A Review on Intelligent Detection and Classification of Power Quality Disturbances: Trends, Methodologies, and Prospects

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ABSTRACT

With increasing global concerns about clean energy in smart grids, the detection of power quality disturbances (PQDs) caused by energy instability is becoming more and more prominent. It is well acknowledged that the PQD effects on power grid equipment are destructive and hazardous, which causes irreversible damage to underlying electrical/electronic equipment of the concerned intelligent grids. In order to ensure safe and reliable equipment implementation, appropriate PQD detection technologies must be adopted to avoid such adverse effects. This paper summarizes the newly proposed and traditional PQD detection techniques in order to give a quick start to new researchers in the related field, where specific scenarios and events for which each technique is applicable are also clearly presented. Finally, comments on the future evolution of PQD detection techniques are given. Unlike the published review articles, this paper focuses on the new techniques from the last five years while providing a brief recap on traditional PQD detection techniques so as to supply researchers with a systematic and state-of-the-art review for PQD detection.

KEYWORDS

Power quality disturbance; renewable energy; feature extraction and optimization; intelligent classification; signal processing; smart grids

Nomenclature

ABC	Artificial Bee Colony
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
DWT	Discrete Wavelet Transform
EEMD	Ensemble Empirical Mode Decomposition
ELM	Extreme Learning Machine
EMD	Empirical Mode Decomposition
EWT	Empirical Wavelet Transform
FNN	Forward Neural Network
GIP	Grayscale Image Processing
HHT	Hilbert-Huang Transform

IMF	Intrinsic Mode Function
KF	Kalman Filter
LVQ-NN	Learning Vector Quantization-Neural Network
PNN	Probabilistic Neural Network
PQ	Power Quality
PQ Event	Power Quality Event
PQD	Power Quality Disturbance
PQS	Power Quality Signal
PSO	Particle Swarm Optimization
PSR	Phase Space Reconstruction
RF	Random Forests
SA	Statistical Analysis
SBS	Sequential Backward Search
SFS	Sequential Forward Search
ST	Stock-Well Transform
SVM	Support Vector Machine
VMD	Variational Mode Decomposition
WT	Wavelet Transform
WVD	Wigner-Ville Distribution

1 Introduction

Renewable energy (e.g., solar, wind and hydropower) has played an increasingly important role in power grids because of its cleanliness and regenerative. It is well known that the stability of the power quality in the grid is of great importance in both stages of factory production and residential use [1]. Despite its various advantages, renewable energy brings intermittent, unstable, and regionally concentrated problems to the grid [2]. The grid demands techniques with PQD detection and intelligent classification to identify these problems for further resolution [3]. Considerable research attention and financial support have been devoted to solving these problems to ensure electricity quality [4].

As shown in Fig. 1, by searching for "power quality disturbance" on the web of science website, we can obtain the number of publications on PQD detection technology per year. Since entering the millennium, power equipment has developed rapidly, and the publication volume of each year on PQD detection technology has steadily increased. It has been stable at more than 70 articles per year. The data provided by the Science website illustrates the growing number of researchers who have conducted studies targeting power quality disturbances. What becomes the consensus is that power quality detection technology is a key technology for building smart grids. We find that the technology is developing rapidly as the number of articles increases. Therefore, we would like to provide a comprehensive review and summary of PQD detection techniques and provide researchers with some new ideas and approaches.
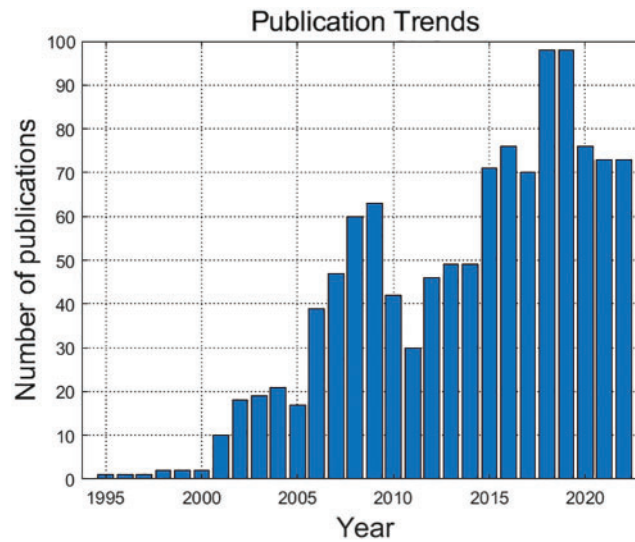
Figure 1: Number of published literature on PQD detection technology

1.1 Technical Background Overview

A consensus exists that disturbances in the grid originate from the three major components. Firstly, voltage and current disturbances in the grid generated by abnormal changes in equipment load could destroy the electrical equipment connected to the grid [5]. Appropriately identifying such anomalous interference is the primary challenge for PQD detection techniques. Second, current home energy devices (e.g., solar panels) are installed in a distributed manner. Such an installation pattern determines that the power transmission and measurement between the grid and the home devices are bidirectional. The bi-directional transmission pattern causes significant disturbances to the grid [6]. Finally, disturbances caused by imbalances in power generation and consumption between different regions can contribute to the instability of the grid [7].

PQD was defined as disturbances in the power grid. It was classified into two types based on its duration: transient and steady-state disturbances [8]. PQD detection technique was used to locate and classify various disturbances in the grid quickly and accurately [9]. Many researchers have designed and improved detection techniques for different application environments and objects to achieve better detection rates and to ensure the stability of power transmission in the grid [10,11]. This paper divides the PQD detection technique into feature extraction, feature optimization, and intelligent classification. As shown in Fig. 2, the pre-processed signals in the grid were obtained utilizing feature extraction with specified features [12]. These features are also sparse representations of the power signal [13]. The feature optimization algorithm was further optimized to extract the features with the highest discriminative power. The intelligent classification algorithm performs PQD classification using optimized features [14].

Figure 2: PQD inspection technology processing process

1.2 Published Review Literature

This paper analyzes many published review articles on PQD detection and classification techniques. The literature [15] analyzed data for all keywords, regions and years in the field of power quality, giving quantitative values for the level of interest in different key technologies in different regions and years. From a technical point of view, the literature [16] provided a comprehensive review of signal processing techniques for power quality disturbance events. The literature [17] focused only on the harmonic distortion of power quality disturbance events, reviewing the techniques for their analysis and classification. Regarding the degree of synthesis, the literature [18] reviewed traditional techniques for detecting and classifying power quality disturbances and analyzes a combination of signal processing and machine learning techniques. Inconsistent with the previous reviews, the literature [19] first proposed the idea of feature optimization in 2015, but later researchers did not pay much attention to this direction. The literature [20] pointed out that the techniques in the area of feature optimization have received more and more attention as the means of feature extraction have become more abundant and the number of features after extraction has become larger. The research in [21] was devoted to the analysis of the power quality of ships. Extensions were made to apply wavelets for harmonic distortion measurement and analysis in power grids. And the literature [22] proposed better solutions for several critical power quality problems.

The published reviews are more concerned with classical PQD detection and classification techniques but lack the discussion of relatively new and cutting-edge techniques and research directions. These published reviews do not provide a complete and precise account of the process of detection technology development. It can be seen from Fig. 3 that the published reviews cite fewer technical articles from the last five years. In contrast, the number of articles cited in this paper from the previous five years represents 60% of the total number of articles cited, reflecting the novelty of the aggregated technology in this paper. As a result of our examination, other reviews of the literature were not summarized, but this paper contains the following:

1. *3.2 Grayscale Image Processing Technology*
2. *3.4 Statistical Analysis Feature Techniques*
3. *3.8 Miscellaneous Feature Extraction Techniques*
4. *4.3 Convolutional Neural Network*
5. *4.4 Probabilistic Neural Network*
6. *4.7 Miscellaneous Detection or Classification Techniques*

Relevant literature is available in specific subsections. This review also gives the development and applicability of various techniques, the accuracy of different techniques and the analysis of future hot technologies.
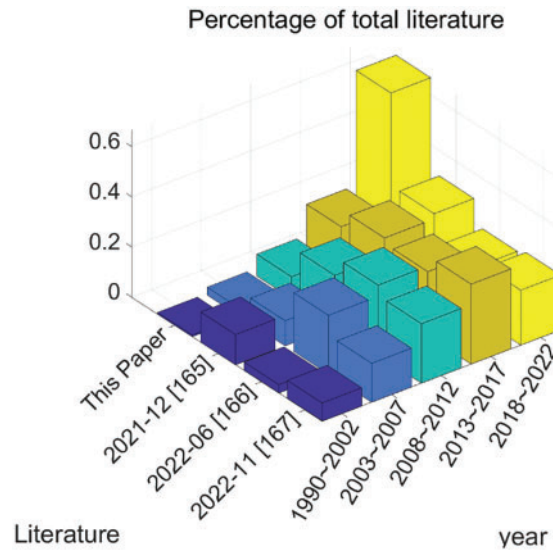
Figure 3: Comparison of reference years for published reviews

This paper compares the analysis of recent years of PQD detection techniques in the literature. The reference distribution of all three reviews is based on the period 2013–2017. This indicates a concentrated explosion of innovative articles in this period, and this section is the focus of this paper. All three reviews cite more literature over time, but the literature is under-cited at the end of the last five years. This paper focuses on the latest technologies, so the literature cited between 2018–2022 accounts for more than 60%. However, it also comes with the disadvantage that some technologies may not be stable or not always practical. The disadvantages are negligible for the advantages we can obtain.

