's generators determines its frequency. Changes in frequency occur as electricity demand and generation levels change, depending on how much electricity is needed and how quickly the system can meet that demand. They occur due to changes in the balance between load and generation and can result from faults in the transmission system, disconnection of large loads, or the shutdown of major generation sources. While rare in modern interconnected systems, isolated generators supplying specific loads are more prone to significant frequency shifts.

Table 3. PQ Disturbances, Sources, and Effects - Part 1.

PQ Disturbances	Sources	Effects
Transients	• External: - Lightning strike - Opening and closing of energized lines - Breaker opening and closing • Internal: - Switching operation - High resistance fault - Welding machines - Capacitor bank switching - High-frequency switching in inverter or switch-mode power supply	Components failure, Hardware reboot required, Software problems, Product quality
Harmonics	• Non-linear loads • High voltage converters • Fast switching power electronic devices (rectifiers, inverters, etc.) • Conventional source (transformers, electrical rotating machines, etc.) • Modern electronic devices (Arc furnace, UPS, PC, TV, etc.)	Transformer and neutral conductor heating leading to reduction of life span, Audio Hum, Software glitches, Power supply failure
Noise	• Electromagnetic interference • Radio frequency interference • Ignition systems	Troubles of sensitive electronic equipment, Loss of data, Errors in data processing

[1] This is a table footnote.

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Table 4. PQ Disturbances, Sources, and Effects - Part 2.

PQ Disturbances	Sources	Effects
Sag	• Faults • Increased load demand • Transitional events such as large motor starting	Machine/Process downtime, Product quality, Repair costs, Clean-up costs
Swell	• System faults • Load switching • Capacitor switching	Equipment does not operate correctly, Production rates fluctuate, Relays and contactors drop out
Interruptions	• System faults • System equipment failures • Control and protection malfunctions	Loss of supply in customer equipment, Motor tripping, Computer shut down
Flicker	Large starting currents	Visual irritation
Power frequency variation	• Faults on the bulk power transmission system • Large block of load being disconnected • Large source of generation going off-line	Decrease in motors speed, De-tuning of harmonic filters
Voltage Imbalance	Unbalanced loads/impedances	Overheating motors/generators, Interruption of 3-phase operations

[1] This is a table footnote.

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3. PQ disturbances Detection and Classification

It is essential to diagnose the PQ Disturbances according to international standards, and suitable preventive techniques should be implemented. In this regard, features extraction of power quality disturbances using methods of power quality analysis and their classification, are the essential tasks of PQ monitoring systems. in order to achieve automatic disturbance recognition and understanding the cause-effect relation to improve the power quality.[7]. The procedure involved in PQ monitoring with RE sources is as illustrated in Figure 11. Power quality disturbances are originated at the point of interconnection, where the conventional generator and renewable energy sources are integrated with distribution loads. Disturbance detection and classification stages are the main components of PQ recognition methods, and RE sources signals need to be considered for adopting changes associated with the output of RE sources. For this regard, the power quality monitoring process involved different stages. [8]

a) The phase of pre-processing: In this phase normalized PQ disturbances are took as inputs where a threshold is chosen for precise detection, and features are collected using signal processing (SP) techniques to identify the events. Additionally, these characteristics are used for optimization, the resulting features will be chosen for classification.[8]

b) The phase of classification: Here PQ disturbances are categorized using AI classifiers[8]

c) The phase of mitigation: the classified disturbances are later mitigated using appropriate techniques like DFACT devices which play a significant role in the field of real-time PQ mitigation.[8]

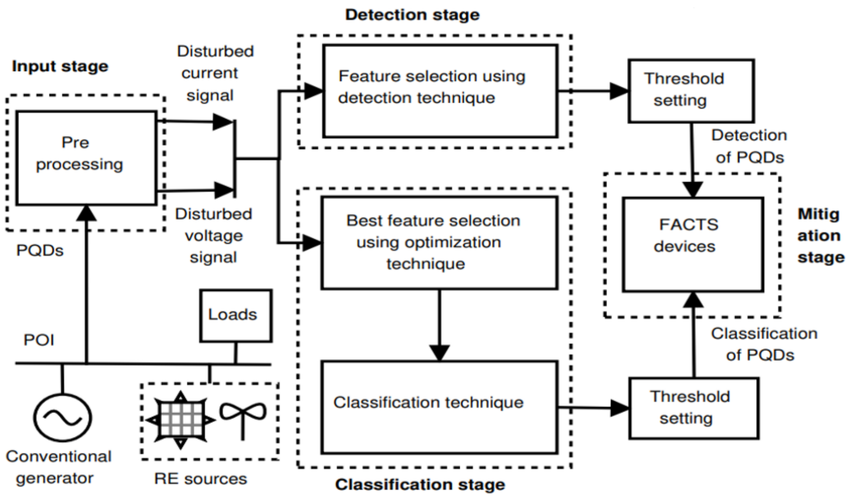

Figure 11. Process to monitor power quality using renewable energy sources [8].

3.1. Signal Processing Technique for Feature Extraction

The RMS technique, although widely used in power quality analysis, has notable limitations. While it effectively identifies and characterizes voltage events based on the RMS magnitude of the voltage supply, it lacks the capability to determine the phase angle or the precise location on the waveform where the event originates. Consequently, this method may struggle with accurate voltage event detection and duration estimation . To overcome these shortcomings, adopting the appropriate PQD characteristics becomes essential in refining the detection process. Feature extraction involves transforming a signal to facilitate information extraction. This can be achieved by directly extracting features from the initial measurement across various domains, including Fourier, wavelet, STFT, HHT, GT, and S-transform, or by utilizing parameters from signal models such as the Kalman filter (KF) and auto-regressive (AR) models[9]. The categorization of various detection techniques is as illustrated in Figure below.

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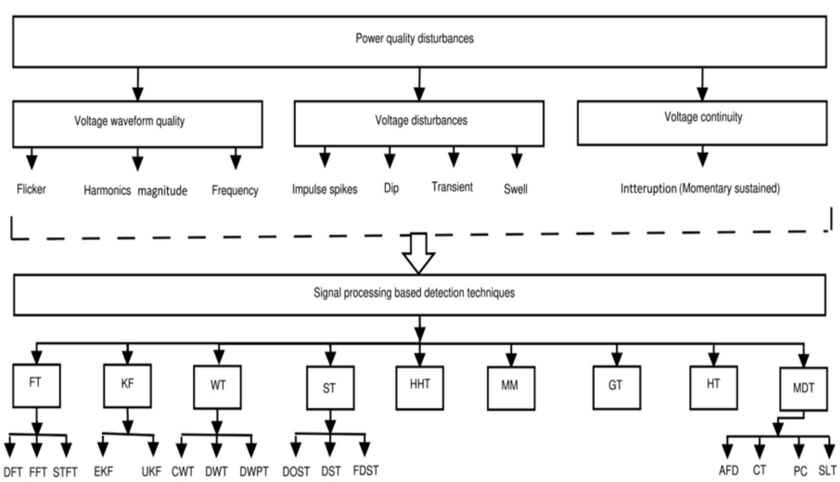

Figure 12. Classification of detecting methods based on signal processing.

1) Fourier Transforms:

- **Continuous Fourier Transform:**

The Fourier Transform (FT) is a commonly used signal processing method that breaks down complex waveforms into sinusoidal components of various frequencies. This helps with spectrum analysis by converting time-domain signals into their frequency-domain representations. While effective in identifying specific frequency elements within stationary signals, it may encounter difficulties with short-term transient issues. This method is applicable to both continuous and discrete signal types. FT uses a basis of sines and cosines of various frequencies to calculate the relative amounts of each frequency in the signal. A continuous signal v(t) has the Fourier Transform defined as [9]:

$$V(f) = \int_{-\infty}^{+\infty} v(t)e^{-j2\pi ft}dt \tag{1}$$

- **Discrete Fourier Transform**

Fourier series provide valuable mathematical insights but face limitations in practical applications due to the finite length of real-world measurement data. To overcome this, the Discrete Fourier Transform (DFT) is utilized, allowing for the analysis of finite-length data and enabling determination of frequency content in periodic signals. The DFT of the sequence x(n) is expressed as[10]:

$$X(k) = \frac{2}{N}\sum_{i=0}^{N-1} x(n)e^{-jk\Omega i}dt \tag{2}$$

where $\Omega = 2\pi/N$ and k is the frequency index.The time domain sequence x(n) may be expressed as follows when taking into account a frequency index that ranges from 1 to $(N/2-1)$:

$$x(n) = \sum_{k=1}^{(N/2)-1}\left[X_R(k).\cos\left(\frac{2\pi kn}{N}\right) - X_I(k).\sin\left(\frac{2\pi kn}{N}\right)\right] \tag{3}$$

where X(k)'s in-phase and quadrature-phase components are represented, respectively, by XR and XI. At the analog frequency ωk, the phasor quantity may be calculated as follows:

$$X(\omega) = X_R(k) + jX_I(k) \tag{4}$$

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- **Fast Fourier Transform**

