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Review Article

A Comprehensive Review of Detection and Classification Techniques for Power Quality Disturbances in Micro-Grid Systems

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Abstract - *The quality upsets of power quality are major operation concerns of Micro-Grid systems due to the increasing use of renewable sources of power, power electronic converters, and dynamic loads. despite the variety of signal-processing, machine-learning, and deep-learning methods that have been suggested regarding disturbance detection and classification, the literature is still disjointed in terms of datasets, evaluation criteria, and real-time implementation. The review is a scientific study of the literature on the subject of power quality disturbance monitoring in micro-grids through a prisma-guided methodology, and the reviews were refined according to the established inclusion and exclusion criteria. The selected works are compared in terms of the nature of disturbance, the tool of extracting the features, the classifier, the dataset, the performance evaluation, the computer complexities, and the capability to implement it. The review shows that hybrid and deep-learning-based models are highly classified, yet limited by the problem of data imbalance, unavailability of real-life three-phase datasets, low noise tolerance, and low interpretability. It is on this synthesis that the paper reflects the key gaps in the research and recommends the roadmap of the future of robust, real-time, and scalable micro-grid power quality monitoring.*

Keywords - *Micro-Grid Systems, Power Quality Disturbances, Machine Learning, Deep Learning, Disturbance Detection and Classification.*

1. Introduction

The possibility to control electricity at the local level, flexibly and resiliently by the coordinated integration of distributed energy resources, energy storage units, controllable loads and intelligent control platforms has made the creation of micro-grids a major architectural paradigm of contemporary power systems.

They have become more relevant due to the rapid penetration of renewable sources of energy, the need to have decarbonized energy systems, and the need to have a stable supply of electricity in both grid-connected and islanded operating modes.

Unlike the traditional centralized grids, micro-grids facilitate two-way power flow, dynamic control, and enhanced service continuity during critical infrastructures like healthcare facilities, data centers, industrial plants, and remote communities [1, 2]. Figure 1 demonstrates the physical and functional structure of a standard micro-grid, comprising of multiple generation and storage units, whereas typical structural categories are depicted in Figure 2. Such properties make micro-grids a prospective solution in the future energy system, but they also bring new challenges of operational complexity related to Power Quality (PQ), system coordination, and disturbance-sensitive operation.

One of the most important operation issues in micro-grids is the maintenance of reasonable power quality in dynamic and frequently unpredictable conditions of operation.

The growing reliance on inverter-based resources, nonlinear loads, switching converters, electric vehicle charging units, and intermittent renewable generation provides a situation where electrical disturbances may be much more frequent and variable than in traditional networks [3-5]. This may result in impaired voltage and current waveforms, affected sensitive equipment, impaired system efficiency, and other severe cases, which have malfunctioning or even unstable protection. Not only is the fact of disturbances noteworthy, but the possibility to recognize its type, source, and the degree of actual functioning in due time and with dependability is also involved.

This difficulty is aggravated in microgrids because disturbance signatures are affected by the transitions in operating modes, control interactions, network topology, local loading behaviour and stochastic distributed generation. Consequently, the monitoring of power imbalance in microgrids ceases to be a one-dimensional issue of measurement; it is now a multi-dimensional problem that entails signal perception, smart classification, control consciousness, and implementation practicability. The coordination of monitoring between microgrid supervisory functions and control layers also underlines the significance of coordinated monitoring, as shown in Figure 3.