1.3 Innovation and Article Structure

This article collects 180 papers, including highly cited and most recent literature, reflecting current research hotspots. The contribution of this paper is threefold: (1) 60% of the recent five-year literature is collected in this paper, as shown in Fig. 2, to present the latest technologies as ultimately as possible; (2) this paper provides a unified summary of the development process and application scenarios for each technology, as shown in Sections 5.1 and 5.2; (3) this paper collects and organizes the most advantageous technology directions in the latest literature, which is placed in Section 5.3.

The rest of the articles are arranged as follows. The introduction is presented in Section 1. The power quality, standard formulation, and definition are briefly discussed in Section 2. The review of feature extraction, feature optimization, and artificial intelligence techniques are presented in Sections 3 and 4. Section 5 provides a summary and future discussion to conclude the paper.

2 Power Quality

The definition of power quality is an electromagnetic phenomenon whose voltage and current vary with time and location [21]. PQ event is defined as an abnormal electrical interference state, including transient duration (oscillation and pulse), short-term duration (interruption, expansion, and depression), long-term duration (continuous overvoltage), steady-state duration (flicker, harmonic, and gap), and frequency offset. PQS is the time domain representation of PQ events. Different PQ Events have different durations ranging from nanoseconds to seconds [23]. By definition, PQD is a

unified description of a series of abnormal behaviors of PQS in the power grid, including but not limited to defined power quality events and undetected and undefined abnormal disturbances in the power grid. Power quality events defined in current standards are listed in Table 1.

Table 1: Types of PQ events

Types of PQ events	Disturbances	Time span	Variation of voltage magnitude
Short duration	Sag	0.5 cycles–30 cycles	0.1–0.9 pu
	Swell	0.5 cycle–30 cycles	1.1–1.8 pu
	Interruption	0.5 cycle–3 s	<0.1 pu
Long duration	Under voltage	>1 min	0.8–0.9 pu
	Overvoltage	>1 min	1.1–1.2 pu
	Sustained interruption	>1 min	0.0 pu
Transients	Oscillatory transient	>500 kHz	–
	Impulsive transient	>2 μs	–
	Low frequency	0.3–50 ms	0–4 pu
	Medium frequency	20 μs	0–8 pu
	High frequency	5 μs	0–4 pu
Waveform distortion	Harmonics	Steady-state	0%–20%
	Notching	Steady-state	–
	DC offset	Steady-state	0%–0.1%
	Interharmonics	Steady-state	0%–2%
	Noise	Steady-state	0%–1%
Voltage imbalances	Voltage imbalances	Steady-state	0.5%–2%

In both IEEE Society's IEEE 1159 standard and IEC Society's IEC 61000-4-30 standard, the PQD is classified in terms of the root mean square value concerning the power voltage and current deviation during the nominal operating conditions. Except for the shared definitions, the IEC 61000-4-30 standard establishes reliable methods for measuring and interpreting electromagnetic parameters in electrical grids. In [24], the author also mentioned and defined the indicators of PQD events.

PQ events are classified according to the status of PQS in the power grid. The whole PQ events classification process can be obtained from the existing scientific research literature. First, extract the features of the redundant signal PQS in the power grid and the critical information in the signal. Then, the extracted features are intelligently optimized and classified, ensuring that enough classification features improve the classification speed and the classification effect.

3 PQS Feature Extraction Technology

The feature extraction technology of PQD aims to transform the PQS from the time domain to the sparse domain and represent the PQS with fewer vectors in the sparse feature space. In this case, an infinitely long signal in the time domain can be represented in a finite-dimensional feature space. According to the literature, signal feature extraction techniques can be roughly divided into a) the sparse transformation technique of the signal, e.g., FT, WT, ST, HHT, and GT; b) the signal decomposition technique based on the time scale, e.g., EMD and VMD; and c) the maximum likelihood technique. The meaning of abbreviations is mentioned in the Nomenclature table before the introduction. See Fig. 4 for more details.
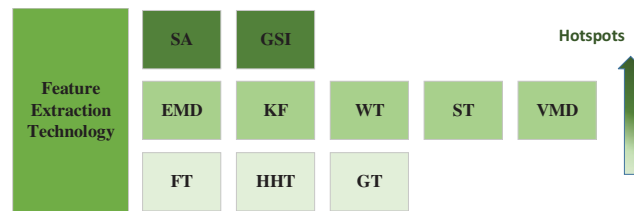

Figure 4: Summary of feature extraction technology

This paper closely searches the relevant literature published in the last five years, and it is found that a) WT and ST are the two most popular feature extraction techniques in the time domain; b) in comparison with other features extraction techniques, ST has relatively more applications in real-world scenarios due to its adoption of Gaussian windows and insensitivity to noises; and c) FT has a limited window and cannot display transformation in real-time.

3.1 Empirical Mode Decomposition

EMD is a feature extraction method that decomposes the signal according to its time scale, which is suitable for analyzing nonlinear and non-stationary signals [25]. Soon after its birth, the EMD was extensively applied to PQD identification. In 2007, an EMD-based PQD detection method was proposed by [26], where the core idea was to perform EMD [27] on the PQD to generate IMF directly. HT is applied to each eigenmode function to obtain the instantaneous spectrum [28] and then obtain the frequency with physical meaning. In [29], researchers compared the detection of voltage spikes and gaps in PQD detection with EMD and S transformation, respectively. It is concluded that EMD is superior to S transform in ignoring the limitations of mode mixing and noise sensitivity. It was pointed out by [30] that compared to EMD, EWT was able to provide a more consistent decomposition. In [31], EMD was applied to the online monitoring of power deviations in the power system, and it was determined that EMD had a lower resolution for PQ events than DWT.

In order to overcome the model mixing problem of EMD, the ensemble EMD approximate entropy was proposed by [32], where white noises were introduced in [33] to assist the EEMD algorithm, and the teaser energy operator was used to obtain the instantaneous amplitude and frequency. The denoising and feature extraction method based on EMD correlation achieved noise suppression [34] and reduced noise susceptibility. The orthogonal empirical mode decomposition method was proposed in [35], with its FPGA implementation also presented. In order to eliminate the limitation of EMD sampling rate, the literature [36] integrates the iterative down sampling phase into EMD, and Salameh et al. [37] proposed a new fast sliding window EMD. These two methods can better extract IMF and reduce the computational burden of EMD. Then the harmonic can be extracted from the non-stationary signal in real-time.

With the further development of EMD, more and more technologies combine EMD with various technologies, reducing the detection time of EMD and improving detection accuracy. It includes the combination of EMD and morphological filter [38]. In [39], EMD and multi-scale mathematical morphology are mixed to achieve PQD detection based on adaptive signal processing. The method based on EMD, and Choi Williams distribution is implemented in [40], effectively reducing Cohen class distribution's cross terms and extracting interference features.

Owing to the rapid rise of machine learning, EMD is also employed to generate feature vectors that can be further used as inputs to ANN, PNN, and other classifiers. For example, a PNN classifier is built based on EMD in [41]. Some researchers combine EMD, random variable moment, and ANN to achieve a better classification effect [42], which achieved 100% accuracy in detecting and classifying PQD. In [43], EMD method was used to extract required feature vectors from time-frequency distribution to build a balanced neural tree. The literature [44] combined EMD and SVM to analyze PQD and compare the results with LVQ-NN.

