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Power quality monitoring in electric grid integrating offshore wind energy: A review

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ABSTRACT

The rising integration of offshore wind energy into the electric grid provides remarkable opportunities in terms of environmental sustainability and cost efficiency. However, it poses challenges to power quality (PQ) caused by variable operational events and power electronic devices used in wind turbines. This renders early-stage disturbance detection and classification tools critical for managing grid systems with renewable energy sources. While existing reviews specialize in the monitoring measures of partial PQ events, this survey offers a deeper understanding by further exploring root causes and disturbance locations, followed by a critical discussion of emerging algorithmic solutions. In contrast with generalists' stances on PQ, this work delves into the impact of offshore wind energy on PQ events and their early diagnosis. Moreover, the principles and applications of synchronized waveform measurement, a promising measurement technology for detection and classification processes, are highlighted. Then, evaluation metrics for detection and classification algorithms are discussed for the first time. Finally, a novel system-wide monitoring framework is proposed given the need for holistic assessment frames in this field. This review not only illustrates the challenges and future research directions in the level of algorithms, measurements, and frameworks, but can also serve as a guideline for real-time disturbance analysis of offshore wind power grid connection and integration.

1. Introduction

Over the last decade, there has been a growing interest in renewable energy installations due to environmental awareness and rising fossil fuel energy prices. As one of the most popular renewable energy sources (RES), wind energy has been widely used due to its relative cost efficiency and matured technology [1]. According to International Energy Agency (IEA), the proportion of wind power is increasing worldwide and is expected to account for 29 % of the annual renewable energy installations in 2023 [2]. Offshore wind energy, compared with the onshore counterpart, enables the efficient use of large capacity wind turbines (WTs) to generate electricity owing to its more abundant and stable wind resources [3,4]. It is recognized as a key driver for achieving long-term global climate goals worldwide. By the end of 2022, the global installed offshore wind capacity has hit an impressive 57.6 GW and is projected to experience significant growth, reaching 519 GW by 2035 [5].

Despite the advantages of offshore wind, the operation of offshore WTs faces significant challenges due to remote connectivity needs and harsh weather conditions [6]. WTs often experience highly variable energy output, creating unpredictable levels of supply in the power system operation. Moreover, the extreme mechanical stress further exacerbates the difficulty of condition monitoring, which can lead to equipment failure and power outages in severe cases [7]. Due to these factors, along with the usage of power electronic devices and high RES penetration into the grid, power quality (PQ) has become a major concern [8]. From the renewable energy side, the intermittent nature of the wind, the variable operational conditions of WTs, and the usages of auxiliary elements inject non-stationary power signals and therefore introduce power quality disturbances (PQDs) to the power grid [9,10]. From the power grid side, solid-state switching equipment creates significant PQ challenges.

When operating an offshore wind energy system, typical PQ concerns include transient, flicker, harmonics, sag, swell, and interruption [11,12]. These issues have become a significant focus due to their potential to cause inaccurate metering, premature equipment deterioration, line overheating, maloperation of protection devices, and interference with

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Abbreviations

AC	Alternating current
AI	Artificial intelligence
ANN	Artificial neural networks
AUC	Area under curve
BLM	Band-limited mode
BN	Batch normalization
CAD	Conventional atomic decomposition
CNN	Convolutional neural networks
DBN	Deep belief network
DC	Direct current
DER	Distributed energy resources
DFIG	Double-fed induction generator
DT	Decision tree
DNN	Deep neural networks
EEMD	Ensemble empirical mode decomposition
EKF	Extended Kalman filter
ELM	Extreme learning machine
EMD	Empirical mode decomposition
EQ	Energy quality
FC	Fully connected
FFT	Fast Fourier transform
FL	Fuzzy logic
GRU	Gated recurrent unit
GT	Gabor transform
HHT	Hilbert Huang transform
HOS	High-order statistics
HVDC	High voltage direct current
IEA	International Energy Agency
ITD	Intrinsic time-scale decomposition
KNN	K-nearest neighbor
LSTM	Long short term memory
MAE	Mean absolute error
MSE	Mean square error
OWPP	Offshore wind power plants
PCC	Point of common coupling
PQ	Power quality
PQD	Power quality disturbance
RES	Renewable energy sources
RMSE	Root mean square error
RNN	Recurrent neural networks
SAE	Stacked auto-encoder
SSR	Sub-synchronous resonance
ST	Stockwell transform
STFT	Short-time Fourier transform
SVM	Support vector machine
SWM	Synchronized waveform measurement
UTC	Coordinated Universal Time
VMD	Variational mode decomposition
WT	Wind turbine

communication circuits, which can result in heavy maintenance costs [13,14]. To avoid serious effects from PQ problems, an early PQ monitoring process is necessary for the grid systems with RES, providing references for troubleshooting at a later stage [15]. PQ monitoring can assist the system operation and control strategies, contributing to reliable and continuous power supplies. Currently, several signal processing algorithms and stochastic models for detecting and classifying PQD have been proposed [16]. However, considering grid points such as the connection nodes of the WTs, two major challenges exist in current PQ monitoring algorithms: real-time signal processing difficulties due to complex computational requirements, and early disturbance diagnosis due to lack of data fidelity. Since most of the current monitoring algorithms are based on a single selected site such as point of common coupling (PCC) [17], there is a gap in the holistic assessment of complex power systems, ensuring sensitivity to operational events and multi-site measurements encompassing both wind farm and electric grid components.

To address these challenges, technologies have recently emerged to support PQ monitoring. Currently, synchronized waveform measurement (SWM) has attracted significant attention in the power system field given its capacity for high-resolution waveform measurements [18]. Due to its strict requirements for time synchronization, SWM-related studies were in the conception stage until recently, when its real-time acquisition became possible with the advances in computational processing capacity, together with their interoperable deployment [19]. It allows coordinated quantitative analysis at multiple locations, including both PCC and WT levels, with realistic network transients and dynamic responses, revolutionizing the measurement techniques for disturbance diagnosis [20].

In addition to effective algorithms and synchronized measurements, a more informative and standardized monitoring assessment process is required as well. Current evaluation metrics in PQD detection and classification studies are mostly centered on the accuracy of the proposed algorithms [12]. However, accuracy is limited by the quality and selection approach of the dataset, further neglects aspects of actionability (such as timeliness and PQD localization), and therefore may not be sufficient for guiding practical applications. Based on the practical demands of real-time PQ monitoring, some studies introduce algorithm runtimes and noise parameters [21,22]. Under this context, a comprehensive evaluation framework that encompasses multiple dimensions should be developed to overcome the limitations of current assessment strategies.

The study of PQD has been covered by multiple reviews, with focuses on their underlying causes [23], source detection [24], and artificial intelligence (AI) based monitoring steps [25–27]. However, these papers have been confined to disturbance problems within the traditional power systems, neglecting the influence of RES grid integration on PQ concerns. Recently, relevant PQ challenges have been introduced in various reviews with the increasing installation of WTs. These discussions primarily revolve around PQ regulations [28], control strategies [29], and PQ improvement approaches [30,31]. Nevertheless, there is no synthesis that thoroughly explores PQ monitoring in the context of the grid integrating offshore wind energy from a broad systemic perspective.

Given the remarkable advancements in offshore wind energy as well as the rapid innovations in algorithms and measurement techniques, it becomes imperative to undertake an in-depth and critical survey of relevant studies. The impact of offshore wind on PQ events, as well as the latest advancements in monitoring algorithms and measurements, have not been critically surveyed so far. To fill this gap, this review aims to give insights into a wide spectrum of related PQ monitoring concerns and explore emerging challenges and research prospects. In this study, Science Direct, IEEE database, and Google Scholar are used for the literature search, with keywords covering offshore wind energy, power quality monitoring, disturbance detection, disturbance classification, and synchronized waveforms. Furthermore, relevant standards and academic reports from recent years are recognized. The number of citations, algorithmic novelty, and undertaken experimental design serve as evaluation indicators for the studies. Following a careful screening process, a total of 167 relevant papers, standards, and academic reports are discussed to thoroughly assess the application potentials of deep learning methods and SWM for PQ monitoring. Furthermore, shortcomings in the evaluation frameworks at both the algorithmic and system levels are identified. The structure of this review is depicted in Fig. 1. As PQ monitoring is essential for ensuring a stable power supply for offshore wind-connected grids, this review introduces important principles to guide researchers and engineers in the analysis of real-time PQ events. The contributions of this work are as follows.

- To the best knowledge of the authors, this is the first review to thoroughly examine PQ monitoring issues within the context of electric grids integrating offshore wind energy rather than conventional power systems. This review systematically analyzes not only the impact of offshore wind energy on disturbance types but also their root causes and necessary collection locations.
- Studies on monitoring algorithms between 2020 and 2023 are carefully reviewed, providing the latest insights into signal-processing-based disturbance detection and machine learning-driven disturbance classification. Moreover, a critical analysis of relevant algorithms is presented to shed light on their effectiveness.
- The principle of the emerging SWM is presented with a twofold purpose: exploring the advantages over other high-precision measurements and evaluating its application potential for different disturbance types and PQ monitoring.
- This work, for the first time, highlights the weaknesses of existing evaluation metrics for algorithm performance, and proposes a principled diagnostic framework to achieve system-wide automatic PQ monitoring within grids integrating offshore wind energy.