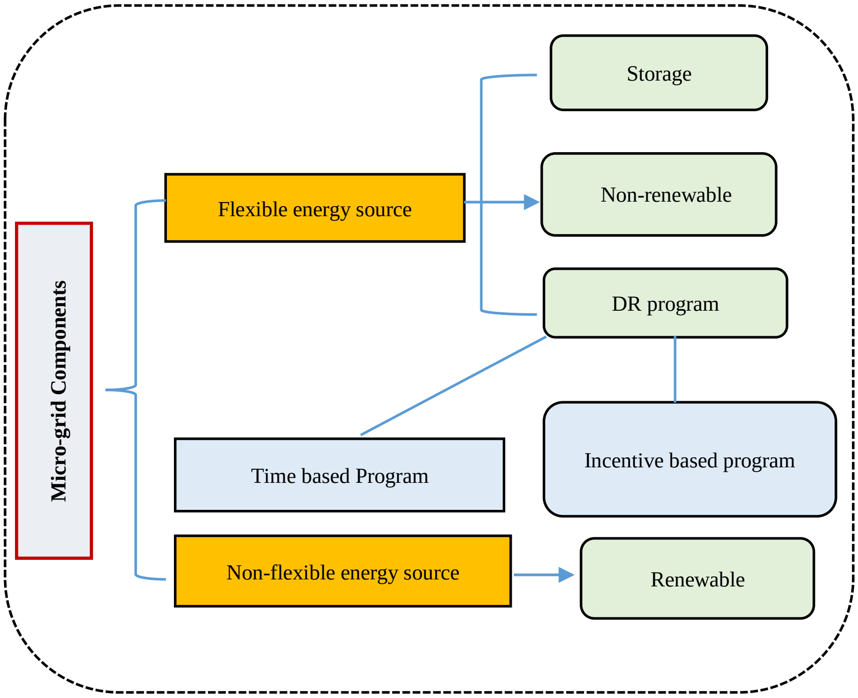


Fig. 1 Micro-grid components with different energy source

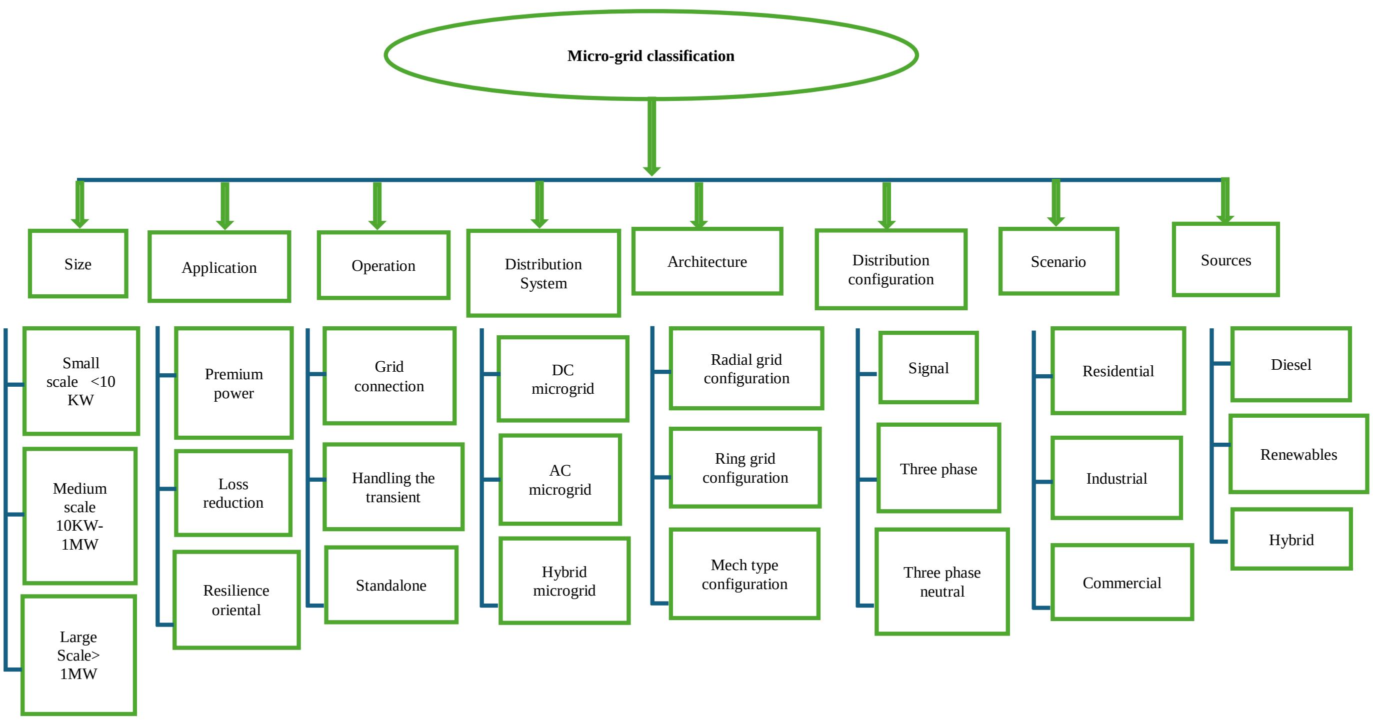


Fig. 2 Micro-grid classifications

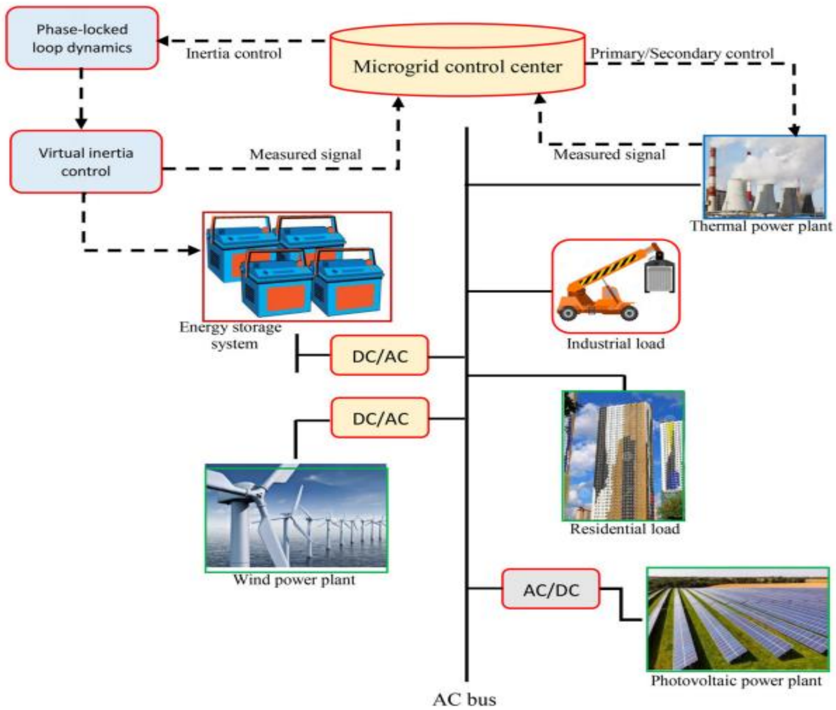


Fig. 3 Micro-grid with controllers

In the past ten years, it has been reported that significant research has been conducted on the detection, classification, and analysis of PQ disturbances through conventional signal processing, Machine Learning (ML), Deep Learning (DL), and hybrid computational frameworks. The available review articles have analyzed significant aspects of this literature, such as digital signal processing algorithms to analyze voltage disturbance, general AI-based PQ classification algorithms, PQ problems in renewable energy systems, and real-time disturbance detection algorithms [7-9, 21, 24]. Despite the fact that these studies have enhanced the knowledge on the disturbance analysis, the review literature available is still disjointed in a number of ways.

To start with, most of the reviews talk about techniques in a broad PQ setting without adequately differentiating the particular operational realities of micro-grids, including islanding transitions, inverter-dominated dynamics, and decentralized control constraints. Second, accuracy-oriented method reporting is frequently highlighted in the literature, whereas dataset realism, three-phase behavior, noise resistance, computational complexity, and real-time deployability are given little consideration.

Third, cross-study comparison is challenging due to the reporting of performance on heterogeneous data sets, with varying assumptions of disturbance, and with varying evaluation measures. As a result, the reader is able to find a plethora of candidate techniques, but remains uncertain as to which are truly mature, scalable or deployment ready to micro-grid-oriented applications.

In order to fill this gap, the current review presents the literature in a microgrid-focused view and integrates the field beyond a mere catalogue of algorithms. Instead of repeating detailed descriptions of individual PQ events or enumerating approaches paper by paper, the review links disturbance taxonomy, monitoring requirements, signal representation, feature extraction, classifier design, data characteristics and practical implementation constraints in a single analytical framework.