3.2 Grayscale Image Processing Technology

The grayscale image processing technique converts the signal into a grayscale image according to pixel conversion. Then, a binary image is obtained based on edge detection, which can be used for PQD classification, see Fig. 5 for more details. In the field of PQD detection, a hotspot in the past five years is to convert certain salient features in PQS into grayscale images [45] and using the current popular two-dimensional image processing technology (e.g., CNN) to achieve the detection of disturbance events. Note that applying GIP-CNN in PQD detection is a new technology to visualize PQ events.

Figure 5: Grayscale image processing flow

With the diversity of machine learning algorithms, more and more researchers are devoted to combining GIP and its processing algorithms to achieve feature extraction. The RF, CNN, LSTM, and other machine learning algorithms are combined to achieve PQD classification [46]. PSR-derived features were used as SVM input in [47], and later PSR was combined with CNN to detect PQD automatically. Small-sample training was achieved in [48], where spectrograms were used to reconstruct PQ events waveforms and CNN. Similarly, power signals with one-dimensional CNN were proposed and converted into images in [49] to improve the classification performance at the same computational complexity.

Besides, for PQD detection in noisy situations, a two-dimensional Riesz Transform is applied to convert one-dimensional signals into two-dimensional signals to obtain efficient features [50]. Feature sparse, and fusion selection was performed on the raw voltage transformed GIP [51] and later combined with ANN to improve the classification accuracy. In addition, GASF was presented to convert one-dimensional PQD signals into two-dimensional image files [52] and subsequently applied to prototype photovoltaic systems. The texture image algorithm was converted into a one-dimensional waveform algorithm in [53] with a satisfactory PQD classification effect. In addition to the combination of GIP and machine learning, a Hilbert transform-based method was proposed by [54] with a viewpoint to transform a one-dimensional curve into a three-dimensional one through the Euler rotation assumption and use the mysterious curve to detect PQD.

3.3 Kalman Filter

The Kalman filter is an optimal parameter estimation algorithm for PQD detection and analysis under noise interference. By introducing state-space models of signals and noises, the KF recursively uses the estimates of the previous moment and the observations of the present moment to update the optimal estimates of current state variables [55]. Due to its high efficiency and denoising capacity, the KF is widely used in PQD detection for parameter estimation [56,57].

It should be noted that Kalman filtering is only suitable for linear systems with Gaussian distributed noises and is not suitable for nonlinear systems or linear systems with low signal-to-noise ratios or non-Gaussian noises. Newly published literature introduces adaptive KF-based methods to address this problem, including maximum likelihood-based KF [58], adaptive process noise covariance KF [59], and extended KF [60]. In addition to adaptive KF, heuristic algorithms are also an alteration. For example, the extended KF was combined with the PSO algorithm in [61] to improve performances such as noise suppression, convergence speed, and estimation accuracy.

In addition to adaptively setting parameters and initial values, the noise and other conditions can be modeled by taking advantage of prior knowledge to enhance the KF performance. To be specific, DWT was used in [62] to model internal noise, and the obtained noise covariance was then used by the maximum likelihood KF, thereby boosting the performance of PQD detection [63].

3.4 Statistical Analysis Feature Techniques

Compared with other transformation-based feature extraction methods, statistical analysis-based feature extraction methods are relatively simple to implement with high interpretability. Some commonly used time-domain features are peak-to-peak, frequency, RMS, etc., and frequency-domain features are mean square frequency, frequency variance, spectral entropy, etc. Among various distributions that can be used for feature extraction, we highlight the WVD technology, the most widely used feature due to its good reflection of the instantaneous time-frequency relationship of signals. Basically, time-frequency features can be used as characteristics of electrical signals in analyzing power quality, and it was pointed out by [64] that the time-frequency relationship can reflect the trend of the signal spectrum over time. Thus, WVD was widely used in power disturbance identification.

Compared with SA and parametric time-frequency methods, which require pre-assumed models, the WVD does not require prior assumptions about signal models but is easily interfered with by cross terms. To solve this problem, researchers introduced windowed WVD and pseudo-smoothed WVD to suppress cross-terms [65,66]. In addition to using the windowing method to hide cross-term influence, deep learning methods were also used to extract features automatically to mitigate the effects of noisy cross-terms. In [67], the WVD was combined with CNN to convert a one-dimensional voltage disturbance signal into a two-dimensional image file. Then a neural network was utilized to classify the images.

3.5 Wavelet Transform

Wavelet transform is often used in PQD feature extraction. As shown in Fig. 6, the discrete wavelet transform uses wavelet decomposition at different resolutions to transform the power quality signal into a series of wavelet coefficients that can be efficiently compressed and classified. The ray-coding genetic algorithm was used in [68] to reduce feature dimensions after wavelet transform, which improves the classification accuracy of PNN. In classification accuracy, discrete harmonic search with an improved difference mutation operator can also achieve the same performance as a ray-coding genetic algorithm [69]. For better classification, WT [70] and PSO [71] were combined with neural

networks and random forest classifiers for perturbation detection. The flexible analytical wavelet transform was proposed in [72] that combined the bagging of the rotating forest integrated classifier to achieve a classification accuracy of 95.33%.
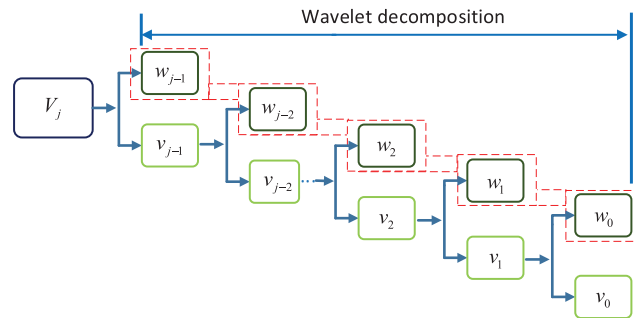

Figure 6: Discrete wavelet decomposition vectors

Compared with continuous wavelet transform, DWT can represent the original signal as coefficients with different levels of approximation coefficients and detail coefficients, and DWT parameters affect the robustness of the classifier towards noises and overall classification accuracy [73]. It was pointed out by [74] that DWT can reduce the required storage space. It was later combined with the PNN model to construct a classifier suitable for classifying different types of electrical disturbances. By using the PNN-ABC algorithm, the performance of the classification system was improved [75]. It was verified by [76] that the combination of DWT technology and adaptive ABC-PSO algorithm can meet the requirements of practical applications and achieve the highest classification accuracy (99.31%).

Subsequently, it was proved in [77] that the combination of DWT and fuzzy logic for fuzzy c-means clustering was equally effective in detecting and classifying events. Cheng et al. [78] developed an adaptive learning framework for depth-weighted sparse self-encoder (AE) using multi-objective evolutionary algorithm (MOEA), which provides a new idea for online monitoring of PQD. At the same time, it was verified in [79] that the efficiency and robustness of the EWT and multiclass SVM methods to noises and disorders of different degrees. The ReliefF algorithm was presented by [80] to achieve further dimensionality reduction optimization with ensured accuracy and reduced computational complexity.

In the case of insufficient training samples, the maximum overlapping discrete wavelet transform (combined with supervised backpropagation training) is studied in [81] to improve the overlapped sparse denoising automatic encoder into a robust classifier. The second-generation wavelet transform proposed by [82] was a time-domain analysis of less processing time. From another perspective, compared with the original WT, the second-generation wavelet transform was simple, easy to implement, and brief to be combined with data mining-based RF. It could be used to distinguish power voltage disconnection events from PQ interference.

3.6 S-Transform
S-transform is an extension of the Wavelet Transform and Fourier Transform with good noise immunity. ST was used in [83] to establish classification rules and decision tree classifiers that could identify PQ events effectively. On this basis, Li et al. [84] proposed a model combined with a grid search method for SVM. The complex-valued classifier combined with S-transform was proposed in [85] for PQD classification.