The remainder of this review is organized as follows. Disturbance events and their root causes are reviewed in Section 2. Section 3 illustrates the monitoring algorithm procedures. Section 4 presents the utilization of SWM as an emerging measurement technique for PQ monitoring. Comprehensive evaluation metrics are introduced in Section 5. A novel system-wide monitoring framework is proposed in Section 6. Lastly, the conclusion is given in Section 7.

2. Power quality disturbance (PQD)

PQ contains a diverse range of electromagnetic phenomena that exhibit voltage and current characteristics at a certain time and location within electric power systems [32]. Within the context of grids integrating offshore wind energy, the analysis of disturbances has become challenging given the extent of sources with variable behavior, encompassing environmental factors and loads. Firstly, offshore WTs often experience highly variable energy output due to harsh weather conditions, creating unpredictable levels of supply in the power system operation. Secondly, wind farms suffer from electromagnetic interference from diverse sources, such as nearby electrical devices, communication systems, and radio frequency equipment, all of which can result in electromagnetic disturbances. Thirdly, nonlinear attributes inherent in electromagnetic equipment and components within offshore WTs can cause harmonic pollution. Lastly, resonance phenomena may emerge from electromagnetic interactions between WTs and the electric grids, which, in severe cases, can lead to system failures and power outages. Consequently, it becomes crucial to identify the relevant PQD types, their root causes, collection locations, and current challenges.

2.1. PQ events

A PQ monitoring process starts with finding out the problem category. Currently, the penetration of RES into the electric grids has introduced complexities to PQ analysis, impeding the identification of root causes and device effects. In this context, the recognition of the disturbance types associated with WTs or wind farms has become a crucial task. Table 1 presents the PQD types investigated in studies focusing on grids integrating wind energy between 2018 and 2022. It can be seen that the most concerned problems are flicker, transient (including impulsive and oscillatory), sag, swell, interruption, and harmonics. Further details regarding their characteristics, mathematical expressions, and impacts can be found in Ref. [33].

A disturbance problem can reveal diverse signal characteristics under different events. For instance, there are distinct transient responses associated with active power events and reactive power events [48]. Consequently, to mine information from monitoring results, the root causes of different disturbance types should be analyzed. Fig. 2 outlines typical PQ issues and their causes in the wind energy generation part (offshore) and the electric grid part (onshore). From Fig. 2, whilst there are common factors like switching actions resulting in PQDs within both the offshore and onshore parts, specific events like variations in wind speed give rise to PQ issues unique to the wind energy generation units [38,44].

In conventional power grids, PQ problems arise from utility sources, internal sources, and power electronic sources [49]. Concerning the grids integrating offshore wind energy, disturbance causes can be classified into internal and external factors. Internal factors primarily relate to the mechanical and electrical conditions of offshore wind power plants (OWPP) [31], while external factors refer to operational events. Typical operational events, listed in order of severity of impact on PQ, include islanding, grid synchronization, wind speed variation, and

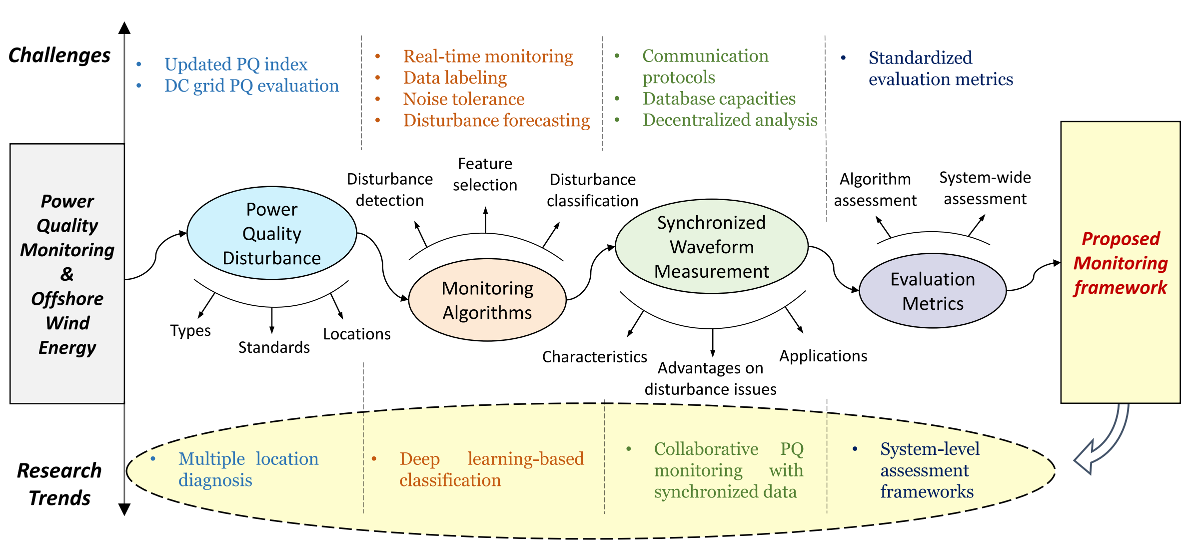

Fig. 1. Structured view of the surveyed contents.

Table 1
Disturbance types in studies for electric grid integrating wind energy over last five years (2018–2022).

Year	Work	PQD types	RES types	Referencestandard
2022	[34]	Voltage fluctuation (sag, swell, transient, interruption), harmonics, and flicker	Wind farm with variable speed synchronous generators	IEC 61400-21
	[35]	Sag, swell, oscillatory transient, interruption, and harmonics	Wind energy conversion and solar photovoltaic system connected to IEEE 13-bus test system via a transmission line and a transformer	IEEE 1159–2009
	[36]	Slow voltage variation, voltage distortion, voltage asymmetry, and long-term flicker	Low voltage utility grid with high penetration of RES	EN 50160
	[37]	Sag, swell, interruption, flicker, and harmonics	Hybrid power system in the presence of photovoltaic modules and a WT	IEEE 1459 and EN 50160
	[38]	Sag, swell, interruption, flicker, harmonics, oscillatory transient, impulsive transient, and notch	Photovoltaic plant and double-fed induction generator (DFIG) based WT system	IEEE 1159–2009
	[39]	Sag, swell, interruption, flicker, harmonics, transient, notch, and spike	Microgrid equipped with DER including a DFIG based wind energy generation	IEEE 1159–2009
2021	[31]	Flicker, harmonics, sag, and swell	Grid-connected wind power system	IEC 61400–21, IEEE 1159, and EN 50160
	[40]	Sag, swell, interruption, flicker, harmonics, oscillatory transient, and notch	Microgrid equipped with three DERs including a photovoltaic generation system, a diesel generator, and a DFIG	IEEE 1159–2009
	[41]	Sag, swell, interruption, flicker, harmonics, oscillatory transient, impulsive transient, and notch	Devices from different vendors combined to equipment such as wind farms, resistive loads, real-time simulators, and an amplifier	IEEE 1159–2009
2020	[42]	Voltage fluctuation, frequency fluctuation, flicker, and harmonic distortion	Grids integrating renewable distributed generation systems	IEEE 929-2000
	[43]	Harmonics, swell, sag, oscillatory transient, impulsive transient, and flicker	IEEE 13-bus power system integrating DFIG and diesel generators	IEC 61400
2019	[44]	Sag, swell, interruption, harmonics, impulsive transient, oscillatory transient, flicker, notch, and spike	Typical microgrid containing distributed generators	IEEE 1159–2009
	[45]	Sag, swell, notch, oscillatory transient, impulsive transient, harmonics, and flicker	IEEE 13-bus power system integrating two WTs	–
2018	[46]	Sag, swell, interruption, harmonics, interharmonics, transient, flicker, notch/spike, and noise	Microgrid test system consisting of grid-connected photovoltaic and wind resources	IEEE 1159–2009
	[47]	Symmetrical sag, asymmetrical sag, swell, voltage unbalance, voltage harmonics, notch, and momentary interruption	Wind-grid model consisting of six 1.5 MW DFIG based WTs	–

outage [43]. Details of these operational events were summarized in Ref. [12].

2.2. Standards

Standards serve as a comprehensive reference for measurement procedures, disturbance parameters, and time limits. PQ standards with their illustrations are outlined in Table 2. IEEE 1159, IEC 61000-4-30, and EN 50160 are three representative documents widely used for PQ monitoring [50]. Recently, along with the widespread attention on offshore wind energy, IEC 61400-21 has been adopted in relevant studies [31,34], as shown in Table 1. Specifically, IEC 61400-21-1 and IEC 61400-21-2 address WT level and plant level considerations, respectively. Moreover, IEEE 1547 discusses PQ issues and operational events associated with the interconnection of utility electric power systems and distributed energy resources (DER).