The development of the fast Fourier Transform (FFT) aimed to lessen the DFT's computing load. The computation of the Fourier coefficients can be accelerated when the waveform's period N is an integer power of two. N log(N) becomes the number of operations instead of $N\hat{2}/2$ [10]. Utilizing this method, one may obtain a reasonable estimate of the fundamental amplitude and its harmonics.[9]

- **Short Time Fourier Transform**

Information of disturbance signals is provided in the frequency domain and time domain (start time, stop time, rise time, duration) using the Short-Time Fourier Transform (STFT). In general, these signals are non-stationary and their properties (amplitude, frequency, and phase) are not constant in time. The discrete transform is defined given a discrete signal x[n] as follows: [7]

$$X[n,\lambda] = \sum_{m=-\infty}^{\infty} x[n+m]w[m]e^{-j\lambda m} \tag{5}$$

where a window function of size L is denoted by w[m]. Typically, the signal x[n] contains a limited number of samples N, and the window w[m] has the following equation:

$$w[l] \neq 0, \quad for \quad 0 \leq l \leq L-1 w[l] = 0, \quad for \quad l < 0 \quad or \quad l \geq L \tag{6}$$

where the size of the window is L, which can be the same or less than the number of samples N of signal x[n]. with $N \geq L$:

$$X[n,\lambda] = \sum_{m=0}^{L-1} x[n+l]w[l]e^{\frac{-j\lambda l}{N}} \tag{7}$$

2) Wavelet Transform

As a feature extraction method, the Wavelet Transform (WT) was developed to address the drawbacks of the short-term Fourier transform. It is used to detect power quality problems.[9] Three methods, referred to as the wavelet series, continuous WT, and discrete WT, may be used to perform WT . The wavelet series map a continuous variable function into a list of coefficients. [10]

- **Continuous Wavelet Transform (CWT)**

Every wavelet in continuous WT is produced by translating and scaling operations in a mother wavelet, this latter is an oscillating function with zero average and finite energy. For a continuous time signal x(t), the continuous WT is defined as follows:[10]

$$CWT_{\Psi}x(a,b) = \int_{-\infty}^{\infty} x(t)\Psi^{*}_{a,b}(t)dt \quad a,b \in R, \quad a \neq 0 \tag{8}$$

where

$$\Psi^{*}_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi^{*}\left(\frac{t-b}{a}\right) \tag{9}$$

The mother wavelet is $\Psi^{*}_{a,b}(t)$. Scaling and translating parameters are denoted by a and b, respectively.

- **Discrete Wavelet Transform (DWT)**

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DWT decomposes a given signal into multiple sets, with each set representing the signal's temporal evolution in a distinct frequency band[11] . Defined as follows:[14]

$$DWT_{\Psi}x(m,n) = \sum_{k} x(k)\psi^{*}_{m,n}(k) \tag{10}$$

Where:

$$\psi^{*}_{m,n}(k) = \frac{1}{\sqrt{(a_0^m)}}\psi^{*}\left(\frac{k - nb_0a_0^m}{a_0^m}\right) \tag{11}$$

m and n are scaling and sampling numbers, respectively.

There are many wavelet functions named as mother wavelets. The choice of mother wavelet is important because different types of mother wavelets have different properties. Several popular wavelet functions are Haar, Morlet, Coiflet, Symlet and Daubechies wavelets. Daubechies wavelets are also well known and widely used in other applications. It is flexible as its order can be controlled to suit specific requirements.[10]

3) Stockwell transform

The S-transform is a time-frequency analysis method that uses a Gaussian window to convert a signal from the time domain to the time-frequency domain. It was introduced by Stockwell and his colleagues in 1996 as a modification of the short-time Fourier transform (STFT) to address its limitations in analyzing non-stationary signals. The S-transform offers higher resolution in both time and frequency domains.[12] The ST can be considered also as an expanded form of continuous WT (CWT). Frequency-dependent resolution of ST has a direct association with the Fourier spectrum. The signal information can be obtained from its phase and amplitude spectrum of a signal. To use the information present in the phase of CWT, it is essential for a phase correction in terms of modifying the phase of the mother wavelet. For a function h(t), its CWT can be presented as [13]:

$$W(\tau,d) = \int_{-\infty}^{\infty} h(t)w(d,t-\tau)dt \tag{12}$$

The width of the wavelet w(d, t) which is responsible for resolution control is denoted by the scale parameter d. The ST of the function h(t) can be obtained from a CWT by multiplying a phase factor with a specific mother wavelet

$$S(\tau,f) = e^{j2\pi ft}W(d,\tau) \tag{13}$$

The integrated mother wavelet used for ST can be expressed as follows:

$$w(t,f) = \frac{|f|}{\sqrt{2\pi}}e^{-\frac{t^2f^2}{2}}e^{-j2\pi ft} \tag{14}$$

The frequency f is inversely proportional to d. An admissible wavelet has to assure the zero mean condition. Under this constraint, (2) is not strictly a CWT function. This is due to the fact that the condition of an admissible wavelet is not satisfied by the wavelet expressed in (3). Considering this fact, the ST can be explicitly expressed as follows:

$$S(\tau,f) = \int_{-\infty}^{\infty} h(t)\frac{|f|}{\sqrt{2\pi}}e^{-\frac{(\tau-t)^2f^2}{2}}e^{-j2\pi ft}dt \tag{15}$$

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The ST can be formulated in terms of Fourier spectrum H(f) of h(t)

$$S(\tau, f) = \int_{-\infty}^{\infty} H(\alpha + f) e^{-\frac{2\pi^2\alpha^2}{f^2}} e^{j2\pi\alpha\tau} d\alpha, \quad f \neq 0 \tag{16}$$

4) Hilbert–Huang transform-

In 1998, Dr. Huang presented a new signal processing technique called the Hilbert Huang Transform (HHT). For the time-domain analysis of non-linear and non-stationary PQD signals, HHT is among the best SP-based methods available. [8] This method often combines two techniques, such Hilbert transform and empirical mode decomposition. Using EMD, the input signal is broken down into a number of small components known as intrinsic mode functions (IMFs).The HT is then applied to the IMFs in order to extract several properties pertaining to the signal's phase, amplitude, and frequency.[14] The Hilbert spectrum analysis can be used to express the original data. It is used to compute the instantaneous frequency of the signal and represented as the real part in the following form, .[8]

$$X(t) = Real \sum_{j=1}^{n} a_j(t) e^{i \int w_j(t) dt} \tag{17}$$

where wj(t) denotes the instantaneous angle frequency.[8]

5) Gabor transform

Dennis Gabor proposed a special case of STFT, formulates into the Gabor transform (GT). This transform is beneficial as the phase content of the local divisions and sinusoidal frequency of a signal.[8]. The GT is an innovative SP tool employed for perfect phasor estimation. Compared with Fourier transform, the GT offers better time and frequency info of a studied signal. It maps the time series data into both time and frequency domains.[14]. GT signal is expressed as [8]:

$$S(\tau, \omega) = \int_{-\infty}^{\infty} f(t) g(t - \tau) e^{-j\omega t} dt \tag{18}$$

where, the amount of the time shift is represented by _ and window function represented by $g(t)$. The center _t and radius 1t are individually calculated as follows:

$$\mu(t) = \frac{\int_{-\infty}^{\infty} t \times |g(t)|^2 dt}{\int_{-\infty}^{\infty} |g(t)|^2} \tag{19}$$

$$\Delta(t) = \sqrt{\frac{\int_{-\infty}^{\infty} (t - \mu_t)^2 \times |g(t)|^2 dt}{\int_{-\infty}^{\infty} |g(t)|^2 dt}} \tag{20}$$

3.1.1. Comparison between Different Transforms in Detecting PQDs

The comparison is summarized in Table 5.

Table 5. Comparison between Transforms.