Regarding the combination of ST and neural networks, the SoftMax classifier was used in [86] for classification equipped with good noise resistance, better real-time performance, and higher accuracy. S-transform was integrated with PNN in [87] to show that distinct PQ events can be efficiently detected and classified, where the features of interfering signals were reduced mainly without losing the original properties, thus requiring less storage space and learning time. Using S-transform, improved discrete artificial bee colony algorithm, and the default parameters of random forest, the classification accuracy was proved to be better [88].

The traditional S-transform method has problems like extensive calculations and high redundancy in detecting and classifying PQ events. Random noise S-transform is often combined with random forest using the SFS method [89]. It was shown by [90] that under the same feature subset, the classification accuracy could reach above 99.7% with conditions of 30 dB. Some researchers have pointed out the use of the Kaiser window with intrinsically best energy concentration properties as a kernel function, which provides better resolution at the fundamental frequency.

In practical applications, the improved S transform effectively reduces the influence of noise on power quality disturbance signals. It was tested by [91] that optimized window parameters can be used to improve time-frequency resolution when combined with a kernel-SVM classifier and achieve the efficient classification of PQ events. The optimal fast discrete Stock-well transform was combined [92] with an improved RF-based classifier. Decision stumps were used as weak classifiers to achieve precise time-frequency localization with higher energy concentration degrees and lower noise insensitivity [93]. It should be mentioned that in comparison with the traditional ST method, the decision tree and multi-resolution S-transform were used less.

3.7 Variational Mode Decomposition

Variational Mode Decomposition is a new adaptive processing method for stationary and non-stationary signals. The principle of VMD in signal processing is to find the optimal solution of the signal model and iteratively update the model to obtain all the modal functions of the signal decomposition. The VMD method overcomes the noise sensitivity and sampling rate limitations of EMD [94] and thus has better classification accuracy than EWT [95]. The modes decomposed by VMD are mainly divided into modes containing signals and noises. The signal modalities decomposed by VMD are often combined with artificial intelligence algorithms such as PNN, SVM, and dimensional transformation to detect PQ events. Specifically, SVM was widely applied to power quality disturbance detection [96] that decomposed PQS into several eigenmode functions to analyze and detect power quality disturbance signals. As shown in Fig. 7, the VMD processes the current or voltage signal to obtain the IMF classification, then extracts and selects the features of the IMF, and finally classifies the PQD based on the selected features [97].

With the acceleration of the application of machine learning in the field of power quality detection, scholars have begun to combine VMD with artificial intelligence to achieve automatic detection and capture of power system PQ events. VMD technology has applications in power generation systems, photovoltaic, and wind power generation systems [98]. The feasibility of VMD has been verified in the laboratory by simulating the signals of multiple PQD events according to IEEE standards [99,100]. With the continuous improvement and innovation of the VMD theory and implementation technology, new algorithms for intelligent classifiers have been continuously adapted to accommodate VMD, which significantly improves the ability of VMD to parse and classify PQD [101,102].
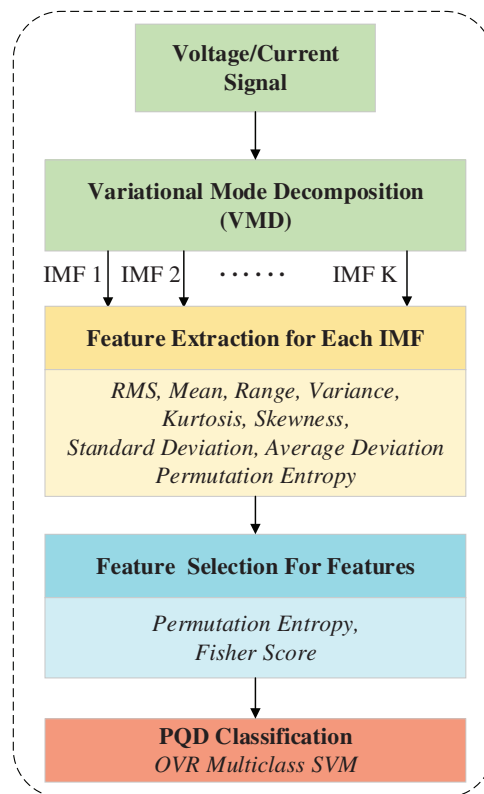
Figure 7: The process of VMD classification of power quality signals

In 1998, Norden E. Huang et al. proposed the Hilbert transform after EMD decomposition, also known as the classic HHT [103]. Inspired by this, S-transform and VMD were combined, where S-transformation was performed on the decomposed eigenmode function to extract potential features to improve detection ability and speed. Similarly, VMD with HT was combined in [104] to modify the IMF to obtain new latent features. To solve value selection problems of penalty parameters in the VMD technique, Chakravorti et al. [105] proposed an algorithm based on adaptive variational mode decomposition. Researchers use the Firefly algorithm to optimize features, speed up convergence, and make VMD output distinguishable. Similarly, it was made possible by [106] to directly output different features by optimizing VMD that can be used to optimize the number of decompositions and data fidelity factors to extract the most efficient band-limited modes.

3.8 Miscellaneous Feature Extraction Techniques

In addition to the techniques mentioned in Sections 3.1–3.7, there are several other special techniques, including transforming the PQS directly through a neural network, making it easy to extract features [107]. The article [108] improve PCA to extract feature. In [109], authors use dictionary learning to decompose sparse PQ signals directly. Different from other conventional feature extraction methods, Aggarwal et al. [110] directly used Convolutional Neural Networks to extract the features of the signal according to the characteristics of the processed image and then uses the Multiclass Support Vector Classifier to detect and classify the power quality disturbance events. Compared with the ordinary convolutional neural network, this method improves performance by about 10%. The

literature [111] also directly extracted features through a neural network and proposes a multilayer severe learning computer autoencoder to optimize input weights and directly extract features of power quality disturbances. Besides the technology of directly extracting features with neural networks, some researchers have further proposed new ideas and improvements to the technology of adaptive decomposition of signals for the sparsity of PQS. In [112], authors proposed a new Adaptive Local Iterative Filter Decomposition method to decompose electrical signals, Sahani et al. [113] proposed a new signal segmentation method to reduce the number of decompositions to extract features efficiently. Signal decomposition techniques include decomposition and sparse decomposition, and dictionary learning in machine learning. Therefore, the literature in [114] proposed to use dictionary learning as a decomposition method of PQ signal to extract the required features. They use Principal Component Analysis as a feature extraction method and continuously reduce dimensionality and decompose to extract features.

4 Feature Optimization and Intelligent Classification

In PQD detection and classification, there are two ways to improve performance with the help of artificial intelligence [115]. The first is to use artificial intelligence to find the best subset of features for classification in the feature space of PQS. The second is to use artificial intelligence to improve the classifier's efficiency. After certain training, artificial intelligence can quickly and automatically identify PQD at a high success rate and a fast speed, which is vital to developing intelligent grids [116,117]. Group optimization algorithms such as ABC and PSO are widely used among feature optimization techniques. Similarly, in the classification technology of artificial intelligence, ANN, SVM, and RF are classic PQD classification artificial intelligence algorithm. Fig. 8 illustrates some basic techniques for feature optimization and intelligent classification.
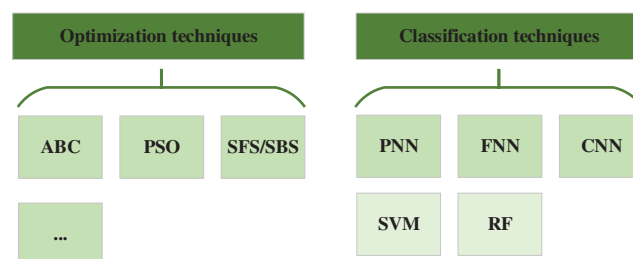

Figure 8: Summary of intelligent optimization and classification

4.1 Feature Optimization Algorithms

The ABC and PSO algorithms are widely used in feature optimization. PSO imitates the predation behavior of bird flocks and integrates the historical positions of the congregation to update the objective function in an iterative way [118]. ABC imitates the behavior of honeybees to find the optimal solution in the search space. Although ABC has low complexity and moderate convergence speed, in case of inappropriate hyperparameters, ABC may fall into the local optimum [119]. Thus, the ABC algorithm is generally combined with other algorithms. The literature [120] used the adaptive chaotic ABC optimization algorithm to optimize the parameters of the objective function. The literature [121] combined ABC algorithms with other optimization algorithms and used PSO as the basis for feature selection.