2.3. Monitoring locations

The selection of monitoring locations plays a crucial role in ensuring effective and reliable early disturbance diagnosis. Extensive studies have been conducted in conventional electric power systems to determine optimal locations for PQ monitors [51]. Nevertheless, research on offshore wind energy-connected grids is still in its early stages. In practice, early PQ diagnosis is predominantly performed at PCC [38]. To ensure the overall reliability of the system, it is essential to consider both PCC and WT levels for PQ monitoring, for the following reasons: Firstly, conducting PQ monitoring at a single location does not ensure the identification of defective WTs with poor-quality power [16]. Secondly, PQ issues, especially flicker and harmonics, can originate from either the offshore or onshore side and therefore should be evaluated from a system-wide perspective [52]. Lastly, PQD signals undergo variations during signal propagation between the WT terminals and the electric grid [53]. Consequently, the waveform characteristics of the same PQ issue detected at the WT terminals differ significantly from those observed in the electric grids, which necessitates acquiring voltage and current signals at multiple locations.

However, multi-level disturbance monitoring has not been taken into account in most studies, primarily owing to the unavailability of high-fidelity data. Thus, there is a need to develop a novel measurement technique that ensures time synchronization to diagnose PQ across multiple locations so that the root causes of PQDs can be unearthed.

2.4. Challenges

- PQ definition: One of the major challenges is the need to update the PQ definition with the widespread usage of offshore wind energy in the grids. A recent development in this field is the introduction of a new index called energy quality (EQ), which emphasizes the quality of power [9]. When offshore wind energy participates in the power supply, the EQ may be weak despite the PQ signals exhibiting a perfect sinusoidal waveform. This is due to the intermittent and fluctuating nature of the active power generated by wind energy. In this context, EQ aims to capture the variations associated with RES, whereas the traditional PQ framework focuses on the quality of voltage and current waveforms. As a novel concept, EQ currently encompasses four principal aspects: energy spectrum, average power level, total power distortion, and standard power deviation. Further discussions and standardization efforts are needed to refine definitions and measurement methods for each aspect of EQ.

- PQ assessment in direct current (DC): DC systems offer numerous advantages over their alternating current (AC) counterparts, including improved PQ, lower installation costs, and plug-and-play characteristics [54]. In the case of long-distance OWPP, high voltage direct current (HVDC) systems have witnessed significant

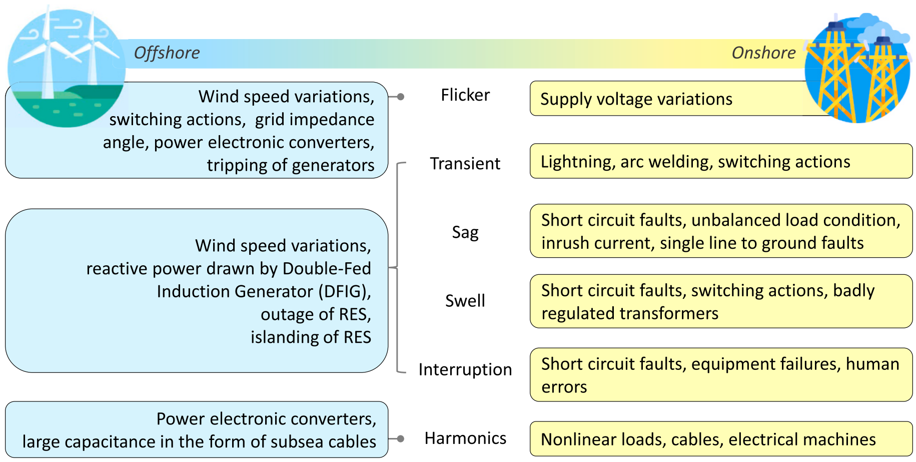

Fig. 2. PQ issues with the integration of offshore wind energy into grids.

Table 2
International standards for PQ monitoring.

Organization	Standard	Year of latest version	Title
IEC	61,400-21-2	2023	Measurement and assessment of electrical characteristics - Wind power plants
	61,000-4-30	2021	Testing and measurement techniques - Power quality measurement methods
	61,400-21-1	2019	Measurement and assessment of electrical characteristics - Wind turbines
	61,400-4-15	2010	Testing and measurement techniques - Flickermeter - Functional and design specifications
EN	50,160	2022	Voltage characteristics of electricity supplied by public electricity networks
IEEE	519	2022	IEEE standard for harmonic control in electric power systems
	1547	2020	IEEE standard for interconnection and interoperability of distributed energy resources with associated electric power systems interfaces
	1159	2019	IEEE recommended practice for monitoring electric power quality
	1564	2014	IEEE guide for voltage sag indices
CIGRE	C4.112	2014	Guidelines for power quality monitoring - measurement locations, processing, and presentation of data

attention due to their ability to independently control active and reactive power [31]. DC systems can operate in islanding mode or interface with AC systems to absorb or transmit power. The latter enables bidirectional power flow in both DC and AC forms over a wider frequency range, transforming unidirectional power flow typical in AC systems [55]. Therefore, PQ problems in DC systems can arise from internal factors, as well as the AC grid side [56]. However, the absence of specialized standards has hindered the evaluation of PQ in DC systems [57]. There is a pressing need to define metrics for disturbance types, signal characteristics, and measurement procedures. Compared to AC-based PQ monitoring studies, ideally constant voltage waveforms and power electronic converters in DC distribution systems introduce distinct sources of PQ problems [58]. Therefore, it is crucial to develop appropriate guidelines for DC systems to ensure accurate PQ assessment and effective disturbance mitigation at a later stage.

3. PQ monitoring

In traditional PQ monitoring and analytical procedures, disturbance detection, feature selection, and disturbance classification are three major goals [59]. Feature extraction and signal decomposition aim to extract patterns and characteristics from the signals through advanced processing for subsequent disturbance analysis or knowledge acquisition [60]. After this processing stage, features with a measurable role for detecting or discriminating PQD are selected. Relevant features should be able to quickly respond and adapt to changes in monitoring techniques associated with wind energy sources, noise, and loads. Subsequently, specific PQ events can be categorized through disturbance classification. The classification phase provides valuable information for understanding the nature and severity of PQ events, enabling appropriate actions and interventions to be taken. In addition to these three key tasks, pre-processing technologies are also highlighted in some studies, involving data normalization [25], compression [61], recovery [62,63], segmentation [64] and denoising [65–67].

3.1. Disturbance detection

The signals collected from WT's condition monitoring systems exhibit non-linear and non-stationary characteristics [16,68]. When extracting features to describe PQ events, two fundamental principles should be considered [69]. First, the features should have the ability to distinguish between different disturbances. This ensures that the extracted features can effectively capture the unique characteristics of each PQ event, enabling accurate classification at a later stage. Second, the applied processing mechanisms, as well as the diversity of extracted and selected features, should ensure that the learning of downstream models yields a balance between descriptive power and computational efficiency.

Fast Fourier transform (FFT) was widely used as a basic feature extraction tool in the initial stages of disturbance analysis due to its simple construction, but only works for stationary PQD signals [70]. To extract discriminative features from complex disturbance measurements, studies have delved into two categories of signal processing techniques: time-frequency domain algorithms and adaptive mode decomposition algorithms.

Various time-frequency domain tools have been employed, involving short-time Fourier transform (STFT) [71], Gabor transform (GT) [72], wavelet transform [73], and Stockwell transform (ST) [74]. Wavelet transform can be further categorized into continuous wavelet transform [75], discrete wavelet transform [76], and wavelet packet transform [77]. As a modified version of wavelet transform, ST has been found to be the most powerful time-frequency domain algorithm, especially in noisy environments, rendering it the emphasis of detection studies in recent years [78,79]. In addition to time-frequency domain algorithms, adaptive mode decomposition methods have gained popularity given their highly adaptive capabilities and data-driven nature. These methods comprise empirical mode decomposition (EMD) [80], ensemble empirical mode decomposition (EEMD) [81], Hilbert Huang transform (HHT) [82], variational mode decomposition (VMD) [41], and intrinsic time-scale decomposition (ITD) [60], which offer flexibility and adaptability in capturing the underlying characteristics of non-stationary signals. Moreover, high-order statistics (HOS) [83], extended Kalman filter (EKF) [64], and conventional atomic decomposition (CAD) [84] have been adopted for feature extraction as well, providing alternative approaches for analyzing PQ disturbances. The characteristics and weaknesses of these typical signal transform methods are summarized in Table 3.

In addition to traditional signal processing techniques, recent breakthroughs in the field of computer vision have also been applied to disturbance detection. Image enhancement methods [85] and visual attention mechanisms [86] have been introduced to enhance feature extraction efficiency and isolate relevant disturbance features. In Ref. [85], gamma correction, edge detection, and peaks and valley detection, as three typical image enhancement techniques, were employed to reconstruct feature information from gray images. In Ref. [86], PQD feature indices were collected through a sequence of procedures involving disturbance region selection, multi-scale spatial rarity analysis, and feature fusion applied to binary images. By leveraging these advancements, the detection of PQ events can benefit from modified feature extraction and representation, leading to more accurate and efficient analysis.

Table 4 lists relevant studies on disturbance detection from 2020 to 2023. Notably, ST has emerged as a prominent technique during this period with a significant focus on optimizing the parameters of the window function. The aim of these studies is to enhance the time-frequency resolution and computational efficiency of ST.