Transform	Advantages	Disadvantages
FT	• Good frequency resolution	• When transforming the signal to the frequency domain, time information is ignored [15]. • Bad resolution of time • Cannot show transformation in real-time and has a small window.[16]
DFT	• Good frequency resolution • Apt for the stationary power quality events[14]	• Not suitable in recognizing sudden variations in PQ events such as where they start and end. [15] • A poor resolution of time
FFT	• In less time, it provides the exact same outcome as the DFT.[15] • Typically employed for PQ disturbances harmonic analysis [15]	• The amplitudes, frequencies and phases of signals cannot be accurately obtained [14].
STFT	•Uses a moving window to determine the sinusoidal frequency and phase contents of local signal sections [15]. • Excellent temporal resolution	•It is challenging to analyze non-stationary signals due to the moving window [14]. •constrained resolution of frequency
WT	•Appropriate for the analysis of signals time-frequency resolution [15] •The detail and approximation coefficients allow for the extraction of statistical parameters, making it useful in PQD classification. [16]	• Noise has a significant impact.[14] •A significant computational burden arises from higher signal decomposition levels.
ST	•Improve the signal's time- frequency representation [15]. • High noise tolerance and satisfactory pattern recognition are assured.[15] • Because it uses Gaussian windows and is noise-insensitive, it has comparatively more applicability in real-world circumstances.	• Compared to other methods, this approach has a longer time for computation.[14]
HHT	• Gives instantaneous frequencies of non- stationary signals.[15]	•Poor capacity to differentiate between various narrow band signals components.[14]
GT	• Useful for precise phasor estimation and offers good signal time-frequency information [14]. • Suitable for measuring and analyzing transient disturbances with short duration.	•The sampling frequency impacts the computational load directly [14].

3.1.2. PQDs Detection Using Transforms Related Work

- **FT, DFT, FFT & STFT:**

In the literature, numerous articles and papers explore the detection of power quality disturbances, employing diverse transforms for analysis. For FT and DFT, few papers were found due to their limitations. FFT, an enhanced version of DFT that provides equivalent results in less time [15], is commonly employed in hybrid techniques. In [17], authors proposed a windowed fast Fourier transform for PQDs detection. This technique offers the advantage of rapid evaluation by widening the window in the absence of disturbances, and narrowing it when an issue arises to focus on the detected disturbance. In [20] an integrated approach combining DWT and FFT is proposed, where the DWT is used for detecting and FFT for classification. In [18], a 2-Stage modified FFT algorithm was introduced to detect harmonics and inter-harmonics, addressing the interference between the two.

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However, this method has drawbacks, including slow detection, and requires further improvement. In [19] a real time PQ analyzer was presented, for the spectral analysis of the signals FFT was used, where harmonics and inter-harmonics components were calculated individually. Due to the limitations of FFT, STFT was introduced to overcome these issues, enabling the acquisition of both frequency and phase information from signals. In [21] a method using STFT applied to the voltage signal in real time at the microgrid's common coupling point, the system demonstrated good identification of events including abrupt frequency changes and under- or overvoltage . In [22] STFT was used for detection of disturbances, the energy and THD of each signal were fed to the bayesian classifier, The results, while promising, it is recommended to test the system under noisy conditions for a better evaluation.

- **WT**

Another type of transform that overcomes the limitation of STFT is the Wavelet transform, the STFT cannot provide simultaneous time and frequency localization, while wavelets are scaled in both time and frequency, allowing for better localization in both domains. In [163] the discrete wavelet transform (DWT) is used to detect voltage disturbances in power systems by decomposing signals into levels, providing detail coefficients,then the type of disturbance is identified through the approximation signal. In [23] DWT was combined with a Kalman filter. DWT assisted in extracting the noise's covariance, and the KF was then utilized to estimate the waveform's amplitude and slope. These parameters were then fed into a fuzzy expert system to classify PQDs. The test results demonstrate the excellent accuracy and short computation time. In [24] authors used WT and SVM, the latter is trained using the extracted features by WT, the system confirms the usefulness of WT against noise. In [25] DWT is used for feature extraction that are used for training the computational intelligent based classifiers: MLP,NB, NN and SVM, then their comparison is done. [26] This study presents a novel approach employing SVM with a RS ensemble classifier to distinguish various PQEs in a PV connected Microgrid model. The MG model is subjected to different PQEs in both on-grid and off-grid modes, and features are extracted through DWT analysis. [165] this paper uses DWT , Fast Hilbert Transform, and AI tools (ANN & SVM) to effectively detect and classify PQ events demonstrated by LABVIEW simulations.

- **ST**

The ST provides an excellent time-frequency resolution and high tolerance to noise, in other words it combines the strengths of both STFT and WT. In [27] an S-transform-based real-time PQ monitoring system is proposed. [28] utilized a modified S-Transform with a second-order Gaussian window, statistical features are extracted and fed into a SVM, which is optimized using the Whale Optimization Algorithm. [29] presents an approach that makes use of the computationally effective S-Transform (ST) to identify PQ issues and their causes. Studies combining ST with Decision trees (DT) only in [30], [31] and DT with HHT in [32] are presented. [33] presents an approach using ST and a random forest classifier. For [34] an improved gray wolf optimization-based kernel extreme learning machine is used with ST for real-time detection and classification of PQDs. [35] examines three Stockwell transform-based methods for analyzing PQ events: DOST, DCST, and DCT. Results highlight DOST's efficiency and lower sample requirements.

- **HHT**

[36] examines PQ issues in smart grids, employing the HHT to analyze power signal disturbances. The advantages of HHT are discussed, emphasizing its adaptability to data and high time-frequency resolution. Several studies combine HHT with hybrid techniques, such as neural networks (FFNN) and neuro-fuzzy systems, and fuzzy-Decision trees as seen in [37], [38], and [39], respectively. Additionally, newer methods like Long Short-Term Memory (LSTM), as presented in [40], have been explored. Other research focuses on optimizing HHT using techniques like genetic algorithms (GAs) and particle

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swarm optimization (PSO), as demonstrated in [41]. [42] introduces a modified version of HHT, incorporating Reduced-Sample Empirical Mode Decomposition (RSEMD) for signal segmentation along with a novel CSWRVFLN classifier.

- **GT**

Regarding the Gabor transform, [43] combines GT with a Probabilistic Neural Network (PNN) model to create a PQDs pattern recognition system. The experiment demonstrates the GT's robustness in noisy environments and strong time-frequency resolution with low computing burden. A method for utilizing DGT and SVM in real-time PQE detection and classification is presented in [44]. [45] evaluates PQ analysis methods, the study compares STFT and GT with varying window lengths. When compared to STFT, GT performs better, attaining more accuracy and using less memory.

6) Kalman filter

The Kalman Filter (KF) was defined by GF Welch and G Bishop.[14] KF is a collection of mathematical formulas that provides a useful computational method for determining a process's state in a way that minimizes the mean of the squared error.[8] It is often used to estimate the noisy harmonic signal's frequency, phase angle, and amplitude.[14] This filter stores the data from previous states and uses it to compute the states that follow. The Kalman Filter algorithm can be summarized in two main equations

State equations :

$$x(n) = A(n-1)x(n-1) + w(n) \tag{21}$$

Observation equations :

$$z(n) = C(n)x(n-1) + v(n) \tag{22}$$

In these equations, the state vector is denoted by x(n), and the observation vector by z(n). Whereas w(n) is white noise, A(n-1) is the state transition matrix. While v(n) is a vector of observation noise, C(n) links the measurement z(n) with the state vector x(n). [15]

- **KF Related work:**

The research is focused on hybridizing KF with : DSP, AI and optimization techniques for the process of detection and classification of PQ events. In [46] a hybrid approach is presented, combining an unscented Kalman filter (UKF) with the Particle Swarm Optimization (PSO) algorithm to track PQD signals. This method addresses challenges in low signal-to-noise ratio scenarios, resulting in improved noise rejection and accuracy in tracking non-stationary sinusoidal signals. [47] employs KF for detection and wavelets with Fast Fourier Transform (FFT) for classification. Features extracted by KF serve as inputs for training a fuzzy expert system, a Multi-layer Perceptron (MLP) neural network, and an Adaptive Neural Fuzzy Inference System (ANFIS) in [48], [49], and [50] respectively. In [51], ANFIS is utilized for identification alongside discrete Packet Wavelet Transform combined with KF for detection. In [52], KF is utilized to calculate (iTHD) and energy that help. decision rules identify and classify PQ events. [53] combines Kalman Filter (KF) and Extreme Learning Machine (ELM) and demonstrates superior performance in simulation compared to KF-Back Propagation Neural Network (BPNN). [54] proposed a lightweight convolutional neural network, integrating maximum likelihood Kalman filter and continuous wavelet transform.