Here, the overall picture of the power quality classification that the studies reviewed are based on is represented by Figure 4, whereas Figure 5 shows the shift in the traditional PQ measurement to more intelligent and data-driven monitoring paradigms.

The paper explains how traditional methods of analysis, ML models, DL structures and hybrid structures are applied in disturbance detection and classification and how they are compared against each other in terms of disturbance diversity, access to data, interpretability, robustness and applicability to real-time micro-grid operation.

By this, the section lends some logical basis to a methodological screening implemented in Section II and a comparative synthesis developed in subsequent sections.

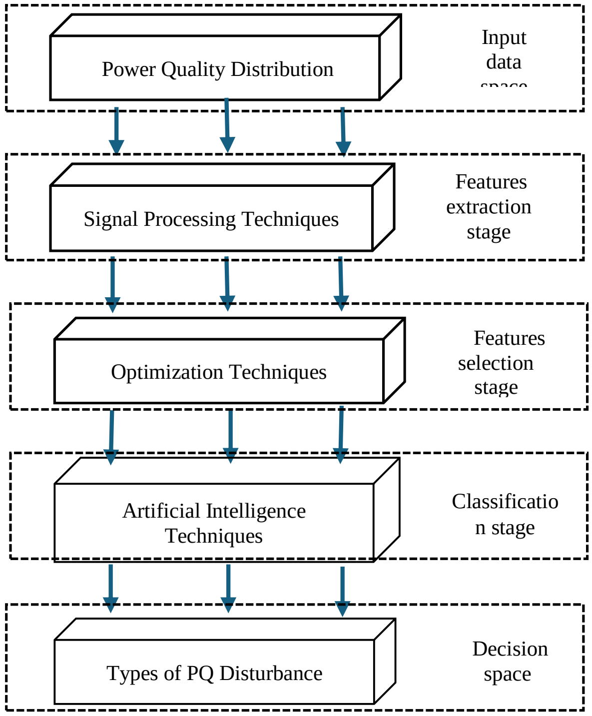


Fig. 4 Power quality classification system

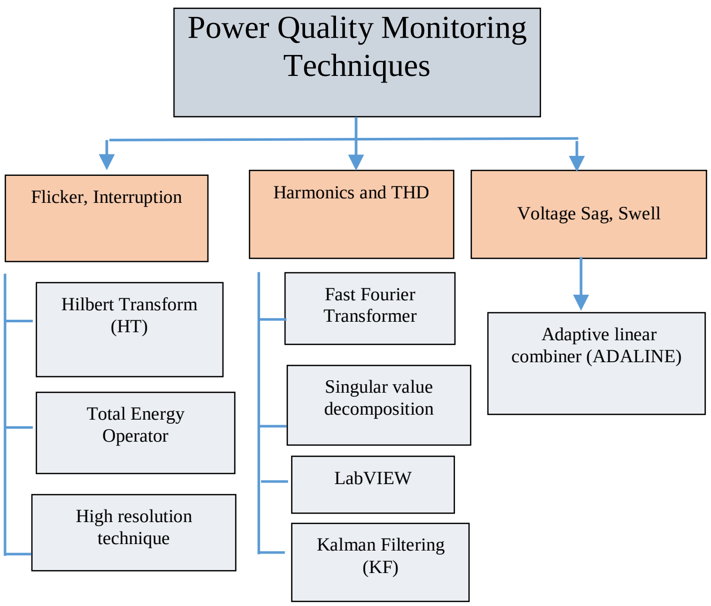


Fig. 5 Traditional power quality measuring techniques

The study has three main contributions. It starts with an effort to develop a taxonomic hierarchy of power disturbances within the specific context of microgrid operation and to relate the disturbance behavior with such causes as renewable intermittency, converter switching, nonlinear loading, and control interactions. Second, it provides a comparative analysis of the traditional monitoring strategies, signal processing strategies, machine learning strategies, deep learning framework and hybrid strategies in light of the perceived advantages, disadvantages, and applications. Third, it constructs a deployment-oriented research agenda by summing up the shared limitations that exist throughout the literature, particularly the limitation of synthetic-data-dependence, the limitation of across-operating-regime generalization, the limitation of bad noise sensitivity, limited three-phase validation and the inadequate consideration of computational cost in real-time systems. In so doing, the review will be situated as not only a compilation of what has already been done in the past, but a decision support framework for the researchers and practitioners who may wish to identify plausible directions of monitoring the PQ disturbances in real-life micro-grids.