3.2. Feature selection

The surveyed feature extraction methods in the previous section produce a large number of features, particularly when considering a fine-grained view of the frequency spectrum and flexible windowing procedures producing features and different time points with varying durations. In this context, choosing precise features and removing redundant information can lower data dimensionality and enhance monitoring efficiency [64]. Supervised univariate filters, such as those based on mutual information theory, can be applied in the presence of PQD annotations. In addition, optimization techniques have been largely considered, mainly containing genetic algorithm, particle swarm optimization, and artificial bee colony [12]. However, these traditional methods often involve a time-consuming and handcrafted-tuning process, lacking a reference and struggling to achieve a balance between accuracy and noise robustness [105]. A research trend is to leverage deep learning mechanisms due to the increasing wind energy penetration and the presence of complex PQ events [44]. Deep learning approaches can extract abstract concepts from high-dimensional data and enable closed-loop feedback, achieving automatic feature extraction [106].

3.3. Disturbance classification

Based on a large amount of grid data and complex PQD signal characteristics, AI based classification techniques have gained significant popularity in PQ monitoring. Machine learning classifiers are commonly employed in current PQ classification methods, including support vector machine (SVM), extreme learning machine (ELM), decision tree (DT), fuzzy logic (FL), k-nearest neighbor (KNN), and artificial neural networks (ANN) [26]. A comparison of these machine learning classifiers was discussed in Ref. [107].

These methods require annotated data and therefore laborious human involvement, which increases the associated overall costs. Additionally, traditional machine learning techniques may face challenges when dealing with complex non-linear PQD signals [108]. To address these issues, deep neural networks (DNN) have been widely employed to recognize PQ disturbances due to their capabilities to automatically learn and extract optimal information from high-dimensional data [109]. Among various DNN architectures, convolutional neural networks (CNN) and recurrent neural networks (RNN) have gained significant attention in recent years for their effectiveness in capturing spatial and temporal dependencies, respectively. CNN is well-suited for extracting local patterns and features thereby suitable for PQ disturbance recognition tasks with temporal (1D), spatial (2D), or spatiotemporal (3D) dependencies. Moreover, RNNs, including variants such as gated recurrent unit (GRU) [69], long short term memory

Table 3
Typical signal transform strategies.

Method	Characteristics	Weaknesses
FFT	Suitable for stationary disturbances such as harmonics	Not sensitive to fine-grained changes in frequency domain statistics over time; Not suitable for transient
STFT	Suitable for transient disturbances due to a shifted window-based Fourier transform to get time and frequency information	Fixed time-frequency resolution
GT	Phase and frequency information	Inadequate time resolution and susceptibility to cross-term issues
Wavelet transform	Suitable for discontinuous and suddenly changing signals in high-grade derivatives	Degraded phase information in noisy conditions
ST	Improvement and extension of STFT and Wavelet Transform; Adaptive time-frequency resolution	More computation and memory overhead
EMD	Complex signals decomposed into intrinsic mode functions and adaptive time-frequency decomposition	Limited decomposition performance by mode mixing and endpoint effect
EEMD	Suppressed mixing phenomenon due to Gaussian white noise with a uniform characteristic frequency	Difficulty offsetting in the final reconstructed signal due to the white noise; More computation overhead
HHT	Time and instantaneous frequency-based features extracted with basic building blocks of EMD and Hilbert transform	Frequency aliasing in the case of incomplete EMD
VMD	Adaptive signal decomposition	Repeated iterations and more computation overhead; Limited decomposition performance due to abrupt signal onset and endpoint effect
ITD	Complex non-stationary and non-linear signals decomposed into baseline and proper rotation components	Limited decomposition performance due to end- point effect and frequency aliasing; Bad noise immunity
HOS	Capable of handling second-order measurements and describing waveform distortion via probability density functions, symmetry, amplitude, and tail deviation	Low resolution
EKF	Less time computation without signal segmentation and feature selection step	Errors due to the mismatch of signals and filter model
CAD	Complex signals decomposition according to the type of PQD components with a sparse result	More computation overhead; Low precision in selected sub-dictionaries

Table 4
Studies on disturbance detection from 2020 to 2023.

Group	Year	Work	Contributions	Advantages
Wavelet transform	2022	[38]	Un-decimated Wavelet Transform for feature extraction	Noise reduction, peak or valley detection, and high-frequency resolution at high frequencies
	2022	[87]	Adaptive wavelet threshold based on energy ratio	High efficiency of PQD identification with noisy signals
ST	2023	[88]	Window width matched with main spectrum energy interval to determine the standard deviation without iterative calculation	Simplified multi-parameter optimization process; Improved time-frequency resolution and computational efficiency
	2023	[89]	Improved Gaussian window function due to a frequency segmentation step with adjustable parameters	Better time-frequency resolution
	2022	[90]	Improved Gaussian window function due to a standard deviation-based detection frequency parameter	Suitable for oscillation transients and harmonics due to better frequency resolution; Suitable for flicker, sag, swell, and interruption due to better fundamental frequency time resolution
	2022	[91]	Adaptive window parameters based on energy concentration maximization using optimized genetic algorithm	Optimal parameters; Better time-frequency resolution
	2022	[92]	Frequency spectrum divided into low-, medium-, and high-frequency bands, and Gaussian window with two parameters in each band	Better time-frequency resolution at different frequency bands
	2022	[93]	Adaptive Kaiser window as the kernel function with the characteristic of inherent optimal energy concentration	Better time resolution at the fundamental frequency
	2022	[94]	Optimal parameters to generate a time-frequency domain contour	Reduced interference of Gaussian noise
	2021	[95]	Adaptive hyperbolic window based on the energy concentration measurement	Enhanced local spectral characteristics for non-stationary PQD Signals
	2021	[96]	Digital prolate spheroidal window for enhancing the time-frequency energy aggregation	Suppressed influences of harmonics, nonlinear loads and the white noise on voltage sag estimation
	2020	[97]	Optimal window parameters based on energy concentration maximization	Improved time-frequency resolution
	2020	[98]	Summing absolute magnitude plot in addition to ST plots	High efficiency of PQD identification
EMD	2022	[99]	Kriging interpolation for replacing cubic spline interpolation	Prominent features with better accuracy and speed
EEMD	2021	[100]	Screening step to remove noise and incoherent intrinsic mode functions by applying improved complete EEMD [101]	Simplified detection of complex PQDs
VMD	2021	[102]	Optimal decomposition number and data-fidelity factor; Band-limited mode (BLM) extracted based on Kurtosis index	Most efficient BLM from the complex PQD signals
	2020	[103]	Recurrence quantification analysis to extract the statistical features	No placed assumptions about the underlying dynamics; Lower computational burden
	2020	[104]	Detrended fluctuation analysis to optimize the decomposition parameters of VMD	Better accuracy and lower the computational burden
ITD	2023	[60]	Added Gaussian noise and integrated multiple subcomponents	Reduced number of parameters without manually designing and screening features
CAD	2022	[84]	CNN-based sub-dictionary predictor added to CAD structure	Reduced scope of CAD search in the dictionary and improved accuracy of the chosen sub-dictionaries

(LSTM) [110], and stacked auto-encoder (SAE) [111], excel at modeling sequential data and capturing long-term dependencies, which are crucial for analyzing PQD time series, including both raw signal and series of statistics with either univariate or multivariate order.

Table 5 shows studies on disturbance classification from 2020 to 2023. CNN is widely regarded as the most popular approach for classifying PQ events, which employs a grid-like topology of neural networks with convolutions to analyze PQD signals. This convolutional strategy exhibits three key characteristics, namely sparse interactions, parameter sharing, and equivariant representation [112]. Within CNN-based classification algorithms, two research trends can be seen. The first trend is to treat the 1D sampling sequences directly as the input to the CNN model. Another one is to convert the 1D sampling sequences into 2D images and extract features by incorporating spatial-aware transformations to perform the classification task [113]. It is worth noting that some pending issues with regard to 2D CNN models need to be addressed, such as the instability of 2D models in noisy environments [114]. These issues call for further research and development to improve the effectiveness and robustness of CNN-based classification methods in the context of PQD analysis. To provide insight into how CNN models function in the context of disturbance classification, two examples are depicted in Fig. 3. Specifically, the CNN framework with 1D PQD data is proposed in Ref. [44], while the one handling 2D PQD data is from Ref. [115].

The stack unit construction is implemented in both examples, each involving 3 units [44,115]. A notable distinction arises in terms of input data dimensions. In Ref. [44], raw voltage and current signals are utilized in the form of 1D sequential data, while in Ref. [115], 2D images with spectral and amplitude information are fed into the CNN. These 2D PQD data are collected via an STFT-based data preprocessing unit. The input data units underscore different emphases in the CNN framework designs within these two examples. The 1D structure centers on the local temporal information within the time series and considers the correlation of PQD signals only exists in a single direction, whereas the 2D structure focuses on the alignment between input signals with the typical CNN model. Another difference refers to the configuration of the convolutional layer, where 1D and 2D filters are performed separately.