7) Mathematical morphology

George Matheson and Jean Serra developed the mathematical morphology (MM) technique in 1964.

Owing to its lowest computing time and high detection efficiency, MMs are the subject of much studies. [8] With MM filter technology [55] , white and impulse noises can be effectively filtered. MM is a nonlinear SP tool by definition, thus it changes a signal's shape. The set theory and integral geometry serve as the foundation for this method. In contrast to FT or WT, which extract frequency information from signals, MM primarily works in the time domain,[14] it uses the structuring element (SE), a useful function that extracts unique aspects around each sample in the signal by sliding through it as a moving window. According to the needs and objectives of the specific application, the size and form of SE should be chosen since they play a major role in this kind of study . Flat SE is most appropriate for power system applications. MM is based on two fundamental operations for signal processing, which are dilatation and erosion. The dilation of X(i) and S(j) , which are the inputs, is defined as [55]:

$$DI = (X \oplus S)(i) = max\Big\{X(i-j) \quad + \quad S(j)\Big\}, \quad (i-j) \in X, \quad j \in S \tag{23}$$

With the integers i > j , and domains of X and S being: DX = m0, m1, ... mi and DS = n0, n1, ... nj . For the erosion, denoted by (X⊖S) is given by:

$$ER = (X \ominus S)(i) = min\Big\{X(i+j) \quad - \quad S(j)\Big\}, \quad (i+j) \in X, \quad j \in S \tag{24}$$

- **MM Related Work:**

In [56], an MM filter is designed to filter out impulses and random white noises in PQ disturbance signals. Then, the filtered results are subjected to a complex wavelet to detect and locate the start and end times of PQ events. [57] combines MM and HHT for PQDs detection and analysis. EMD is used to recover the intrinsic mode function (IMF) components from the denoised signal after the improved MM filter suppresses noise. For every IMF component, the instantaneous amplitude and frequency can be calculated by applying the Hilbert transform afterwards. The use of MM for the real-time recognition of power system disturbances is studied in [58]. Highlighting the use of numerical optimization, specifically the CODO operation, to find an optimal structuring element for detecting power system faults.

[59] proposes a morphological max-lifting scheme for the recognition and classification of low-frequency power disturbances. The waveform features are extracted utilizing MM for noise removal and max-lifting for information preservation. In [60] an approach to PQDs detection is presented, incorporating morphology singular entropy (MSE) that integrates mathematical morphology (MM), singular value decomposition (SVD), and entropy theory. [61] utilizes (MM) and the Teager energy operator (TEO) for feature extraction, forming a feature vector. A probabilistic neural network (PNN) is then employed for classification of PQDs. [62] proposes a methodology that employs Decision Tree (DT) using an MM filter for signal features extraction.

3.2. *Artificial Intelligence Techniques for PQDs Classification*

3.2.1. Classifiers Used in PQD Classification

Artificial intelligent classifiers are typically employed for automated categorization and/or decision-making tasks, which make them suitable for the classification of PQDs.[14] Each event is characterized by a collection of unique properties or parameters that these classifiers utilize, and these features have to be pertinent to the object that has to be categorized. There are several published methods for classifying PQ disturbances using both supervised and unsupervised classification approaches. The pre-trained data set is the basis for supervised learning, which uses it to categorize objects [8]. It may be divided into : **a) Regression** where the output is continuous, like : *Linear regression, Decision Tree, Random forests and Neural Networks.* and **b) Classification,** the output is discrete like in :

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Logistic Regression, *SVM*, *Naive Bayes*, *Decision Tree*, *Random forests* and *Neural Networks.* In contrast, there are two categories for unsupervised learning: **a) dimension reduction** and **b) clustering**. But with the latter, such as K-means, optics, hierarchical clustering, etc., training is not required.[8]

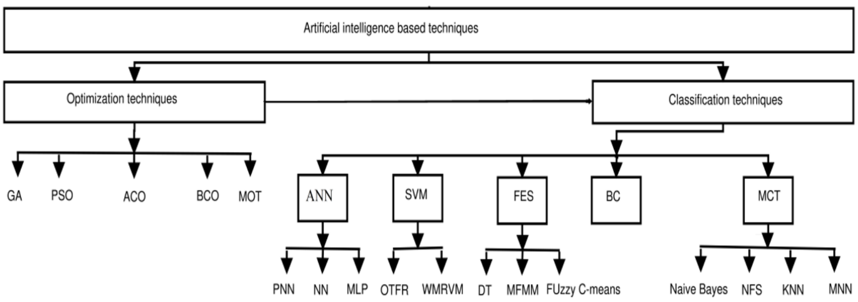

Figure 13. Different AI techniques.

Artificial neural networks (ANN) principle

Neural networks are computational models inspired by the structure and function of the human brain, consisting of interconnected nodes, or neurons, organized in layers. They process input data through a series of weighted connections and activation functions, learning from examples to perform tasks such as pattern recognition, classification, and regression. Fig. displays the block diagram illustrating the neuron model. [63]

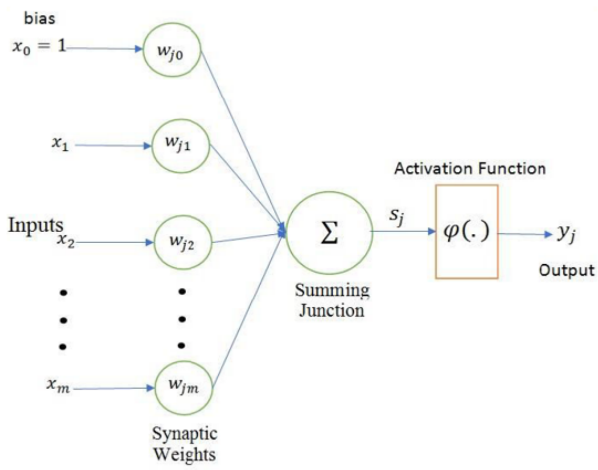

Figure 14. Neuron Model [63].

The Sj is given by:

$$S_j = \sum_{m=0}^{m} w_{jm} x_m \tag{25}$$

where the bias is represented by x_0 = 1, and the input signals are x_1, x_2,...,x_m . The synaptic weights of neuron j are w_{j0}, w_{j1},...,w_{jm} . The activation function is $\phi(.\ )$, and the output signal of the neuron is y_j. The induced local field S determines the neuron's output, which is specified by the activation function ϕ(S). The following is a description of three different kinds of activation functions:

The neural networks principal types are : MLP, MLFNN, RBF and RNN.