Based on this scope, the review is structured based on the following research questions:

RQ1: Which types of power disturbances are the most commonly investigated in literature on micro-grids with a PQ focus?

RQ2: Which feature extraction and classification techniques are the most prevalent in the literature, and in what data conditions do they work best?

RQ3: What are the primary constraints to sound real-time implementation in real-life micro-grids?

RQ4: What are the most promising future research directions of robust and scalable disturbance monitoring?

The rest of the paper is structured in the following way. Section II contains the review methodology, which encompasses the search strategy, screening process, eligibility criteria, and synthesis framework to be used in the literature selection process.

Section III addresses the microgrid situation of PQ disturbances and forms a systematic taxonomy of the key disturbance types of interest in monitoring and classification. Section IV critically compares and contrasts the main disturbance detection and classification methods, including standard analytical methods, signal-processing-based methods, machine-learning-based models, deep learning models, and hybrid models.

Section V summarizes the key findings into a critical synthesis, defines the most significant gaps in the research, and provides a future roadmap of reliable, scalable, and deployment-oriented PQ monitoring in microgrid systems. Lastly, Section VI brings the paper to an end by giving a conclusion on the main insights and their implications to future research and practice.

2. Review Methodology

In this review, a systematic method of identifying, screening, evaluating the eligibility and analyzing the literature was applied to enhance the review in terms of transparency, reproducibility and analytical rigor. The methodological design was supposed to take the paper out of a narrative survey and into a format of critical review that would be able to facilitate the evidence-based comparison through disturbance type types, feature extraction pipeline types, classification model types, dataset setting types, and deployment constraints types. The review process was divided into three steps, which comprised of search strategy development, screening and selection of studies and finally systematic data extraction to compare and synthesize results. Particular consideration was made to the papers that directly lead towards the identification, categorization, or observation of power quality disruptions in micro-grids or in a directly related distribution-system context, with a transparent ability to extrapolate the conduct of micro-grids.

2.1. Search Strategy and Data Sources

The search of the literature was done in the digital libraries and indexing sites utilized in this review. The review included publications published since 2015, and backward reference screening was also conducted to include the foundational studies that are directly relevant to the power quality disturbance detection, signal analysis, and classification in the context of micro-grids and closely related power systems.

The review took into account peer-reviewed journal articles, conference papers, book chapters, and methodologically relevant preprints in cases where they contained sufficient technical detail to be comparatively evaluated. Articles were only taken into consideration that have been published in English.

The domain scope was limited to papers that dealt with at least one of the following themes: quality disturbances in power quality, disturbance monitoring, event detection, waveform analysis, feature extraction, intelligent classification, and real-time disturbance analysis in micro-grids and related distribution systems. At the screening stage, studies that were purely about the general operation of power systems, control problems not related to disturbance monitoring, or artificial intelligence applications were excluded.

The search strategy was a combination of core disturbance terms and micro-grid, and method-related terms to ensure a high coverage of the search and topical accuracy. The search strings that were used as representatives were:

- “power quality disturbance” AND micro-grid
- “power quality event classification” AND micro-grid
- “voltage sag swell harmonics” AND “machine learning”
- “power disturbance detection” AND “deep learning” AND micro-grid

Further keyword variants were also used to enhance the recall, such as combinations of signal processing and intelligent diagnosis, such as wavelet transform, S-transform, support vector machine, convolutional neural network, LSTM, feature extraction, real-time monitoring, and power quality event detection. Where necessary, Boolean operators, phrase matching, truncation, and database-specific filters were used. All the records were then retrieved and transferred to a screening sheet, and duplication was checked before title and abstract review.

The search strategy was developed to achieve both methodological breadth and relevance in application. Based on this, the studies in related contexts, like smart distribution grids or inverter-based distribution systems, were only retained where their disturbance models, monitoring architecture or classification pipelines were evidently applicable to micro-grid-oriented PQ analysis.