In addition to the convolutional layer, some other layers, including pooling, batch normalization (BN), fully connected (FC), and softmax layers, are incorporated to automatically capture features from an extensive set of disturbance samples. The pooling layer undertakes the role of under-sampling, thus contributing to lowering the dimensionality and highlighting the disturbance features. The BN layer can mitigate overfitting and strengthen the generalization capacity of the CNN models. Subsequently, the FC layer facilitates the transformation of the feature space. Finally, the softmax layer, essentially a normalization function, calculates and outputs the disturbance class with the highest probability value. These two instances adhere to the conventional structures of CNNs. Alternative architectures, including deeper stacking with residual connections (such as ResNet blocks), are further expected to emerge in the field.

The choice between supervised and unsupervised classification

Table 5
Studies on disturbance classification from 2020 to 2023.

Group	Year	Work	Multiple events	Real time	Contributions	Advantages
SVM	2020	[97]	Y	Y	Combination of kernels to classify multiple features	Modified data mapping capabilities and discriminative information
DT	2022	[116]	–	Y	Combination of poly-exponential and random forests	Reduced calculation burden due to fewer sample requirements
KNN	2021	[100]	Y	Y	Outlier exclusion step based on AdaKNN [117]	Better accuracy with noisy signals
Sparse classifier	2020	[118]	Y	Y	Combination of sparse recovery theory and a new high-dimensional convex hull approximation framework	Reduced calculation burden without any training step
CNN	2023	[60]	Y	Y	ShuffleNetV2 [119] with a global depth wise convolution layer and PReLU	Reduced parameter numbers and information loss
	2023	[89]	Y	–	Multiclass SVM to replace the softmax of CNN based on AlexNet [120]	Improved training efficiency and classification accuracy
	2022	[121]	Y	Y	Instantaneous amplitude and phase converted into images by visualization trajectory circle, and the usage of ResNet50 [122] to recognize PQD types	Sequence expressed as a visualization method
	2022	[123]	–	Y	Combination of features from YOLO [124] and SSD [125] based on VGG-16 architecture [126]	More than one disturbance identified in a single window
	2021	[115]	Y	–	Combination of 1D and 2D CNN to obtain both signal and image features simultaneously	New framework to understand the dynamics of signal processing
	2021	[127]	–	Y	Bayesian optimization algorithm to determine optimum hyper-parameters	Better network architecture
	2021	[128]	Y	Y	Multi-fusion 1D CNN framework to integrate information from different domains; Composite convolution and batch normalization (BN) layer to improve the diversity of network features and speed up training, respectively	Shorter training time with a more compact structure
	2020	[129]	Y	–	Five-layer 1-D-modified inception-residual modules to extract feature	Higher convergence rate and stronger generalization ability
RNN	2023	[59]	Y	–	Red deer algorithm [130] to optimize the number of hidden layers	No manual operations and less complexity
	2022	[131]	Y	Y	Label-decoupling module with label-guided attention to learn label-related features; Bidirectional RNN to model correlations between different PQD labels	Better learning of higher order label correlations
	2021	[132]	Y	Y	Simple recurrent cell structure with two gates and two weight matrices	Robust to vanishing gradient of RNN; Long-term memory preserved
Deep belief network (DBN)	2022	[87]	Y	Y	Combination of an ELM and a DBN	Reduced computation; Global fine-tuning averted
SAE	2020	[133]	–	–	Sparse denoising SAE combined with supervised back-propagation training	Better robustness, especially with insufficient training samples

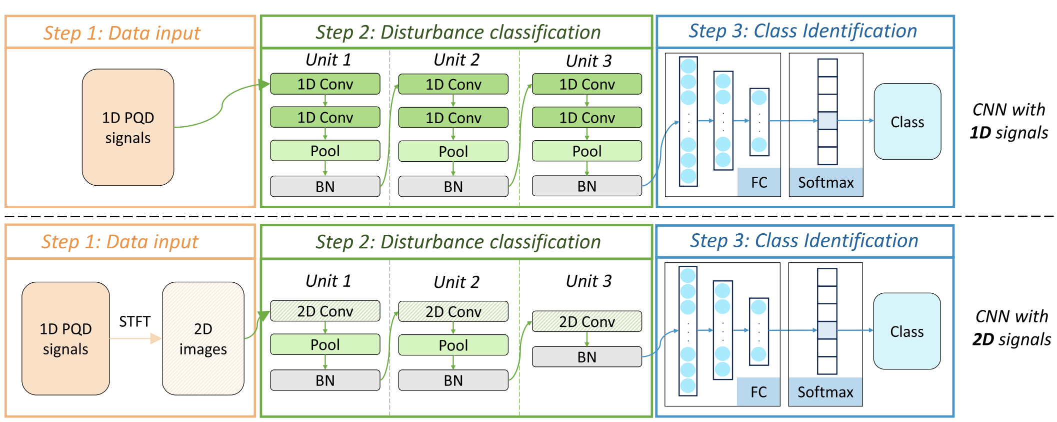

Fig. 3. CNN frameworks with 1D and 2D signals.

techniques depends on the availability of prior information and the number of categories involved. As shown in Table 5, the majority of the papers primarily focus on supervised learning methods, where labeled data is utilized for training the models. However, there are also a few studies that explore semi-supervised learning techniques [134], as well as unsupervised learning techniques [87,111]. These alternative approaches provide opportunities to classify PQ issues in situations where labeled data may be limited or unavailable, offering potential avenues for further PQ monitoring analysis. In addition, it is worth noting that the classifier type must match with appropriate feature extraction methods, otherwise the performance of PQ monitoring will be degraded [60]. To address this issue, a new framework concept has been proposed that fuses disturbance detection and classification as a coherent unit [105,106].

3.4. Challenges

- Real-time monitoring: While disturbance classification has been studied extensively in offline settings, a research challenge still exists to achieve real-time PQ monitoring, particularly relevant for power grids with offshore wind turbines. Basically, PQDs are detected at PCC, where the entire offshore network is connected with the onshore power system. Real-time PQ monitoring helps the grid operation, guiding the decision-making process pertaining to the entire energy system. Feasible future research directions involve obtaining discriminated features without sophisticated signal processing methods, increasing the speed of the signal processing methods, and evaluating the prerequisites for identifying different PQD types using prognostic windows. The testing efficiency of the classifiers should be further guaranteed for the activation of real-time actuators in response to PQDs. Complementary, the incremental nature of the classifiers should be further considered to accommodate unseen grid configurations and updates.
- Data labeling: Multiple disturbance types often occur simultaneously in the grids integrating offshore wind energy, leading to correlation issues among PQD labels. The current approach, where each multiple disturbance is treated as a new category, essentially follows a single-label classification scheme [131]. Hence, failure and performance degradation of complex disturbance classification are prone to appear due to the mutual influence between PQD labels and an excessive number of fault categories [60]. To overcome these challenges, current strategies include exploring the intrinsic relationships between events and minimizing the number of labels [135]. In addition, pre-training of models using synthetic data models, semi-supervised learning principles, and recent advances in self-supervised and multi-task learning stances can be utilized as effective solutions [136,137].
- Noise tolerance: The PQD signals are susceptible to multiple sources of interference in noisy environments, causing difficulty in disturbance detection and classification. Existing classifiers often exhibit sensitivity to noise, while convolutional network structures have shown promising performance in addressing this issue [129]. Future research trends involve combining signal processing advances with the subsequent automated learning of predictive models, improving neural processing algorithms, and innovating high-precision measurement techniques to enhance the accuracy of PQD signal analysis [138].
- Disturbance forecasting: By harnessing the synergy between PQ event records and meteorological data, as well as monitoring long-term PQ deterioration, disturbances may be forecasted with considerable anticipation, promoting actionability [139]. In this context, disturbance forecasting pursues the modeling of event uncertainties to establish and maintain stable operational conditions for photovoltaic plants [140]. A prediction of severe power quality disturbances, such as oscillatory transients, can facilitate the timeliness of disturbance detection and further benefit the subsequent problem-solving phases [141]. Despite recent advancements, a research gap persists in the field of offshore wind energy. As offshore WTs become increasingly integrated into electric grids, the degradation of PQ introduces higher levels of uncertainty, driven by the influence of weather dynamics. This underscores the compelling need to incorporate disturbance prediction within the PQ monitoring process, offering essential proactive insights to the algorithmic models.

4. Synchronized waveform measurement (SWM)

The widespread deployment of RES amplifies the dynamic nature of modern power system behavior. In the electric systems integrating offshore wind energy, waveform data capturing signs of emergent system malfunctioning are anticipated to be collected at different locations to address system-wide PQ issues, as mentioned in Section 2.3. Moreover, high-fidelity measurements are crucial for analyzing high-frequency disturbances originating from power converters and their impact on system operation. Thus, high-resolution measurements at multiple locations are needed for decentralized and stochastic energy sources to implement systematic disturbance diagnostics. Presently, SWM has demonstrated significant potential for conducting coordinated quantitative analysis across different locations, enabling the study of authentic transient and dynamic responses of a network.

4.1. Characteristics

SWM, also known as point-on-wave measurement, is witnessing a great deal of attention owing to the advent of high-performance sensors [142]. The typical SWM devices and their general hardware framework were presented in [143,144], respectively. Up to now, three data forms have been provided in these devices, namely single snapshots, multiple snapshots, and continuous snapshots [20], where adaptive sampling rates of 0.8–12.8 kHz are usually available [18,108].