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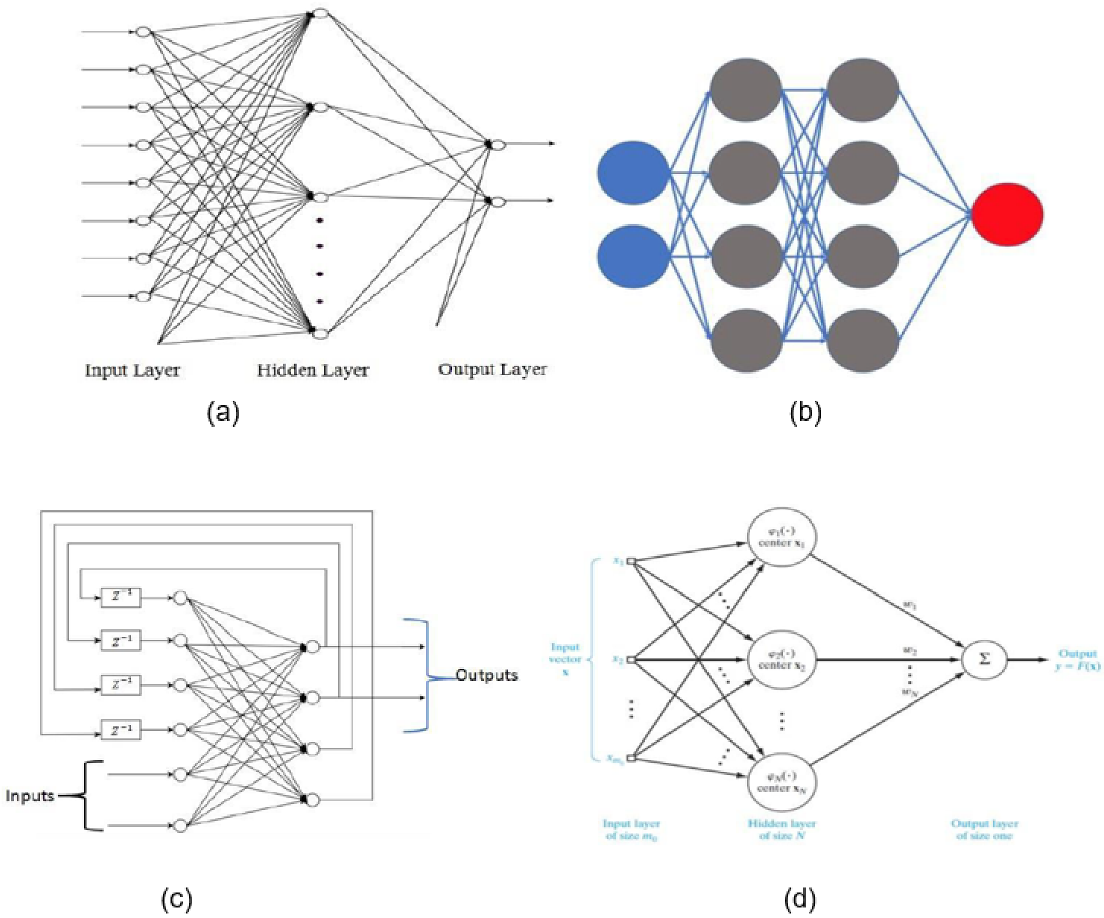

Figure 15. a) MLFFNN, b) MLP , c) RNN , d) RBF

Table 6. Principle of different NN types.

NN Type	Principle
MLP	Multilayer Perceptron (MLP) consists of multiple layers of nodes, including an input layer, one or more hidden layers, and an output layer. Each node applies a weighted sum of inputs and passes the result through an activation function. Training is typically done using backpropagation with gradient descent.
MLFNN	Multilayer Feedforward Neural Network (MLFNN) operates similarly to MLP, utilizing feedforward connections where information flows in one direction, from input to output layers. It's used for tasks like classification, regression, and pattern recognition. Can be divided into single layer and multilayer FFNNs.
RBF	Radial Basis Function (RBF) networks use radial basis functions as activation functions. They have one hidden layer where each neuron computes its output based on the distance between its input and a reference vector (center) and passes the result through an activation function. RBF networks are often used for function approximation and classification.
RNN	Recurrent Neural Network (RNN) includes connections that form directed cycles, allowing information to persist over time. This architecture makes RNNs suitable for sequence data processing tasks such as language modeling, speech recognition, and time series prediction.

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Table 7. Comparison of training methods and learning algorithms

Category	Training Methods	Learning Algorithms	Advantages	Disadvantages
MLFFNN	Batch Learning, Online Learning	Backpropagation, Levenberg-Marquardt	Basic composition, easy to apply, efficient in a range of scenarios, superior classification outcomes may be obtained with more effective networks than RBF networks	Training procedure requires a high number of input and target pairs
RNN	Epochwise training, Continuous training	Backpropagation through time (BPTT), Real-time recurrent learning (RTRL)	Computationally strong, useful in a variety of temporal processing models and applications, approximates arbitrary nonlinear dynamical systems	Challenging to correctly train, network stability is difficult to determine
RBF	—	—	Operates more quickly, suggested for function approximation issues, outperforms MLFFNNs in robustness and tolerance with noisy input data sets	More neurons in the hidden layer complicate the network, unable to simulate strong nonlinear systems
Generalized RNN	—	—	Enhances learning, lessens computational complexity, useful for estimating continuous quantities, functions well in noisy environments	—

Comparison between different ANN techniques

This section is summarized in Table 8.

Classification of PQDs using NNs related work

In literature, there is a notable focus on the PQDs classification using NNs due to their advantages. Used in diverse applications, including pattern recognition, classification, function approximation, optimization, and data clustering. Several variants of ANN find application in the classification of events within power systems. DWT is used as feature extraction tool of PQDs in both [64]and [65], combined with NN-FL and with Feed Forward ANN respectively. [66] and [67] employ a real-time NN system for classifying electrical disturbances in PQ monitoring, the latter combine it with different transforms : DFT,FFT,STFT and DWT, then a comparative study is made. [68], [69] combine ST and NN for recognizing PQDs . In [70] the integration of DMWT with a BPANN model is proposed. In [71] ANN is developed for detecting the voltage dips. [72] proposes hybridizing DT-Complex WT for feature extraction with ANN for categorization. [73] presents a real-time PQ assessment system using a conjugate gradient BPANN. [74] studies WPT and ANN for automatic identification and classification of PQ issues in power systems. [75] describes an FPGA-based smart sensor to detect and quantify PQDs in electrical installations with ANN employed for classification. Convolutional neural network CNN gained a noticeable interest from researchers the last few years, found in [76], others used other variants of CNN like Multi Fusion CNN (MFCNN) in [77] that uses frequency information as extra inputs and ensemble CNN (ECNN) in [78] where the objective was to incorporate features from different angles. Hybrid methods utilizing this type of neural network with GRU was found in [79] and [80]. In [81] a novel approach using CNN with an attention model to classify PQDs is discussed. Reccurent neural networks (RNNs) are another kind of NN that are well-known for their capacity to handle and learn from sequential input . However, in order to improve RNN capabilities by resolving the vanishing gradient issue, long short-term memory (LSTM) networks were created [164]. A recent study on LSTM can be found in [164], where LSTM-based method is applied to identify and categorize different PQDs, exhibiting good accuracy even in noisy environments.

Support vector machine (SVM) principle

Vapnik made the first presentation of SVM. This supervised machine learning technique [14] is used to categorize patterns of incoming data into previously determined classes.[82] It is often used to the concept of statistical learning. Building intelligent machines, forecasting, fault classification in power systems, dependency estimation, and forecasting are just a few of the fields in which SVM is successfully applied. The key benefit of Support Vector Machines (SVM) over other traditional methods in big classification tasks is its ability to handle a large dimensional input vector effectively. Furthermore, as compared to conventional classifiers, it exhibits better generalization characteristics. SVM was primarily created for binary classification, with just two classes—value 1 and -1—in its architecture. However, it is imperative to categorize events with more than two classifications in a real-time setting. For the multiclass classification, two distinct methods—one against all (OAA) and one against one (OAO)—are often taken into consideration.[14].

- **Binary Classification for linearly separable data:**

In binary classification with SVM, the goal is to find a clear boundary (hyperplane) that separates two classes of data points with the maximum possible margin between them. SVM is highly regarded for its ability to handle diverse datasets and find effective decision boundaries, making it a reliable tool for binary classification. Figure 16 illustrates the SVM classification principles. Assuming that there are several input vectors in the data space X, xi :(i = 1, 2,.... N), where xi are components that fall into one of two classes and N is the total number of samples. yi = 1, -1 is the class label of xi, denoting the class to which xi belongs. [82], For a hyperplane, the following equality equation is true for data that are linearly separable:

$$w^T x + b = \sum_{i=0}^{N} w_i x_i + b = 0 \tag{26}$$

where b is a bias that indicates the distance from the origin and w is a normal vector on the hyper-plane.

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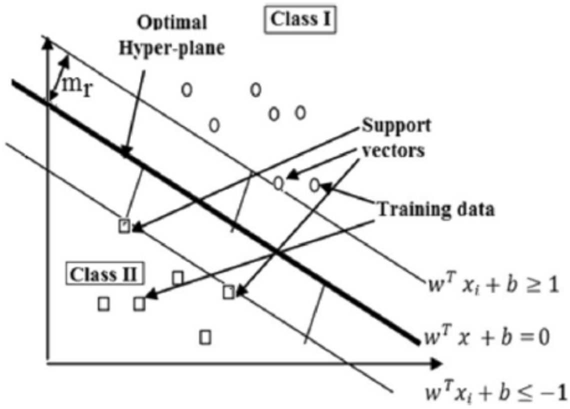

Figure 16. SVM Principle [82].