The thematic coherence was preserved by this boundary condition without excluding technically significant studies, the insights of which are directly applicable to microgrid settings.

2.2. Screening, Eligibility, and PRISMA Flow

After retrieval and deletion of duplicates, the records identified were filtered through a staged process of selection. Titles and abstracts were reviewed during the first stage to filter out obviously irrelevant publications.

At this point, records were eliminated when they were not dealing with power quality disturbances, were not dealing with micro-grids or technically similar distribution settings, or when they lacked some sort of monitoring, detection, or classification element.

During the second step, the entire text of the possibly relevant studies was evaluated in terms of methodological relevance, technical depth, and inclusion in a comparative review. The third stage involved the verification of the final study set on overlap, consistency of the scope, and sufficiency of the information reported to be used in the synthesis.

To be included in the final qualitative corpus, a study had to meet all of the following criteria:

i. It dealt with one or more disturbance-related monitoring issues or power quality disturbances;
ii. It suggested, assessed, examined, or comparatively assessed a detection, classification, or signal-processing structure;
iii. It provided adequate methodological data to permit qualitative comparison; and
iv. It was located in a micro-grid environment or in a directly related electrical distribution environment that has direct applicability to the micro-grid disturbance analysis.

The studies were not included in case they satisfied one or more of the following criteria:

i. The paper did not target disturbances in power quality;
ii. The experiment had no association with micro-grids or disturbance situations of distribution systems;
iii. The work lacked a detection, classification or monitoring contribution;
iv. The methodological detail was not enough to conduct a review synthesis;
v. The publication was more or less the same as another study retained;
vi. The article was not written in English;
vii. The full text was not accessible; or
viii. The article covered an irrelevant AI application that lacked the relevance of PQ-monitoring.

A PRISMA-style flow diagram is used to summarize the study selection process to enhance the clarity of reporting. Since the methodological credibility of the records depends on the correct number of records, the numerical values in the diagram can only be filled in once the final search log is consolidated. No estimated or assumed values should be inserted. The PRISMA flow for this review is contain the Figure 6.

Studies included in qualitative synthesis: [n = 50]. This process offers an auditable connection between the original search result and the final study pool, thus enhancing the reproducibility of the review and explaining the foundation upon which the following critical synthesis is built.

2.3. Data Extraction and Synthesis Framework

As soon as the set of studies was narrowed down to the final set, the extraction matrix was developed, which was designed in a way that would be comparable. The review did not summarize the studies strictly chronologically or according to the authors, but a common set of technical descriptors of all eligible studies was established and classified into similar dimensions of analysis.

This approachology permitted cross-study integration of documented performance, in addition to methodology beliefs, dataset realisation, and implementation suitability.

The following were captured in both studies: disturbance, phase setup, signal model, feature extraction algorithm, analytics model, data source, and type, evaluation measures, noise-handling approach, computational impact, real-time application, and limitations. The latter aspects have been selected because they directly influence the utility of disturbance-monitoring methods in microgrids. In particular, the classification accuracy has not been taken as one measure of merit in the review. Also, like priority was given to data realism, disturbance diversity, noise robustness, multi event condition, computational load and potential transferability to real-time implementation. Table 1 presents the items extracted and the importance of the extracts to the synthesis of the review.