The voltage and current signals with precise time alignment carry essential information about PQ phenomena, helping to understand and characterize disturbances [145]. Hence, for early-stage PQ diagnosis, voltage and current waveforms are the most suitable SWM types to accomplish accurate information extraction [16,20]. In addition, derived data have been employed in certain applications to reduce the burden of data transmission, with examples of time of arrival, modal power, and impedance [20]. The selection of the domain for derived data depends on the feature extraction method.

Whilst synchrophasor measurements have been widely used for false identification in modern power systems in recent years, it is worth noting that they differ from SWM [146]. Synchrophasor measurements share characteristics with SWM in terms of high resolution and time synchronization but require a phasor and frequency estimation step, which involves various windowing and filtering techniques [147]. This additional processing can lead to measurement inconsistencies and inaccuracies [148]. In contrast, SWM offers several distinct benefits over synchrophasor measurements. Firstly, SWM provides more precise measurements without an estimation process. Secondly, it is more sensitive to non-stationary signals, allowing for better detection and analysis of complex disturbances. Lastly, SWM entails fewer acquisition costs, making it a cost-effective solution. More details with respect to their differences can be found in Ref. [20].

4.2. Benefits for PQDs

Many disturbance events present unique characteristics in the voltage and current waveforms, necessitating system-wide analysis through innovative measurement techniques. Four advantages of SMW for PQ monitoring are apparent, namely high resolution, time synchronization, authentic waveform, and high availability.

- High resolution: Recording non-stationary disturbances in a timely manner is of utmost importance to timely detect PQDs in a real-time monitoring setting. It not only facilitates the detection of conventional disturbance events but also enables the identification of new high-frequency PQD types. An example is supra-harmonics, which typically occurs above 2 kHz and emerges in wind-integrated grids [31].
- Time synchronization: SWM incorporates a time stamp based on Coordinated Universal Time (UTC) and therefore has an edge for coordinated quantitative analysis across different locations. This capability enables SWM to derive meaning from the system level and to be implemented in distributed detection frameworks [149].
- Authentic waveform: In SWM, real sinusoidal information is directly sampled instead of being force-fitted through measurement estimation processes. As a result, the acquired voltage and current

measurements capture the actual network transients and dynamic responses without distortion. This provides reliable information about the events and apparatus for analyzing system-level PQ events.

- High availability: Access to the SWM is available even in the event of a system outage [142].

Fig. 4 outlines the benefits of SWM to different PQ events, encompassing flicker, transient, sag, swell, interruption, and harmonics. These issues are the key challenges within electric grids integrating wind energy, as discussed in Section 2. Based on the extent of the contributions of SWM, Fig. 4 categorizes these events into three groups, distinguished by green, yellow, and red. PQ events marked in green derive specific benefits from SWM, those highlighted in yellow gain advantages from both SWM and synchrophasor measurements, while disturbances in red cannot receive benefits from either SWM or synchrophasor measurements.

In alignment with this categorization, the left-hand side of Fig. 4 employs different colors to denote the advantages offered by SWM as well. Specifically, "time synchronization" and "authentic waveform" are in green, underscoring their status as unique attributes of SWM. "High resolution" is placed in the yellow category as it is the shared feature of SWM and synchrophasor measurements. In addition, "high availability", unrelated to high-fidelity data, is highlighted in red.

Analyzing Fig. 4, it can be seen that harmonics, transient, and flicker profit from SWM, whereas sag, swell, and interruption are not affected by this new measurement technique. SWM enables collaborative harmonics monitoring at both WT and PCC levels, thanks to its high resolution, time synchronization, and authentic waveform capabilities. Transient, as a non-stationary signal, shows more fidelity information through SWM compared to high-resolution synchrophasor measurements. Flicker, which exhibits less frequent fluctuations than transients, benefits from both measurement types. Note that different PQ events typically occur simultaneously in offshore wind integrated grids. Therefore, although SWM does not exhibit significant strengths in sag, swell, and interruption, it facilitates the practical implementation of complex disturbance analysis. Furthermore, the high availability of SWM is independent of these disturbance types, but rather serves as a prerequisite for continuous PQ monitoring.

4.3. Applications in PQ monitoring

Due to the variable operations of WTs, disturbance extraction methods in the time-frequency domain are preferred given their ability to identify non-linear and non-stationary signals [16]. To this end, the time-domain transformation of SWM data can be exploited to detect PQDs, given their more sufficient and accurate information. SWM also enables noise smoothing as a pre-processing process by leveraging the strong temporal correlation between the sequences. However, the application of SWM in disturbance detection is still in its infancy. Synchronized Lissajous curves obtained from voltage and current waveforms have been utilized to monitor PQ events including high impedance faults, capacitor bank switching, and incipient faults [150]. Another approach proposed is a sensor-level anomaly sequence detection method using continuous SWM, in which no assumptions or parameters are required for the data model [149]. These examples showcase the potential of SWM in PQD detection, but further research and development are needed to fully explore its capabilities in this domain.

Experiences of PQ monitoring have shown that even abnormal waveform data can be overwhelming [151]. Hence, SWM-based PQ monitoring should rely on algorithms able to further digest disturbance-containing data through, for example, pattern recognition and characterization principles. Unlike the traditional PQ monitoring process, more general algorithms are needed here to identify and group "similar" anomalous waveforms ranging from switching transients and power oscillations to initial faults. The temporal synchronization properties of SWM should be fully explored to improve the disturbance detection algorithmic framework.

In addition to the field of disturbance detection, there is a growing focus on utilizing CNN architectures to extract meaningful features from SWM data and achieve accurate disturbance classification [150]. The high-resolution nature of SWM enlarges the available dataset that can be leveraged for disturbance classification, making it well-suited for the adoption of deep neural networks. In Ref. [150], synchronized Lissajous curves were transformed into image representations using voltage and current waveforms. Employing a four-layer CNN framework, disturbances were systematically categorized based on variations in the shape and area of the ellipse curve. The classification process depended on a multitude of factors, encompassing the nature, types, locations, and other parameters of the PQ events. This trend underscores the effectiveness of CNN in handling the complex and rich information captured by SWM, leading to promising results in the field of PQ monitoring.

Due to the time synchronization capability of SWM, it has become feasible to conduct systematic and coordinated analysis at both PCC and WT levels. Recurrent fault causes were assessed by evaluating the PQD similarity in Ref. [128]. A dual-channel CNN based method was suggested to identify distribution system fault causes using realistic data from SWM units [108]. In addition to cause identification, studies on SWM-based location assessment have covered various events like transmission faults [152], transient [153], and short-circuit faults in distribution networks [154].

Moreover, SWM has also found utilities in other fields, including

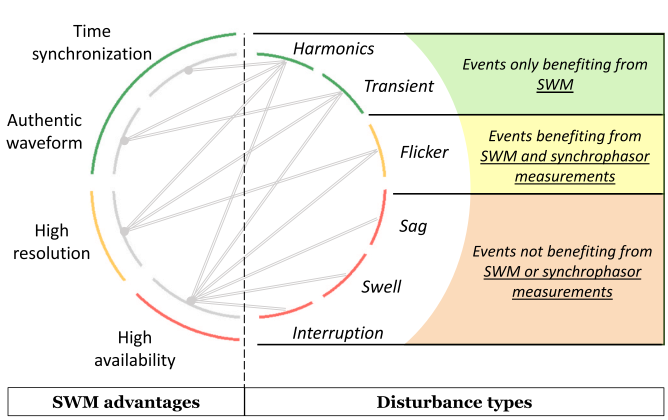

Fig. 4. Contributions of SWM for different PQ events.

wideband oscillation monitoring [143], dynamic state estimation [18], sub-synchronous resonance (SSR) mitigation [155], and SSR source identification and responsibility ranking [156]. These applications demonstrate the versatility of SWM beyond PQ events, opening up opportunities for its utilization in various domains for enhanced system analysis and performance improvement.

4.4. Challenges

As a relatively new measurement technique, SWM has started to be deployed in PQ monitoring. However, there are several research gaps and challenges that need to be addressed for its practical implementation. The challenges of SWM technologies are threefold so far, pertaining to data architecture, storage, and transfer.

- Communication protocols: One of the primary challenges of SWM is the development of standardized communication protocols and networks. Given the high data rates, updated communication protocols are essential to guarantee the timeliness and reliability of data transmission [20]. To this end, reference can be drawn from existing communication protocols such as IEEE standard C37.118.2, which is used for wide area monitoring systems [144]. Leveraging the principles and concepts from C37.118.2 can serve as a starting point for developing communication protocols specifically tailored to SWM requirements. Another valuable resource is the NASPInet 2.0 architecture proposed by the synchrophasor community, which provides a framework for the integration and exchange of synchrophasor data [20].
- Database capacities: The growing deployment of offshore wind energy into the electric grids is associated with higher complexity at the system design and power equipment levels. System-wide PQ monitoring using SWM technologies calls for more measurement devices. However, bottlenecks in database capacities may occur as the data amount soars, especially for continuous waveform recording [157]. Typically, access to streaming SWM data is limited to substation local area networks due to the high data bandwidth and storage requirements involved [158]. In this context, expanding database capacities is crucial to accommodate the increasing data influx [143]. Two primary research trends have emerged in addressing the storage challenge. The first trend focuses on optimizing the sampling scheme to save data storage space. Adaptive sampling frequency techniques have been explored in recent papers, where the sampling frequency is adjusted based on different power system states [144]. In addition, filter-based resampling processes have been investigated to reduce data volume while preserving essential information [159]. The second research trend focuses on data compression techniques [157,160]. These techniques aim to reduce the data size while retaining the key features and information necessary for analysis.
- Decentralized analysis: In PQ monitoring applications, SWM is usually recorded locally and transmitted to a central location when needed [20]. However, with the increasing presence of distributed generations, there is a growing need for decentralized PQ monitoring and analysis systems [161]. A promising approach is to reduce the computational burden by using derived data instead of raw data in the data transfer between nodes. Moreover, the application of distributed learning algorithms can be considered for real-time disturbance identification. Distributed learning frameworks enable collaborative learning among multiple nodes, allowing them to collectively analyze PQD signals while sharing limited information in decentralized monitoring systems.