In addition to the classic PSO and ABC, other feature optimization algorithms can achieve dimensionality reduction and screening of feature subsets in addition to the traditional PSO and ABC. In [122], the features of dimensionality reduction and optimization of the neural network were used to realize the optimization of PQS features. In [86], the features extracted by CNN for S transform were directly employed. Secondary extraction is performed to optimize the number of feature subsets. Zhao et al. [83] proposed an optimal feature selection method based on a probabilistic neural network with the help of PNN, which gradually eliminated redundant and irrelevant features in a noisy environment and improved the classifier's performance.

Apart from the neural network, SFS and SBS are commonly used feature optimization methods. In [123], SFS and SBS were adopted to extract optimal perturbation features, and the classification accuracy can be maintained above 99.7%. Dempster-Shafer evidence theory [124] introduced the concept of trust functions, forming a set of "evidence" and "composition" mathematical methods for dealing with uncertainty reasoning. Unlike the Bayesian theory, the Dempster-Shafer evidence theory can represent uncertainty fully without prior probabilities and is widely used to deal with uncertain data. Regarding this point, the Dempster-Shafer evidence theory is also a good choice for feature optimization of PQS [125,126]. For some up-to-date feature optimization approaches, please see the non-dominated sorting genetic algorithm [127], Fischer linear discriminant analysis [99], and mutation operators [69].

4.2 Artificial Neural Network

Artificial Neural Networks imitate the neuron network of the human brain to establish a simple model that forms different networks according to other connections. Due to their non-localization, nonlinearity and non-convexity, ANNs are found to be highly suitable for feature classification and are widely used in the field of PQD classification and detection. ANN is ideal for feature quantities extracted by various feature extraction methods such as WT, ST, EMD, VMD, and KF. Utilizing wavelet transform WT, Sun et al. [71] proposed PSO-based FNN to detect the islanding phenomenon. As shown in Fig. 9, Researchers use ANN to train networks with different disturbances offline. After training, the features of PQS are passed to multiple ANN networks in parallel for online discrimination. In the paper [81], the researchers used WT to extract PQS features and then used the improved stack sparse denoising automatic encoder for classification. The training process of this algorithm is carried out by supervising the backpropagation. It effectively identifies voltage sags and interruptions. At the same time, WT and ANN were directly combined in [128] to realize wavelet network WN and complete the extraction and classification of PQS at one time.

Both WT and STFT techniques perform windowing on the signal before analysis to overcome the disadvantage that FT cannot perform time-frequency analysis. Nevertheless, the added fixed-width windows cannot adapt to different signals [129,130]. To solve this problem, ST uses a Gaussian window function whose width is proportional to the inverse of the frequency so that more noise-insensitive feature quantities can be used in PQD detection and classification. In [58], the PQS waveform was filtered by the KF technique and then transformed by the multi-ST feature extraction technique. After feature optimization, the author used a multilayer FNN to achieve perturbation extraction under various high-noise disturbances. In [85], the authors used ST technology as the extraction method, combined with a complex extreme value learning neural machine network and complex value radial basis function network, to achieve single and joint disturbance detection in the power grid.

An adaptive neural network is an artificial neural network with adaptive learning capability. Combining various classical PQD extraction algorithms with neural networks can realize adaptive

extraction of PQD. The method of an adaptive neural network to achieve PQD classification has the advantages of high accuracy and high noise resistance. As early as 2004, Kim et al. [131] proposed to combine DWT with an adaptive neuro-fuzzy inference classifier. DWT uses multi-resolution signal decomposition to achieve feature extraction. The adaptive neuro-fuzzy inference was then used, showing better efficiency. Over time, scholars have combined adaptive neural networks with different feature extraction methods to provide various approaches for detecting PDQ classification and have established the advantages of each. For example, a new scheme combining ANN with information theory [132] has very high robustness. It can accurately estimate the PQD even in noisy environments. And, the literature [133] used the traditional HHT transform and NFS classifier. The combination of neural networks and fuzzy systems effectively improves the adaptability of neural networks. This approach enhances the efficiency of the traditional HHT method.
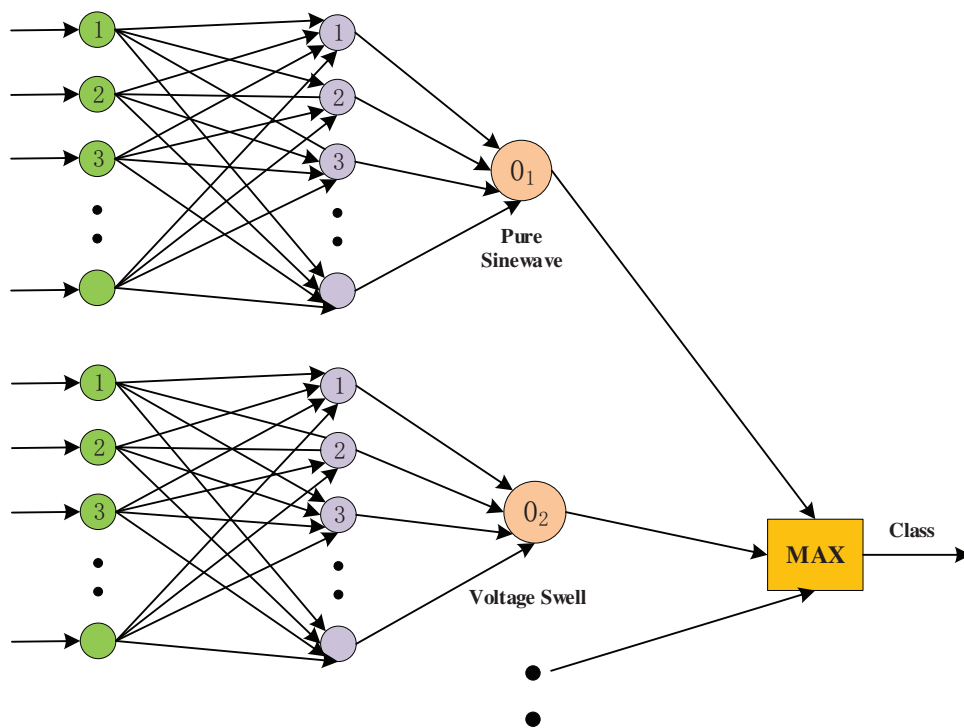

Figure 9: Artificial neural network for PQD classification

Moreover, based on deep learning, the proposed three-stage diagnosis method [134] achieves almost 100% accuracy. Different adaptive feature extraction and classification methods have recently achieved good results. For example, an adaptive rate time domain analysis method was used to extract the correlation features of the segmented signal [135], achieving a compression gain of 13.26 times. It further tuned the parameters of the extreme learning machine (ELM) [136] by the gray wolf optimization (GWO) method to improve the accuracy.

Unlike traditional clasS-transformed feature extraction methods, the dimensional transformation was used in [51] to convert PQS to grayscale images. An FNN classifier selected the features to distinguish single PQ events from combined PQ events. The EMD and VMD are used by [42] and [101] to decompose PQS, select valuable features, and classify different perturbations, where the detection

rate reaches 100%. In [57], the authors estimated the harmonic components of the post-fault voltage signal as eigenvectors through a KF and used SVM and ANN for fault diagnosis and localization.