The ideal separating hyper-plane is the one depicted in Figure 16 that establishes the largest gap between the plane and the closest data. To train SVMs, a variety of kernel types can be employed. Linear, polynomial, and Gaussian radial basis functions (RBF) are the most often utilized kernel functions in power system applications. They are described as follows:

$$Linear : K(x_i, x_k) = x_i.x_k \tag{27}$$

$$Polynomial : K(x_i, x_k) = (x_i^T.x_k + 1)^n, \quad n > 0 \tag{28}$$

$$Gaussian(RBF) : K(x_i, x_k) = \exp(\sigma \left\| x_i^T - x_k \right\|^2), \quad \sigma > 0 \tag{29}$$

n is the kernel inner product degree with $\sigma = 1/2\gamma^2$, where γ is the kernel width parameter.

Classification of PQDs using SVM Related Work:

In Research, Support vector machine classifiers outperform conventional ones when it comes to PQ disturbance classification according to [8]. An SVM's ability to classify data accurately is influenced by the training set, kernel parameters, and feature choice. Many academics preferred SVM because of its ability to address problems related to pattern recognition and categorization.[83] presents an SVM classifier with WT for extraction of the features. [84] combines wavelet packet energy and multiclass SVM (MSVM) outperforming ANN classifiers. [85] employs two discrete WT with different wavelet filters for feature extraction and SVM for classification of PQDs. [86] suggests a method for PQD identification and classification using Independent Component Analysis (ICA) and SVM. [87] considers variations in load, wind speed, and solar insolation, employing statistical features extracted through Stand utilizes modular probabilistic neural networks (MPNN), SVMs, and least square support vector machines (LS-SVMs) for classification. [88] addresses disturbances related to load changes and environmental factors, utilizing hyperbolic S-transform and a genetic algorithm for optimal feature selection and employs SVMs and decision tree (DT) classifiers for classification. [89] presents Variational Mode Decomposition (VMD) and Empirical Wavelet Transform (EWT) with SVM, [90] uses Ensemble Empirical Mode Decomposition (EEMD and Rank Wavelet Support Vector Machine (Rank-WSVM). EEMD is employed. [91] combines double-resolution ST (DRST) for efficient feature extraction with directed acyclic graph support vector machines (DAG-SVMs) for predicting disturbance classes. [92] introduces a method for multiclass PQ events classification, utilizing SVM with Error-Correcting Output Codes (ECOC-SVM) and DWT. [93] presents a two-stage process involv-

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ing feature extraction with dq Transform, WPT, and ST and classification is performed using a binary tree Support Vector Machine (BT-SVM) and a dynamic event tree. [94] introduces an ST-based SVM classifier for PQD classification. employs the ST for precise identification of PQ issues and utilizes SVM for effective classification.

Neuro-fuzzy system (NFS) principle

In order to construct the neuro-fuzzy method, two key notions must be hybridized "Neural networks" and "Fuzzy system". Fuzzy logic is a mathematical framework that deals with reasoning and decision-making in situations where information is imprecise or uncertain. Unlike traditional binary logic, which operates in a crisp, true or false manner, fuzzy logic allows for degrees of truth. It uses linguistic variables and fuzzy sets to represent and manipulate imprecise information. Fuzzy logic is particularly useful in systems where human-like reasoning is needed, such as in control systems, expert systems, and decision-making processes where there is ambiguity or uncertainty. A function known as the "membership function" (MF), represented as μA(x), and defined for every x ∈ X, determines a fuzzy set A in X. We refer to X as the "support set." The grade at which x is a member of A is indicated by the membership function μA(x). It is typical to relate μA(x) to a number in the interval [0, 1]. A fuzzy set A in X is defined as [96]:

$$A = \{x, \mu_A(x) | x \in X\} \tag{30}$$

where $\mu_A(x)$ is between 0 and 1 and it is the MF of x in A.

Neuro-fuzzy system:

In 1993, Jang proposed the Neuro-fuzzy systems, that combine the principles of neural networks and fuzzy logic to create intelligent systems capable of learning from data and making decisions based on uncertain or incomplete information. They use fuzzy logic to handle uncertainty and imprecision in data and neural networks to learn from patterns and adapt to new information. Neuro-fuzzy systems are particularly useful for tasks such as classification, prediction, and control, where traditional methods may struggle with complex or uncertain data [97]. Three types can be distinguished by [98] regarding the Neuro-Fuzzy system

- **Cooperative Neuro-Fuzzy System:**

Here, the NN uses training data to identify the fuzzy system's sub-blocks. Then, the neural networks are eliminated, leaving only the fuzzy system to operate. The fact that the structure of cooperative neuro-fuzzy systems cannot be fully interpreted is a drawback

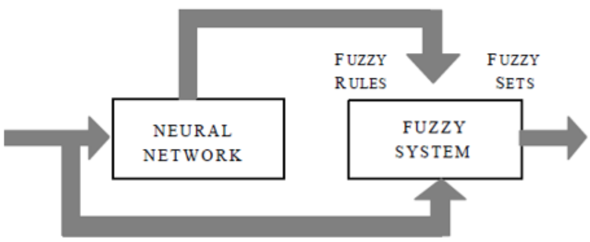

Figure 17. Cooperative NFS

- **Concurrent Neuro-Fuzzy System:**

Neural networks and fuzzy systems work simultaneously in this type of systems. The NN processes the outcomes of the concurrent system after the preprocessing of the inputs that enter the fuzzy system is done, or vice versa. One drawback of this system is that their results are not entirely interpretable.

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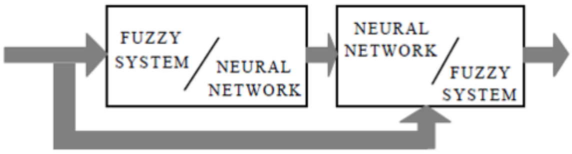

Figure 18. Concurrent NFS

- **Hybrid Neuro-Fuzzy System:**

In this type, a neural network (NN) is used to iteratively learn some fuzzy system parameters, such as fuzzy set parameters, fuzzy rule parameters, and rule weights. While there are other approaches to creating hybrid neuro-fuzzy systems, the FALCON, ANFIS, GARIC, NEFCON, and EFuNN Architectures are the five most often used neuro-fuzzy architectures.

Classification of PQDs using Neuro-fuzzy system Related Work Neuro-fuzzy logic has been used to classify PQ events from the beginning of research on this topic . [96] and [99] present an automatic PQD recognition system for power systems using WT and Neuro-fuzzy logic. Adaptive neuro-fuzzy inference (ANFIS) classification technique is widely used with different SP techniques for feature extraction , found in [100], [101], [102], [103] and [38]. In [104] a neuro-fuzzy classifier is combined with an automatic four-step algorithm to classify the PQDs. In [105] Different classifiers : SVM, ANN, and ANFIS classification methods are combined with EWT and DWT methods to estimate PQEs. The disturbances. [51] employs DPWT-Kalman filter with Adaptive Neuro-Fuzzy approach for identification and classification of PQ events.

Bayesian classifier principle

By applying Bayes' theorem, the Bayesian classifier (BC) gathers and incorporates new data and evidence from the research using a generic inference mechanism. According to the following expression [R3], the conditional probability (of given y) is determined by the Bayes theorem:

$$p(\frac{x}{y}) = \frac{P(x)P(y/x)}{P(y)} \tag{31}$$

4. Optimization Techniques for Optimal Features Selection

The use of methods of optimization is essential for improving the efficiency of detection and classification of PQ events. These methods are mostly used in the categorization process, optimizing the features, reducing mistakes, and boosting overall accuracy by fine-tuning the parameters of machine learning algorithms, such SVM or NNs. The most effective methods for classifying PQDs in the utility network are GA, PSO, ACO, and BCO. [R3] Reliable and effective systems for PQD identification and classification development is possible because of these techniques.