5. Evaluation metrics for monitoring algorithms

Evaluation metrics play a crucial role in optimizing and verifying algorithms, and have garnered wide attention in various fields, such as signal classification, object detection, and image segmentation [162,163]. Depending on different purposes, they can generally be categorized into three types: threshold, probability, and ranking metrics [164]. As one of the threshold metrics, accuracy has become the only indicator in most work on disturbance detection and classification. However, accuracy is unable to distinguish false positives from false negative observations and can be influenced by dataset selection and hardware facilities, making it insufficient for evaluating real-time algorithm efficacy for practical applications with noisy signals. Illustrating, consider a scenario where PQD detection is applied over sliding windows where the frequency of windows with occurring disturbances is 1 %. In such a scenario, negative labeling of all observations is associated with high accuracy levels and thus alternative metrics, such as precision, recall, specificity, or their combination via F-measure and receiving-operator or precision-recall curves should be preferred. When considering multiple PQD events, accuracy alone is insufficient to assess the degree of efficacy to classify each of the selected events. In this context, resorting to low-level confusion-based matrices and scores is necessary. In this light, it is essential to standardize evaluation metrics to facilitate future advancements in monitoring algorithms.

Performance evaluation metrics for monitoring algorithms used in the studies from 2021 to 2023 are shown in Table 6. Herein, only studies considering multiple criteria are reviewed. It can be seen that three factors are widely regarded as complements to accuracy, namely computational complexity, number of PQDs, and features.

- Computational complexity: refers to the duration spent per sample or epoch on algorithm testing, which aims to examine the timeliness for practical monitoring applications, as well as to guarantee prognostication prior to critical failures. Typically, the overall running time is utilized to analyze complexity. In a few papers like [87,102], computational complexity is split into both training and testing processes to gain more insights.
- Number of PQDs: represents the total count of single and complex PQ events analyzed. The PQ events are usually selected based on their frequency and severity. To be in line with the extensive applications of neural processing learning (e.g., CNN, RNN) in PQD classification, current studies generally disclose the number of events (labels), yet should further consider their representativity or imbalance.
- Features: covers the number of features, as well as their discriminative power and extraction scheme, which help analyze redundant feature information. Currently, automatic feature selection has become the mainstream research trend and replaced the feature optimization process as mentioned in Section 3. Leveraging feature metrics, studies aim to retrieve fewer but more informative features, thereby lessening the computational burden of the subsequent classification process.

The metrics for disturbance detection and classification are compared in Table 6. For disturbance detection, reconstructed similarity and orthogonality are of major interest, reflecting the signal transformation or mapping process in different domains. Additionally, mean square error (MSE), mean average error (MAE), and root mean squared error (RMSE) are applied to penalize higher deviations from expectations [90]. Meanwhile, studies on disturbance classification treat evaluation metrics as a discriminator in order to optimize the classifier. Accuracy, as the key metric for classification evaluation in practice, lacks sufficient information and is poorly discriminated [164]. Hence, in the last three years, machine learning classification metrics such as sensitivity, specificity, precision, recall, and F1-score, have been introduced to evaluate the algorithmic efficacy in PQ monitoring [35,150]. Area under curve (AUC) has replaced accuracy in Ref. [123] to analyze the overall ranking performance of the classifier.

In general, evaluation metrics should be able to assess the generalization ability of the algorithms when working with signals collected at different locations, different environmental conditions, or different power systems. In addition, it is crucial to incorporate strategies to

Table 6
Evaluation metrics of PQ monitoring algorithms in recent three years (2021–2023).

Year	Work	Procedures	Metrics	Noise range (dB)
2023	[60]	Detection, classification	Accuracy, test time per sample, number of PQDs, feature extraction scheme (manual/automatic)	10–40
	[59]	Classification	Accuracy, precision, recall	Up to 50
	[89]	Detection, classification	Accuracy, number of PQDs	20–40
	[88]	Detection, classification	Accuracy, time, number of PQDs	10–50
	[165]	Detection, classification	Accuracy, number of features, number of PQDs, hardware setup	20–40
	[110]	Detection, classification	Accuracy, time per epoch, number of parameters, model size	20–50
2022	[35]	Detection, classification	Accuracy, sensitivity, specificity, precision, F1-score, Matthews correlation coefficient	20–40
	[77]	Detection	Accuracy, time, reconstruction MSE, orthogonality, number of modes	15–25
	[90]	Detection	MSE, MAE, RMSE	20–40
	[91]	Detection, classification	Accuracy, test time per sample, number of PQDs, number of features	20–40
	[131]	Detection, classification	Accuracy, complexity (floating point operations per second, parameter number, computational time), hamming loss, number of PQDs, feature extraction scheme (manual/automatic)	20–50
	[64]	Detection, classification	Accuracy, extracted feature types, number of samples, number of classes	20–30
	[84]	Detection	Accuracy, time, number of fit function calls, reconstructed similarity	–
	[150]	Detection, classification	Accuracy, sensitivity, specificity, precision, F1-score	40–80
	[87]	Detection, classification	Accuracy, number of PQDs, training time, test time	20–50
	[39]	Detection, classification	Accuracy, number of classes, number of features, sampling rate, detection time	20–40
	[121]	Detection, classification	Accuracy, number of PQDs, proportion of complex PQDs	20–30
	[123]	Detection, classification	Precision, recall, F1-score, AUC	–
2021	[95]	Detection, classification	Accuracy, precision, sensitivity and false positive rate, number of PQDs, feature extraction scheme (manual/automatic)	20–40
	[102]	Detection, classification	Training (loss, accuracy, total time, epoch time), testing time, number of PQDs, signal source (practical/synthetic)	20–40
	[127]	Detection, classification	Accuracy, recall, precision, F1-score, specificity, number of PQDs, number of classes	43–57
	[41]	Detection, classification	Training (number of classes, samples per class, time, total trainable parameters), testing (number of classes, samples per class), validation accuracy, recall, precision, F1-score	40–50

isolate evaluation on validation folds, such as implementing early stopping in ANN, particularly in the presence of optimization requirements. Training-testing differences, objective measures of their capacity terms (bias-variance), and analysis of learning curves with varying numbers of observations should be considered during this process. This comprehensive approach helps evaluate the susceptibility of algorithms to overfitting and underfitting risks, providing insights into their generalization capabilities across different scenarios.

Along with the timeliness and efficacy, noise tolerance is also important for offshore wind energy-integrated grids. A typical signal-to-noise ratio setting range in papers is 20–40 dB. It is worth noting that the noise characteristics of the virtual signal used for algorithm development should be consistent with the actual scenarios to ensure the reliability of the results.

6. Discussion on system-wide monitoring framework

This work aims to complete a review of PQ monitoring issues in the context of offshore wind-connected grids. In doing so, it delves into PQ events associated with offshore wind, recent advancements in monitoring algorithms, the application potentials of SWM, and evaluation metrics at the algorithmic level. The key findings are as follows.

- PQ monitoring plays an important role in the operation and maintenance of the grids connecting offshore wind energy, contributing to stable and continuous power supplies. Despite the abundance of research on PQ events and standards, there is a noticeable absence of guidelines specifically tailored to PQ issues in offshore wind environments. In addition, most existing studies rely on the PCC level-based disturbance data, neglecting the critical aspect of determining the optimal monitoring locations. This deficiency inhibits the ability to accurately evaluate the PQ health of wind farms. Specifically, PQ diagnosis at a single location does not guarantee the identification of defective WTs with poor-quality power. Consequently, a coordinated system-level PQ analysis framework that incorporates multiple monitoring points is required.
- Monitoring algorithms facilitate the timely detection and classification of perturbation events, serving as a reference for the subsequent PQ mitigation stage. The development of these algorithms has received wide attention from both academia and industry. Prominent trends include ST-based feature extraction and neural network mechanism-based disturbance classification for automatic PQ diagnosis. However, due to the increasing penetration of offshore wind energy in the grids, disturbance monitoring has grown in complexity. The simultaneous occurrence of multiple perturbations and noise interference poses challenges to the accuracy and real-time performance of monitoring algorithms. To address these issues, feasible strategies involve pre-training of models using synthetic data models, semi-supervised learning principles, and recent advances in self-supervised and multi-task learning stances. Moreover, fusing

feature extraction and perturbation classification into a coherent unit also represents a research direction to streamline the surveillance model.