4.3 Convolutional Neural Network

The Convolutional Neural Network is one kind of deep learning network with convolution operation. It has the characteristics of no loss of parameters, high training efficiency, and good prevention of overfitting when dealing with large-scale two-dimensional image problems. In PQ event detection, the PQS waveform is often converted into a two-dimensional image. Then the perturbation detection and classification are carried out with the advantage of CNN processing techniques [137,138]. Fig. 10 depicts the flow of CNN processing grayscale images of PQS, which can be converted to 2D frequency images by WVD distribution and time-frequency analysis, in addition to grayscale images. With the advantage of CNN in processing images, PQS can be converted into different images that CNN classifies. The CNN can automatically distinguish between the behaviors of typical power systems and power quality disturbances (e.g., voltage dips, voltage swells, and interruptions) at a higher level of accuracy after training [139]. This lays a good foundation for the automatic detection of artificial intelligence when identifying the interference of the power system, reducing the failure rate in future extraction [140,141].
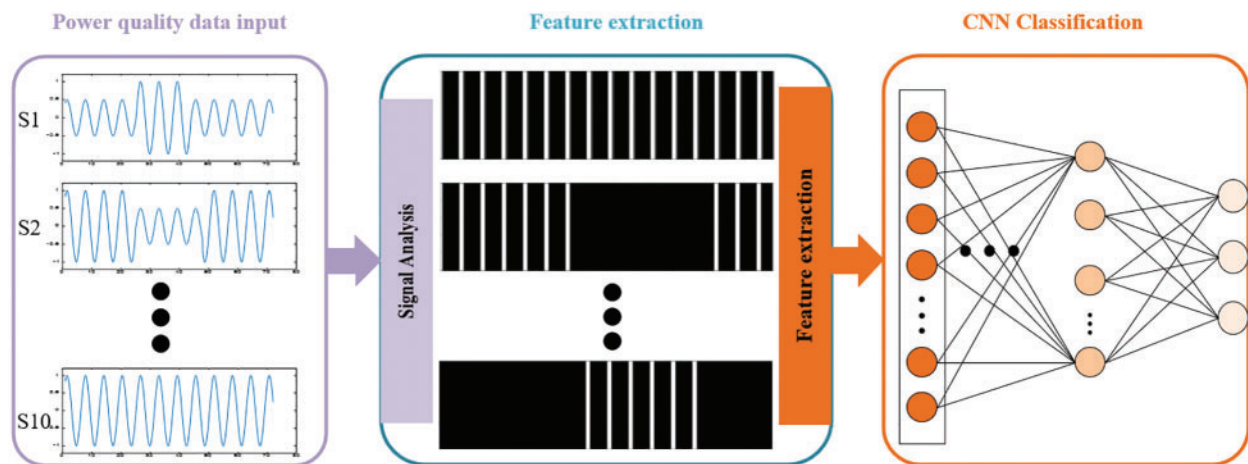

Figure 10: Convolutional neural network processing of grayscale images of PQS

The requirement for using CNN is that one-dimensional interference signals must be converted into two-dimensional image files before the classification process [142]. After combining with a CNN, WVD can determine follow-up remedial actions [67]. The combination of S-transform and CNN can avoid the complex problem of window function selection with fixed window width, good noise immunity, better real-time performance, and higher accuracy [86]. Subsequently, CNN was combined with PSR in [143] to provide remedial measures without human interventions.

On the other hand, CNN can also extract features by utilizing a convolution base composed of two-dimensional convolution normalization to capture grayscale image features [48]. One-dimensional and two-dimensional structure groups were combined in [49] to build a hybrid CNN to ensure satisfactory performance with moderate computational complexity. CNN was further integrated with adaptive variational modal decomposition in [106] to effectively obtain features and thus achieve high classification accuracy, good noise resistance, and short detection time.

4.4 Probabilistic Neural Network

Probabilistic Neural Networks are a simple structure, and extensive neural networks are built based on Bayesian decision theory. Compared with BP neural network, PNN has faster learning speed, good robustness, and classification capability for the PQD classification study, and its structure is shown in Fig. 11. In [144], the IMF of the narrowband frequency was extracted by HHT as the input of PNN, and the simulation results indicate that HHT can effectively classify the PQ events. HHT was used as a feature extraction method in [41], and the obtained results were compared with that of classification, learning vector quantization neural network, and feed-forward multilayer neural network. The study found that the classification performance of PNN was superior to LVQ and FFML.
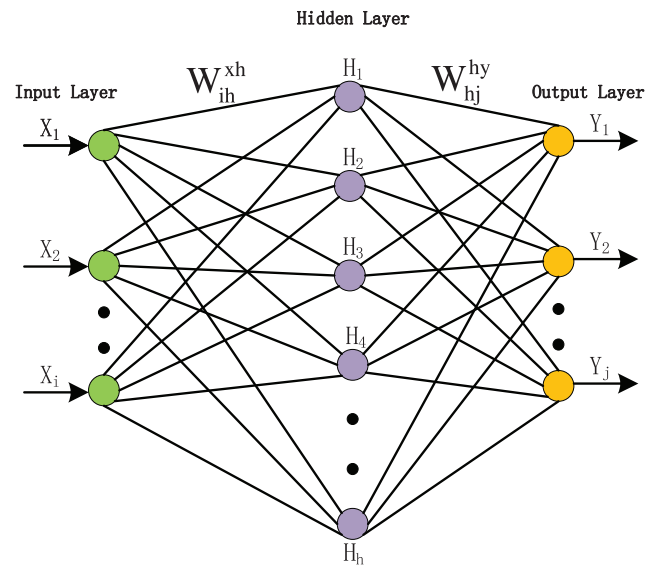

Figure 11: Probabilistic neural network structure

Note that PNN can also be combined with Gabor transform without any iterations to adjust weights, and the results confirmed the effectiveness of the GT-PNN method in PQD recognition [145]. Even in an environment with noise interference, the PFS method combined with the adaptive probability neural network can gradually remove redundant and irrelevant features in the noise environment, effectively eliminating non-essential characteristics and improving the classifier's performance [120]. Several features were extracted by three-order primary component analysis decomposition in [109], taking advantage of PNN to identify disturbances.

4.5 Random Forests

PQD has been classified by Random Forests, a machine-learning approach using multiple decision trees to improve classification ability. Wavelet transform and S transform can be utilized together with RF in [70] to show that RF classifiers based on wavelet transform WT better performance classifying data. Literature [73] used RF to develop DWT to extract features to build a model. Literature [30] combined WT and ST extraction to establish a decision tree classifier that can effectively identify mixed interference signals. Zhao et al. [83] achieved 95.33% accuracy by bagging with a rotating forest ROF ensemble classifier [72]. Data mining-based RF [82] was also applied to distinguish power voltage disconnection events from PQ disturbances [146]. An improved RF-based classifier was applied to the

optimal fast discrete ST PQ detection framework [92]. The generalization error of RF was used as the objective function in [88], where MDABC was adopted to optimize the forest scale and the number of input features.

Compared with the RF classifier before optimization, the MDABC-RF classifier has better classification accuracy for complex PQD signals. The PQD signals were identified in [147] by using a construct-set RF classifier which determined optimal feature subsets by a sequence of forwarding search methods. The new process accurately identified PQD signals in different noise environments by selecting the optimal classification subset [148,149]. It was proposed in [150] that based on the Decision Tree and multi-resolution S-transform, the characteristics of the analyzed PQS were quantitatively reflected.

It was shown in [151] that the decision tree and VMD could be used to estimate phasors accurately, classify mixed PQ events, and extract features such as pattern center frequency to process and localize PQ events without noise accurately. It was pointed out in [94] that the IMF function can classify different power system disturbances with improved decomposition quality and classification accuracy. Pan et al. [152] proposed a new Gradient Boosting Decision Tree method, which adopted the SA statistical calculation method based on statistical features at a small cost calculation.

4.6 Support Vector Machine

Support Vector Machine is a class of supervised generalized linear binary classifiers whose classification is based on the labels of the data, and the hyperplane with the most significant margin is obtained to ensure sparsity and robustness. The features of PQD are extracted as the input of SVM, and then the classification of PQD is realized.

PQD classification was proposed in [153] with fewer samples and higher accuracy by using the interference features extracted by PSR as the input of SVM. Malik et al. [44] analyzed PQD distribution based on the SVM method, and such PQD distribution was later compared with the traditional AI methods of LVQ-NN. Literature [97] used SVM and Random Kitchen Sink algorithms to perform classification, and the accuracy of the Random Kitchen Sink method was 94.44%. SVM was later combined with feature extraction methods such as EMD, HHT, and GIP. Based on SVM and EMD [25], PQD classification was implemented to provide simplicity and good noise immunity with few features.

The performance evaluation of SVM and the classification method of PQD monitoring was introduced by [154]. The HHT technique for extracting feature vectors from the sampled power signal used as input to the SVM classifier is very effective. Similarly, in intelligent grid systems, the literature [155] combined SVM with HHT to detect PQE signals and to improve classification accuracy [3]. At the same time, the electrical energy signal was first converted into GIP, and then the data features were extracted by the image processing method [53].