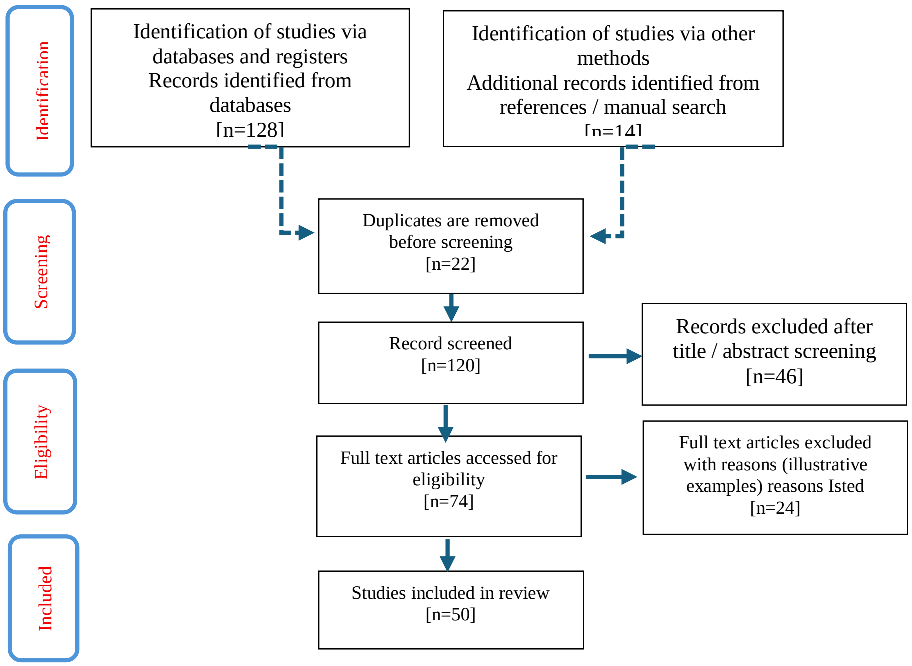


Fig. 6 The PRISMA flow for the present review

Table 1. Data extraction and synthesis framework adopted in the review

SN	Extracted Item	Description Used in Review	Purpose in Comparative Synthesis
01	Disturbance type	Sag, swell, interruption, harmonics, transients, flicker, unbalance, frequency variation, or compound events.	Identifies the scope of event coverage and reveals which PQ events are overrepresented or underexplored
02	Phase configuration	Single-phase, three-phase, or mixed configuration	Assesses practical relevance to real microgrid operation and identifies limitations of single-phase validation
03	Signal representation	Raw waveform, time-domain signal, frequency-domain representation, time-frequency map, image/scalogram, or phasor features	Enables comparison of how studies transform electrical signals for detection and classification
04	Feature extraction method	Statistical features, FFT, DWT, S-transform, Hilbert transform, entropy measures, image features, or automatic feature learning	Distinguishes hand-crafted feature pipelines from end-to-end learning approaches
05	Classifier/model	Rule-based model, SVM, DT, RF, ANN, CNN, LSTM, ensemble model, or hybrid framework	Supports method-family comparison across conventional, ML, DL, and hybrid categories
06	Dataset type	Synthetic, experimental/laboratory, field/real-world, or mixed dataset	Evaluates data realism and highlights dependence on simulated environments
07	Evaluation metrics	Accuracy, precision, recall, F1-score, RMSE, MAE, specificity, sensitivity, confusion matrix, or computational time	Allows structured comparison of reported outcomes while accounting for inconsistent reporting standards
08	Noise handling	Clean signal setting, noisy simulation, denoising stage, robustness test, or no explicit treatment	Assesses resilience under realistic operating conditions
09	Computational complexity / real-time suitability	Training cost, inference cost, latency indication, hardware suitability, online/offline capability	Connects algorithmic performance with deployment feasibility in microgrid monitoring systems
10	Reported limitations	Data scarcity, overfitting, interpretability, poor generalization, class imbalance, or hardware burden	Supports the research gap analysis and future agenda developed in the later sections

After the extraction, the synthesis of the studies was done in three complementary axes. The previous axis was disturbance-centred, in which it was preoccupied with the most frequently discussed and least studied PQ events in a compound event or a three-phase environment.

The second axis was method-centred, in which the conventional aids of analysis, signal-processing pipelines, machine-learning models, deep-learning architectures and hybrid frameworks were compared by their assumptions, strengths and weaknesses. The third axis was deployment-based, which evaluated the potential of reported approaches to work in noisy conditions, real-time limits, and the heterogeneous micro-grid operating conditions.

The general purpose of the review is not only to provide a report on what methods are available, but to determine which approaches are methodologically developed, which ones are experimentally limited, and where the literature does not yet have the solutions to micro-grid power quality disturbance monitoring which are robust and deployment relevant.

The synthesis strategy of three layers helps to achieve the main goal of the review. The resulting evidence structure provides the basis for the disturbance taxonomy, presented in Section III, the method comparison, presented in Section IV, and the discussion of critical research gaps, presented in Section V.