- High-fidelity measurements are crucial for analyzing high-frequency disturbances originating from power converters and their impact on system operation. Specifically, SWM techniques provide valuable insights into the highly dynamic and transient characteristics of offshore wind-connected grids, enabling multi-location quantitative analysis with neural network mechanism-based monitoring methods. Until recently, the adoption of SWM in research was still in its infancy, primarily due to stringent time synchronization requirements. There is a pressing need for further development in communication protocols and data storage strategies related to SWM. Moreover, while SWM is currently applied primarily in conventional grids, its practical applicability in grids integrating offshore wind energy is yet to be comprehensively evaluated and verified using real waveform data from wind farms.
- Evaluation metrics set out to assess the generalization ability of the algorithms when dealing with signals collected from different locations, different environmental conditions, or different power systems. While confusion-based scores, such as accuracy, are widely used as the principal threshold metrics, the potential information embedded in perturbed waveform data and monitoring results requires alternative performance views. Therefore, the need arises for a more informative and standardized evaluation framework that encompasses multiple dimensions (e.g., time-aware detection statistics for preventive and reparative actions and source localization). This framework would address the limitations of existing assessment strategies and provide a deeper understanding of the real-time status of grids integrating offshore wind energy.

In this context, a comprehensive assessment process is highly beneficial for algorithm validation and later problem-solving stages. The evaluation metrics can be identified at different levels, including end-to-end PQD event detection-and-classification performance, and the ongoing PQ state of the target power system. After standardizing the evaluation metrics, it is necessary to interpret PQD detection and classification results for subsequent decision-making. As mentioned in Section 4, SWM has provided new insights into the behavior of power systems and devices, offering the capabilities for mining data-level information. On this basis, a novel comprehensive monitoring framework is proposed in Fig. 5.

Illustrated in Fig. 5, SWM facilitates the realization of multiple location monitoring at both PCC and WT levels. The raw voltage and current waveforms are fed into the feature extraction unit, where information such as spectrum and amplitude can be derived through signal processing algorithms, exemplified by ST in Section 3.1. Subsequently, the CNN-based deep learning models discussed in Section 3.3 execute automatic perturbation classification to identify the current PQD type of the systems. Finally, a comprehensive PQ status of the power grids incorporating offshore wind energy can be obtained by system level evaluation metrics. The proposed monitoring framework leverages the potential of SWM and deep learning mechanisms for collaborative diagnosis and data mining, respectively. Furthermore, the multi-point monitoring process aligns with the requirements of electric grids integrating offshore wind energy.

Nevertheless, the current evaluation metrics cannot shed light on the potential reasons for the performance variance in different algorithm frameworks. Considering this gap, explainable AI has been employed to measure the explainability and trustworthiness of the presented monitoring scheme at the system level [166]. Another evaluation perspective relates to the comprehensive PQ status in the whole system. There are cogent needs for the recognition of disturbance severity as well as a timely alert when PQ events occur. To this end, an analytic hierarchy process has been implemented to benchmark the PQ performances of grid-integrated renewable energy systems [167]. This assessment tool considers the computed results of the disturbance detection, classification, and elimination processes as a holistic group to identify their weights.

Real-time PQ monitoring has become the way forward for offshore wind energy-integrated grids, exacerbating the algorithm complexity and the difficulty of performance evaluation. Hitherto, both algorithm-level and system-level evaluation metrics are arguably incomplete. Thus, a promising research direction is to develop a multi-criteria assessment framework so as to uncover underlying actionable information and further enhance PQ monitoring strategies. Nevertheless, the

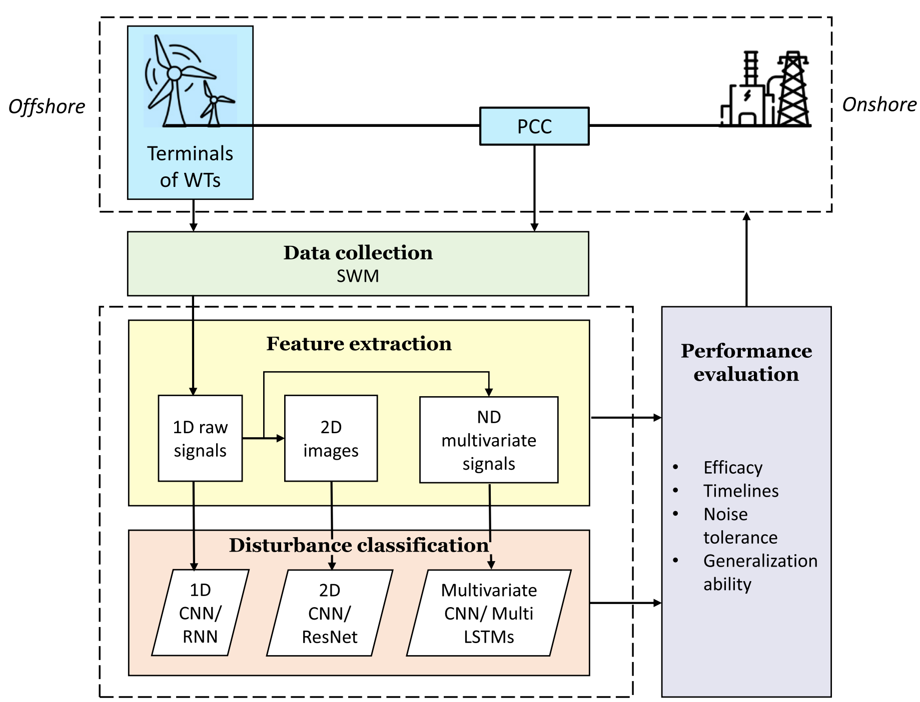

Fig. 5. Proposed system-wide monitoring framework.

focus of this study is confined to algorithms and measurements with fixed data types, i.e., current and voltage waveforms. Moreover, it does not consider the specific design aspects of wind farms within the proposed monitoring framework. Future research endeavors may seek to broaden the scope to address these limitations.

7. Conclusion

While the integration of RES in power generation brings economic and environmental benefits, it also poses challenges to PQ analysis. This work proposes the first comprehensive review of PQ monitoring in electric grids incorporating offshore wind energy. Disturbance types, their underlying causes, necessary collection locations, and relevant standards are covered to explore the overall impact of offshore wind energy on PQ issues. Research conducted between 2020 and 2023 on monitoring algorithms is reviewed, offering insights into the state-of-the-art in signal processing-based disturbance detection and machine learning-based disturbance classification. The advantages and applications of SWM in early PQ diagnosis are holistically discussed. Algorithmic evaluation metrics are described, underscoring the importance of attention to metric selection and PQ result interpretations. A system-wide monitoring framework is given to provide insights into collaborative PQ analysis strategy.

For the review topic under consideration, the following remarks regarding PQ monitoring issues are drawn:

- The measures, signal characteristics, and measurement procedures of PQ issues in offshore wind farms and DC systems are to be further refined and updated in the standards.
- Stockwell transform and deep learning methods, primarily CNN and RNN, have become the current research focuses on disturbance detection and disturbance classification, respectively. Neural network mechanisms have demonstrated great potential in compensating for the deficiencies of traditional diagnostic strategies, including real-time monitoring, data labeling aspects, and noise tolerance.
- Compared with synchrophasor measurements, SWM holds remarkable potential for PQ monitoring thanks to its advantageous features such as high resolution, time synchronization, authentic waveform, and high availability. Nevertheless, it is crucial to standardize communication protocols and enhance the data storage capabilities of SWM. To enhance the efficiency of SWM, one promising approach is to employ a distributed learning framework in offshore wind energy connected grids, enabling collaborative analysis among multiple nodes, considering both PCC and WT levels.
- Deep learning-based automation disturbance monitoring frameworks with high-fidelity data, which fuse disturbance detection and classification, hold significant promise as a research direction to extract meaningful information from monitoring results and to analyze the holistic status of the entire system.

To conclude, encompassing not only the impact of offshore wind energy on PQ issues, this review also delves into algorithms, measurement techniques, evaluation metrics, and promising monitoring frameworks. This review provides valuable insights into PQ events in the electric grid integrating offshore wind energy and highlights emerging technologies and approaches that offer the potential to tackle the disturbance monitoring problems. Since PQ monitoring plays a pivotal role in securing a stable power supply for offshore wind grid-connected systems, the primary objective of this review is to provide a comprehensive guideline for researchers and engineers to analyze real-time PQ events. As highlighted in this review, relevant standards, synchronized waveform applications, algorithmic evaluation strategies, and monitoring frameworks require further attention from the academic community. Studies on these aspects can greatly contribute to the efficient operation of the grids integrating offshore wind, and thus mitigate maintenance costs.

This study is limited to PQ monitoring for disturbance response, mainly with a focus on the analysis of voltage and current waveform signals. Collaborative fault diagnosis including more types of data would facilitate further research on offshore wind grid integration. Furthermore, additional work in this area also includes the investigation into the specific impact of offshore wind turbine design and wind farm topology on power quality concerns.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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