In addition, the combination of SVM and VMD is also handy in detecting PQD classification. Aneesh et al. [95] used SVM to classify PQD based on VMD and EWT, and it was shown that VMD outperformed EWT in the feature extraction process. To localize disturbances, Multiscale Recurrence Quantification Decomposition was combined with a hybrid approach of SVM [156] for PQD monitoring in grid systems. Similarly, VMD and SVM were combined in [157] to obtain feature vectors. Then, SFS, SBS, and Gram-Schmidt Orthogonalization were applied to eliminate redundant features, and SVM was employed to improve the anti-interference ability, speed, and accuracy [158,159].

Different from the previous feature extraction algorithm, the Fisher score algorithm was used by [100] to remove redundant features in the permutation entropy. Scholars have recently combined WT and SVM to detect PQD categories [79,80], achieving high accuracy and robustness in noisy environments. Besides, a method based on SA statistical analysis and SVM classifier was proposed by [160] to detect PQD classification automatically and in real-time.

In addition to combining SVM with various feature extraction algorithms, much research was also devoted to developing SVM. For instance, the Kernel Support Vector Machine classifier was proposed by [91] and was combined with kernels to classify multiple features to improve the detection of PQD performance. Furthermore, Li et al. [84] employed a grid search method to optimize the parameters to determine the optimal parameters of the SVM. Under different signal-to-noise ratios, this method of SVM could accurately identify 14 kinds of signals.

4.7 Miscellaneous Detection or Classification Techniques

In addition to the techniques of intelligent classifiers described in Sections 5.1–5.5, some other classifier techniques should also be concerned. For example, exploiting Kullback-Leibler divergence was used in [161] to evaluate distributions' differences. If the Kullback-Leibler divergence is greater than the threshold, there is an abnormal event. In [162], different PQ events in power systems were identified based on statistical time-domain joint neural networks.

In addition, the researchers introduced different machine learning algorithms to implement PQD classification and provided more ideas for subsequent researchers, including locally weighted projection regression [163], balanced neural trees [43], random vector function linkage networks [105], quantum neural networks [124], class-specific weighted random vector function linkage network classifiers [114], and SoftMax classifiers [164].

5 Discussion and Conclusion

This paper comprehensively reviews the existing literature on PQD detection and classification. Table 2 lists specific information on 23 of the 180 articles with relatively high citation rates for technical reference. All 23 methods achieved a correct identification rate of 90%, with the vast majority reaching 95%.

Table 2: Comprehensive analysis

Ref. paper	Feature extraction technique	Feature optimization algorithms	Classification technique	Data used	Noisy data	Accuracy
[29]	EMD	–	–	Simulation	No	97.22
[41]	EMD	–	PNN	Simulation	No	98.63
[43]	EMD	–	Balance Neural Tree	Simulation	Yes	97.9
[57]	KF	–	ANN	Simulation	No	99.49
[62]	KF	–	FL	Simulation	Yes	96
[71]	WT	PSO	ANN	Simulation	No	97.8
[75]	DWT	–	PNN	Simulation	Yes	90
[76]	DWT	ABC	PNN	Simulation	Yes	99.875

(Continued)

Table 2 (continued)

Ref. paper	Feature extraction technique	Feature optimization algorithms	Classification technique	Data used	Noisy data	Accuracy
[87]	ST	–	PNN	Simulation	Yes	96.65
[90]	ST	SFS	RF	Simulation	No	99.17
[99]	VMD	FDA	ELM	Experimental	No	97.84
[102]	VMD	PSO	ELM	Simulation	Yes	95.11
[105]	EWT	ReliefF	SVM	Experimental	Yes	98.33
[118]	DWT	PSO	ELM	Simulation	No	93
[119]	ST	PSO	FL	Simulation	No	96.33
[120]	–	–	PNN	Experimental	Yes	94.4
[123]	VMD	SFS+SBS	SVM	Simulation	Yes	99.66
[142]	SA	–	CNN	Experimental	No	99.52
[147]	GSI	SFS	RF	Simulation	No	98.84
[151]	VMD	–	RF	Simulation	Yes	96.7
[154]	HHT	–	SVM	Simulation	No	96
[161]	SA	–	KLD	Experimental	Yes	97.89

The ranking in Table 2 shows that the feature extraction means with the highest correct rate are still wavelet transform and correlation derivative techniques. Among them, Liang et al. [76] achieved a nearly 100% detection rate by combining wavelet transform and probabilistic neural networks. To achieve such results, the feature optimization algorithms ABC and PSO were added to obtain faster convergence and higher detection rates further. Neural networks PNN and ANN, and ELM have increasingly replaced the traditional machine learning algorithms RF and SVM as the new classifiers. Similarly, adding feature optimization algorithms in the middle of feature extraction and classifier can significantly improve the detection rate and speed.

5.1 Development and Performance of Feature Extraction Methods

Power quality disturbances were first introduced at the beginning of the twenty-first century when grid nodes were small, and generation was low. Time domain analysis techniques are suitable for analyzing PQD problems at the beginning of the twenty-first century because of their simple mathematical expression and precise physical meaning. The PQD problem has been made complex due to the rapid development of high-voltage transmission and distribution grid technologies. Due to the fast development of high-voltage power transmission technologies and distributed grid technologies, PQD could get more complicated. Accordingly, the original PQD problem is expected to be transformed into other forms to obtain desired features quickly and accurately. As one of the most classical signal processing methods, FT plays a vital role in detecting steady-state disturbance of power quality. Unfortunately, due to shortcomings in time-frequency analysis, FT is not feasible for testing temporary perturbations such as sudden drops and rises. The suitable candidates capable of solving such a problem are the STFT and WT, which have satisfactory window analysis capabilities.

It is worth mentioning that WT cannot extract any frequency signal alone, and the wavelet coefficients are greatly affected by noise, making WT unable to quantitatively detect the amplitude

characteristics of interference signals containing noise or harmonics. The combined WT and STFT proposal overcome the individual limitations of WT and STFT regarding the choice of window function and fixed window width. As a result, it is insensitive to noise in PQD analysis. The idea of combining the S-transform with other analysis tools has produced a large number of findings on PQD.

In addition to transform-based feature extraction methods, PQS feature extraction methods can also be implemented through pattern decomposition. The most classical implementation of EMD is based on the idea of smoothing the signal to obtain feature functions for different frequencies. The EMD method has the advantage of multi-resolution of the wavelet transform. The primary function of the decomposition is obtained adaptively according to the local time scale of the signal, avoiding the drawback that the analysis result of the wavelet transform depends on the accuracy of the wavelet transform. However, short-term data anomalies in the actual signal can interfere with the decomposition process of the EMD, creating localized high-frequency signals and thus affecting the decomposition results of the high-frequency part of the EMD. This problem is known as the modal aliasing phenomenon, and VMD has emerged to solve this problem of EMD. Therefore, in recent years, VMD has attracted continuous research interest as one of the most popular modal decomposition techniques to avoid modal aliasing by decomposing the time scale.

We rigorously counted the number of publications from 2000 to 2022 by searching the web of science for "power quality disturbance" and specific technical terms. As shown in Fig. 12, wavelet transform is the most popular means of feature extraction. Although WT's publication volume occasionally fluctuates from year to year, its total publication volume is almost at the top, especially in 2008 and 2019. The Kalman filter and empirical modal decomposition techniques, which have evolved over the decade from 2005 to 2015, are consistent with WT in terms of publication volume.
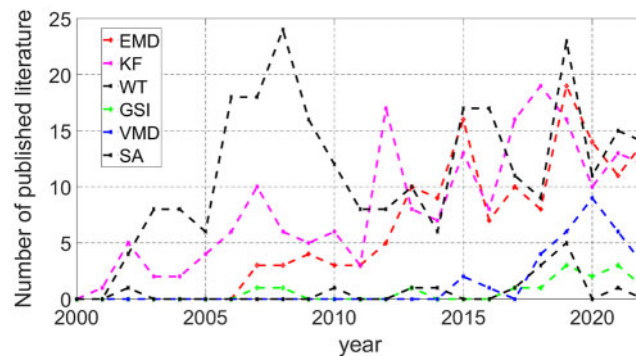

Figure 12: Analysis of the number of publications for feature extraction techniques

As the representatives of new technologies, GSI, VMD and SA have developed year by year as a specific trend in the application of PQD detection tools since 2006. Similar to the development process of EMD and KF, we predict that more papers related to GSI, EMD and SA will appear next. More evidence can be observed in our given Fig. 13. we classified the collected literature over a five-year period according to the different techniques. The uncited literature was removed and the total number of citations was divided by the total number of citations. It can be obtained that although WT has a high number of published articles, the average number of citations is 12.1, which is smaller than VMD's 15.6. The classical EMD and KF techniques have an average number of citations between 6 and 7, while the newly proposed SA technique has reached 9. The GSI technique has just received attention and its number of citations is not high for the time being, but the journals in which it is published are at a high level, so we have reasons to believe that it has some potential for development.