4.1. Genetic Algorithm (GA) Optimization Technique

GA is an optimization problem-solving meta-heuristic algorithm [106], characterized for the search tasks by imitating genetic behavior and the natural world [107]. The goal of this iterative process is maintaining a population of structures that could potentially solve particular domain challenges . Using particular genetic operators like reproduction, crossover, and mutation [106], a new population of candidate solutions is created during each temporal increment (generation) based on evaluating the effectiveness of structures in the current population as domain solutions . The population approaches the optimal solution with each increment [R3]. Figure depicts the GA's operational concept. Table summarizes the main GA application steps and their possible strategies.[108]

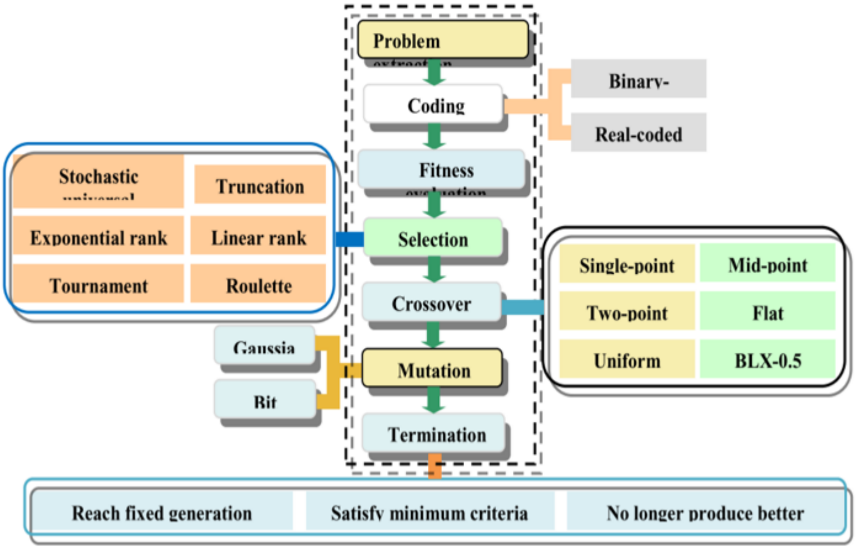

Figure 19. Working Principle of GA, dashed area is the main method.[108].

Table 8. GA application steps and their possible strategies.

GA Steps	Role & Strategies
Initialization	Configuring various parameters, such as population size, maximum evolutionary generation, crossover probability, and mutation probability.
Selection	Choosing individuals to breed a new generation from the current population. A variety of selection techniques are available, such as the roulette wheel, tournament, ranking, generator, truncation selections, etc.
Crossover	To create two new children, two chosen parents are switched.
Mutation	Changes one or more gene values in a parent individual to preserve genetic variability.
Termination	Finishing the search by using various strategies, such as stopping after a certain number of generations, stopping when the solution satisfies the predetermined minimum requirement, or when the process reaches an end point and and no more improvements can be achieved.

- **GA Technique for PQDs related work:**

In [109] the WPT and Fuzzy k-Nearest Neighbor (FkNN) classifier is used with genetic algorithm for feature selection. [110] employs GA for feature selection and smoothing parameter optimization in a PNN classifier for classifying PQ events. [107] introduces a one-step methodology using micro-genetic algorithms for direct identification and classification of electrical events. [111] introduces nondominated sorting genetic algorithm II (NSGA-II) for multi-objective feature selection in classifying PQDs. It aims to minimize classification error and the number of features simultaneously for improved accuracy and computation time. [112] proposes a fuzzy classifier with GA-based methodology for detecting and classifying transient PQDs. It optimally suppresses the fundamental frequency component, allowing better identification of anomalies. [113] uses ST to extract waveform features, forming input vectors for machine learning methods (K-NN, DT, SVM). Genetic algorithm (GA) and competitive swarm optimization algorithm (CSO) optimize the procedure. [114] introduces a hybrid approach using non-dominated sorting genetic algorithm III (NSGA III) and directed acyclic graph support vector machine (DAG-SVM) for recognizing and classifying PQDs.

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4.2. Particle Swarm (PSO) Optimization Technique

For solving optimization issues, one popular population-based metaheuristic approach is particle swarm optimization (PSO). It imitates how birds in a flock interact with one another in order to find food [115]. The process begins with a first group of particles in a multi-dimensional search space. It is evident that certain particles are in better positions than others. The particles move around in this region until they come into contact with the algorithm's stop criterion. This criteria reduces the amount of distinct representations in the algorithm or moves toward an ideal state [116]. Every iteration updates the velocity and location of every member in the population. Global best value (gbest) and personal best value (pbest) are the core of these improvements. The PSO formulas are summarized below:

$$V_k(i+1) = V_k(i) + c_1 r_1 (p^k_{best,i} - X_k(i)) + c_2 r_2 (g_{best,i} - X_k(i)) \tag{32}$$

with:

$$X_k(i+1) = X_k(i) + V_k(i+1) \tag{33}$$

Where:

$V_k(i+1)$: It is (i + 1)th iteration velocity of particle k ; $X_k(i)$ It is ith iteration position of particle k ; $p^k_{best,i}$ is individual best position of the particle k in the ith iteration; ; $g_{best,i}$ is the global best position of the any particle in the ith iteration ; c_1 and c_2 are the real acceleration coefficients that control how much the global and individual best positions should influence the particle's velocity; ; r_1 and r_1 are uniformly distributed random numbers in the range 0 and 1, used to maintain an adequate level of diversity [115]

- **PSO Technique for PQDs related work:**

In the subject of identifying and classifying PQDs, we find [117] that proposes a generalized ST and Fuzzy C-means clustering , the algorithm is refined using particle swarm optimization (PSO).In [118] relevant features are collected from the disturbances through FT and WT. A fuzzy system is employed for classification, and PSO optimizes the parameters of the membership functions for improved accuracy. In [119] features of PQDs signals are extracted using wavelet multiresolution analysis (MRA) and Multi-class SVM is employed for classification, PSO optimizes parameters for improved performance. [120] combines fuzzy logic (FL) and RBFNN with features being extracted through wavelet analysis, PSO is employed to enhance the classification accuracy of FL. In [121] a rule-based DT classifier is designed and PSO is used for feature extraction. [122] proposes a discrete-valued PSO with continuous-valued PSO, optimizes input feature subset selection and the number of hidden nodes in ELM. [123] introduces a stacked autoencoder with PSO algorithm being utilized to enhance the classification process. [124] combines WT and PSO-SVM for detection and classification of PQ events. [125] proposes a hybrid approach, combining GA and PSO, to automatically detect a wide range of PQDs in voltage or current signals. [126] presents a Hybrid Kernel Function SVM (HSVM) for enhancing the classification accuracy of multiple PQDs. The optimization is achieved through PSO algorithm. [127] employs an enhanced one-against-one SVM algorithm to classify multiple PQDs. Addressing parameter selection challenges, an improved PSO algorithm is introduced for optimal parameters selection.[128] uses EWT and a MLP-ELM with PSO. In [129] a novel algorithm, "adaptive ABC-PSO is used with DWT for feature extraction and a PNN as the classifier. [130] utilizes RBFNN trained by PSO, contrasting with the commonly used Back Propagation (BP) algorithm.

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4.3. Ant Colony Optimization Technique

ACO is based on the concept of pheromone trail deposition to determine the best routes; it is inspired by the foraging behavior of real ants.They deposit pheromones while traveling to a food source, and upon returning, they follow the same path, reinforcing the pheromone trail. ACO mimics this behavior, where shorter paths accumulate pheromones faster due to the quicker return of ants. The algorithm involves artificial ants (representing data packets) building solutions to an optimization problem and communicating information about solution quality through pheromone deposits. Paths with frequent pheromone deposits are maintained, guiding new ants to follow shorter, well-marked paths. ACO, formalized as a metaheuristic by Dorigo, addresses combinatorial optimization problems by leveraging collective intelligence and information exchange among artificial ants [131]

- **ACO Technique for PQDs related work:**

[132] uses a fuzzy C-means algorithm for clustering and generates a decision tree then a hybrid ACO technique is applied for enhancement of classification. [133] introduces an ACO model for optimal feature selection, emphasizing minimized feature set size and classification error product. Utilizing S-T and TT- transform and three classifiers: decision tree, k-nearest neighbor, and support vector machine. [134] addresses the prediction of PQDs using machine learning techniques, utilizing ACO for feature selection and employs five ML classifiers: k-NN, ANNs, DT, logistic regression, and naïve bayes. In [135] a novel method based on ACO is presented called MLACO, for selecting multi-label relevance–redundancy features. In order to find promising characteristics with minimal redundancy (unsupervised) and high relevance with class labels (supervised), this method uses both supervised and unsupervised heuristic functions.