Our conclusion on feature extraction techniques indicates that the wavelet transform is still the most popular feature extraction technique. Although the wavelet transform has been proposed in combination with power quality disturbance detection for more than a decade, the stability and efficiency of the WT make it the most published technique in the field of PQD detection technology. At the same time, the VMD technique is starting to develop and its potential is so great that we predict that it will gradually replace the WT as the most popular technique in the field of PQD detection in the next few years. In addition, both GSI and EMD techniques are worthy of attention and study.
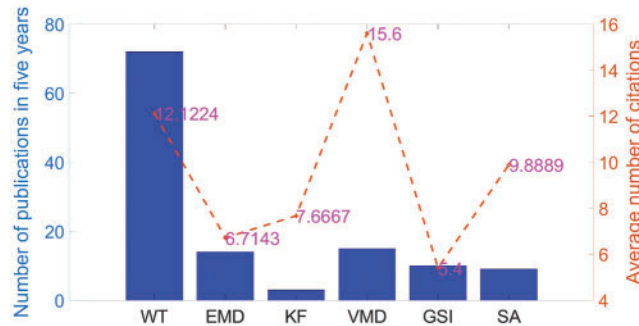

Figure 13: Five-year average number of citations

In summary, current research hotspots in feature extraction methods focus on S-transform (see Section 3.5) and VMD (see Section 3.7). Image processing of features in PQS is also a hot direction (see Section 3.2), with popular techniques such as grey-scale image and phase space reconstruction techniques to convert 1D PQS into 2D images. Interference recognition in PQS is achieved by exploiting the CNN processing image's outstanding performance to achieve this. In addition, researchers have found more significant advantages in using mainframe computers to distribute and identify statistical features in the time domain of PQS and then complete real-time capture and classification of PQDs due to the tremendous development of computer computing power (see Section 3.4).

5.2 Development and Performance of Feature Optimization and Intelligent Classification

The traditional literature in the field of PQD has focused solely on feature extraction and classifier design. In contrast, the workload and misjudgment rate of the classifier has not been fully considered, especially in cases of complex feature extraction, large feature amounts, and high coupling degree. As a result, feature extraction is usually conducted before classifier design utilizing statistically analyzing classification effects or implementing intelligent algorithms, including ABC and PSO (see Section 4.1) for automatic feature selection. Some scholars use feature optimization technology in neural networks or the dimension reduction algorithm in machine learning to directly optimize the extracted features. For better PQD detection, a promising research direction should be feature optimization approaches that can be applied to different feature extraction methods and classifiers.

In order to obtain the research trends of classifiers in PQD detection techniques, we conducted statistics for the number of classifiers published. As shown in Fig. 14, ANN and SVM, as the hottest classification techniques, are rising in the number of publications yearly. Researchers have found that converting PQS signals into 2D images and leveraging the advantages of CNN in processing images can substantially improve the efficiency of PQD detection, so the number of papers on CNN applications in PQD detection is overgrowing. This direction is worth thinking and researching.
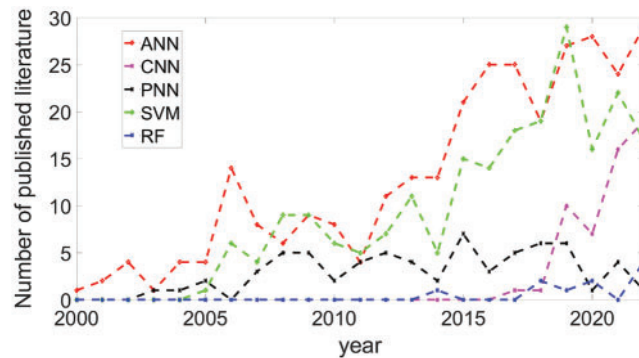
Figure 14: Analysis of the number of publications for Intelligent Classification

Regarding the classification and recognition of various PQ events, ANN, SVM, ES and RF are all good choices. Traditional ANN-based classifiers are generally slow to train, not very accurate, and prone to under-learning, over-learning, and getting stuck at local extremes. RF and SVM methods work well in solving sample classification problems, but face much more difficulties than neural networks and Bayesian methods. Therefore, more research has been done to develop combined strategies for pattern classification to compensate for the shortcomings of any method and obtain better classification performance, such as the combination of ANN and SVM, fuzzy theory and ANN, SVM and Bayesian theory. In addition, researchers are also focusing on more cutting-edge machine learning methods, including CNN, PNN and QNN, to solve the traditional PQD problem.

In recent years, researchers increasingly used the integration of artificial intelligence algorithms to simultaneously achieve feature extraction, feature optimization, and classifier. The wavelet neural network replaces the nonlinear sigmoid function in the ordinary neural network with the nonlinear wavelet basis. It constructs a new layered, multi-resolution artificial neural network model. This neural network model can directly input signals into the neural network for classification without additional feature extraction. Similarly, one-dimensional PQS is converted to a two-dimensional gray image, and then the image processing algorithm is used for direct classification. In a convolutional neural network, the 1D-CNN algorithm also supports the direct input of signals and the direct output of classification results. The commonness of these methods is that researchers ignore the features extracted in the middle and the optimized features but only the final output of the classification results. The internal operation is similar to the black box, which is closed to the outside world. Adjusting different parameters can speed up the classification, but the disadvantages are also prominent. Specific environments need specific debugging parameters, and the parameters of different environments are inconsistent. If future researchers can produce an intelligent integrated classification algorithm with adaptive parameter adjustment, it will further expand the combination of this field and artificial intelligence.

5.3 Future Possible Research Hotspots of PQD Detection

The integration of PQD detection with information systems is a significant research trend to achieve intelligence and practicality. Considering the importance of PQD detection for the development of human society, this field will be even more promising and flourishing in the future. This paper mainly introduces the PQD detection of artificial intelligence with a focus on the following four aspects:

1. Develop more adaptive/transformation feature extraction methods based on artificial intelligence algorithms for better detection and classification [165–167].
2. Another idea is to select an appropriate subset of features and optimization methods for redundant features [168–170] which further influence the classifier's efficacy to optimize the classification process.
3. New research could consider converting the power quality signal into a two-dimensional greyscale image by extracting phase and frequency features. PQD detection is then performed with the help of popular image processing tools. Rely on existing convolutional neural networks with effective image processing performance and their variants to isolate the interfering features. Recovering the original image ensures that PQDs can be correctly captured and classified in the presence of inherent noise.
4. New research requires further efforts to compress the many power quality data generated by the continuous operation of the grid [171–175] to ensure real-time monitoring of power quality.

In summary, there is great potential for future PQD detection technologies to be combined with research hotspots in other fields, such as data fusion, distributed computing, data mining, cyber-physical systems, etc. This new detection technology undoubtedly brings more development opportunities and technical challenges to PQD detection, especially in large energy systems, which is certainly one of the most promising development directions for power grids.

5.4 Conclusion

This review collects 180 papers, nearly 60% of which were published in the last five years. Compared to other reviews, this review presents the latest technologies as ultimately as possible. It includes GSI (Section 3.2); SAFT (Section 3.3); VMD (Section 3.7); CNN (Section 4.3); PNN (Section 4.4). Other state-of-the-art techniques are placed in Section 3.8 and Section 4.7 Miscellaneous Techniques. In Section 5, this review summarizes the development process and applicability of each technology. And the accurate capture rates provided in each technology article are collected in conclusion to provide a reference for new researchers to select technologies for further research. This review presents for the first time the keywords. Grayscale image processing techniques; statistical analysis feature techniques; and for the first time, the application of PNN and CNN neural network techniques to the PQD problem is summarized. Finally, we give suggestions on the development process and the scope of application of various techniques to save the time of new researchers. And we also make predictions on the future hot directions. These works are uncommon in other published reviews. The next step is to continue to delve into neural networks and explore the deep collaboration between the field of PQD detection and neural networks.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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