4.4. Bee Colony Optimization Technique

The Bee Colony (BCO) algorithm is a meta-heuristic method used to solve optimization problems. [136] Inspired by the behavior of honey bees in finding nectar, BCO effectively explores solution spaces to find high-quality solutions. It organizes bees into three groups: employed bees, onlooker bees, and scout bees. These groups collaborate to discover the best solutions by sharing information about potential sources. Employed bees initially search for the best solution and share this information with others, leading to an iterative process that continues until the optimal solution is found. [129]

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{34}$$

where i is the number of iterations, j is the feature dimension, k is a random feature at each iteration, ϕ is a random value in the range $[-1\ ,1]$, and xij is the feature vector. Vij is an updated vector based on the remembered feature vector. The bee updates the feature vector based on the previously learned result by the employed bee. The onlooker bee's new feature data position will replace the current one if it exceeds the observation bee's result. The onlooker bee then examines every feature vector that the employed bee has gathered.[]

- **BCO Technique for PQDs related work:**

When it comes to the PQ events identification and classification, BCO technique is found in [137], where the use of DWT and BCO is for feature extraction and selection respectively, and PNN for classification. [138] proposes a hybrid approach using a modified discrete BCO algorithm for feature selection and parameter optimization of the random forest in PQD signal analysis. [129] As mentioned before, this work uses "adaptive BCO-PSO," for feature selection in PQD classification .In [139] DWT is used for signal decomposition, and PNN with the adaptive Arrhenius artificial bee colony method to accomplish an optimum feature selection for the classification.[140] proposes optimizing a kernel extreme learning machine (KELM) classifier using a BCO algorithm, employing WT for feature extraction and addressing the computational complexity of traditional methods like back-propagation neural networks.

5. Mitigation Techniques for PQDs

Over the past quarter-century various methods have been created to address power quality issues [1]. In research, these are sometimes termed mitigation techniques or power quality improvement (PQI) techniques. Regardless of the terminology, the goal of these methods is to lessen the impact of PQ problems and enhance the efficiency and reliability of the power system. By utilizing lossless passive components like capacitors and reactors, several PQ issues, such as low power factor brought on by reactive power requirements, may be lessened. Furthermore, UPQCs, DVRs, and other custom power devices (CPDs) are frequently employed to mitigate voltage, current, or both kinds of PQ problems. The application of power filters, both passive and active, is vital for compensating nonlinear loads and voltage-related issues and for mitigating harmonics and other issues. Furthermore, modern equipment incorporates PFC , multi-pulse and matrix converters, contributing to the intake of clean power and rendering systems resilient to PQ challenges in the supply. Various converter circuits, such as boost, buck, and multi-pulse types, are employed to enhance equipment immunity to power quality problems. [1] The different techniques are classified into three generations according to [2], with the purposes and topologies are all summarized in table 10.

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Table 9. Comparison of Power Quality Mitigation Techniques

Generation [2]	**Mitigation Technique**	**Purpose**	**Structure** [142]
I	***Passive Filters*** [2]	Current harmonics elimination - Reactive power compensation	Combination of capacitors and inductances (series or parallel)
	Active Power Filters [2]	Harmonics reduction, Improvement and compensation of PF Unbalances and flicker compensation - voltage regulation	Different topologies in [141] (Shunt, series, and Hybrid APFs)
II (CPDs)	***Dynamic Voltage Restorer (DVR)***	Source-side voltage sags/swells mitigation [4] Voltage regulation, flicker [7]	Energy storage, DC link, converter, filter, injection transformer, bypass, and disconnection equipment [5]
	Automatic Voltage Regulator (AVR)	Maintains the output voltage at a sufficient level [8]	Amplifier, exciter, generator, sensor, and comparator [8]
	STATCOM	Reactive power compensation [2], Suitable for transient, voltage fluctuation/flicker Damping oscillation [7]	Voltage Source Converter (VSC) Fixed Inductor or Power Transformer Coupling Transformer, DC Energy Storage
	Static Transfer Switch (STS)	Mitigate Interruptions and voltage dip [2]	Circuits for control, circuits of measurement of voltage and current, thyristor, breaker, and bus assembly [4]
	Static VAR Compensator (SVC)	Suitable for Flicker & unsymmetrical loads [7]	Thyristor controlled reactor (TCR), thyristor switched capacitor (TSC), Capacitors and inductors [2]
	Uninterruptible Power Supply (UPS)	For Emergency power shortage [7] PF correction [2]	Rectifier, UPS Batteries, Inverter Static Bypass Switch
III	***Smart Impedance***	Compensate harmonic current, harmonic unbalances, Improve QF, tuned factor and displacement PF, Improving voltage regulation [8]	Capacitor bank, active impedance, and suitable control approach [142]
	Multifunctional DGs	Reactive power and voltage control, supply of reserves, voltage regulation and stability [146]	Depends on the application, refer to [146]

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- **Mitigation techniques for PQDs Related Work:**

This topic was reviewed by plenty of researchers, some informative reviews are found in [141],[2], [142], [143], [144], [145] and [146], each review provides detailed insights into specific techniques. For simulation related works, [147] presents DVR as a mitigation solution for voltage sags and swells in the medium and low voltage distribution grid. [148] is about a combined system to enhance the PQ of MGs, composed of : APF for mitigating harmonic currents at the micro source inverter outlet, and SVC to provide reactive power near the microgrid load . [149] analyzes an APF implemented with cascaded H-bridge multilevel inverters for medium and high voltage power distribution systems, aiming to compensate for harmonics, reactive power, and improve PF. In [150] Shunt APF (SAPF) is employed for compensation of harmonic disturbances and WT for identification, while Hysteresis Regulator (HBCC) generates gate pulses for the Voltage Source Inverter (VSI) of SAPF. The PI controller parameters are optimized using PSO. [151] presents an adaptive hysteresis control technique for the UPQC. It employs separate adaptive controllers for series and shunt APFs using ANN and Fuzzy Logic Controller (FLC). The method reduces voltage sag, swell, and current harmonics. In [152] APF is employed in photovoltaic (PV) renewable energy system to mitigate harmonics, regulate reactive power, and adjust voltage. [166] This work employs phasor measurement units and renewable energy systems to mitigate power quality issues, activating renewable energy blocks to generate power during undervoltage or charge batteries during excess power. [167] this work investigates DVR and D-STATCOM mitigation techniques to protect induction motors from power quality disturbances, effectively reducing excessive temperature and rotor vibration torque pulsation. For [153], static VAR compensator, STATCOM and DVR are modeled for the mitigation of PQ events resulting from fault voltage. [154] presents a quasi-Z-Source (qZS) based DVR. The proposed DVR utilizes a multi-constraint model predictive control (MPC) approach to inject compensation voltage in synchrony with the grid during voltage disturbances. [155] utilizes a customized IEEE 16 bus radial distribution system to simulate the performance of CPDs like DVR, AVC, and APC. in addressing voltage sags, harmonic distortions, and voltage disturbances. [156] proposes two systems to enhance wind energy quality. The first integrates wind energy and the grid using a STS, and the second employs a DVR to mitigate fluctuations caused by varying wind speeds.[157] focuses on mitigating PQDs, especially voltage-related problems, using the UPQC controlled by the Unit Vector Template Generation (UVTG) technique. [158] addresses PQ issues in wind energy integration, focusing on harmonics and voltage variations. It proposes a mitigation approach using inverter-based reactive power compensation. [159] introduces a novel solution, the multi-feeder interline UPQC (MF-IUPQCs), utilizing fuzzy logic for effective mitigation, where it reduces THD, improves dynamic performance, and maintains a smooth voltage profile. [160] presents a novel approach utilizing Clarke transformation for voltage quality detection and compensation signal extraction in DVR. [161] introduces a novel approach for simultaneous optimization of APFs and capacitors in distribution networks to address harmonic constraints. Using a modified PSO algorithm, the method improves harmonic conditions, network losses, and voltage profiles.

6. Conclusion

In this comprehensive review, we explored power quality theory, providing detailed insights into the sources and impacts of power quality disturbances (PQDs). We conducted a thorough examination of Digital Signal Processing (DSP) techniques for PQD identification, offering a comparative analysis of various transforms. The review systematically presented related works for each technique, following a chronological order to provide a historical perspective. Additionally, we investigated classification methods based on Artificial Intelligence (AI), particularly focusing on Neural Network (NN) techniques. A comprehensive comparison of NN techniques was undertaken, and relevant research in the field was thoroughly examined. Furthermore, our review covered mitigation techniques for PQDs, offering detailed related works for each strategy. Notably, the presented works span the last two decades and are presented in a chronological order, providing a comprehensive overview of power quality research. This review serves as a valuable resource for researchers and practitioners entering this field, offering insights and a foundation for future work in power quality.

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