3. Power Disturbances in Micro-Grids: Taxonomy, Sources, And Monitoring Context

The analysis of power quality oriented to micro-grids needs to go beyond the detection of isolated abnormalities in the waveforms. Micro-grid architecture, converter-dominated interfaces, operating-mode transitions, communication structure, and interaction of renewable generation with dynamic loads are all very strong shapers of disturbance behavior in practical systems.

In this regard, a technically meaningful review should place power disturbances in their context of operation and not as abstract signal events. This section thus determines the interdependence between the structure of the micro-grid, source of disturbances, and monitoring needs, and thus, forms the conceptual foundation of the comparative approach review that was established in the next section.

3.1. Micro-Grid Architecture and Control Context

A microgrid usually combines units of distributed generation, energy storage, controllable and non-controllable loads, power electronic converters, and supervisory control layers in either grid-connected or islanded mode. This architecture is shown in Figure 1, Figure 2, and Figure 3 as a combination of several sources and control interfaces on a local electrical boundary. Although such a setup enhances the flexibility, resilience, and use of renewable energy, it also exposes the system to voltage distortion, switching-related transients, harmonics, and control-coupled disturbances [1, 2].

Specifically, the inverter-based distributed energy resources change the dynamic characteristics of the voltage and current waveforms and may increase the sensitivity of the network to fast load change, nonlinear power conversion, and mode switching.

PQ disturbances directly depend on the control structure of a micro-grid, which determines their generation, propagation and detectability. Centralized control can provide coordinated decision-making and system visibility, but it depends on the stability of the communication and can introduce latency to disturbance response.

Distributed and decentralized designs are more scalable and have more local control, but are able to rely on partial measurements and local decision rules, so that it may be hard to localize disturbances and correlate events across the network. Similarly, the control levels of a micro-grid that are hierarchical, such as the primary, secondary and tertiary ones, do not have equal effects on PQ.

Primary control is expeditious and directly related to converter-level voltage and frequency behaviour, secondary control is related to restoration and regulation, and tertiary control is more inclined towards optimization and energy management. Wisdom-wise, these layers have an influence on the time scale of the disturbance occurrence and the resolution of the disturbance to be identified with accuracy [2, 17]. To bring this relationship between architecture and monitoring to a more intense level, the information about the control in the above section is recapped in Table 2.

The hierarchical control interactions and multi-level structure of a micro-grid are further illustrated in Figure 7, which is applicable since performance monitoring does not only depend on the disturbance itself, but also on the location in the control hierarchy where the event is observed, interpreted, and acted upon.

The aspect that can be argued on with regard to review is that the analysis of PQ disturbance in micro-grids could not be driven by a single assumption of universal monitoring. A method that is effective in a centralized and grid-connected and low-noise environment may not be equally effective in islanded mode, in a distributed control environment, or in a network with a large number of converters.

This structural dependency is among the causes why the findings are not homogeneous in the literature and why a disturbance taxonomy, and which is evidently connected to the circumstances of micro-grid functioning, is required.

Table 2. Micro-grid control structures and their relevance to power quality disturbance monitoring

SN	Control dimension	Representative modes	Monitoring relevance in PQ disturbance analysis
01	System architecture	Centralized, decentralized, distributed	Determines observability, fault localization capability, coordination level, and response latency during disturbance events
02	Communication dependency	With communication, limited/no communication	Affects data synchronization, event correlation, and the feasibility of wide-area or node-level disturbance diagnosis
03	Operating mode	Grid-connected, islanded, transition mode	Alters disturbance propagation paths and changes the severity and detectability of voltage and frequency deviations
04	Control hierarchy	Primary, secondary, tertiary	Influences the disturbance timescale, signal dynamics, and the selection of monitoring windows and detection thresholds
05	Source interface	Inverter-based DERs, synchronous sources, storage converters	Shapes harmonic content, switching behavior, waveform distortion, and transient response
06	Load composition	Linear, nonlinear, sensitive, stochastic loads	Affects distortion patterns, compound-event formation, and the persistence of PQ deviations

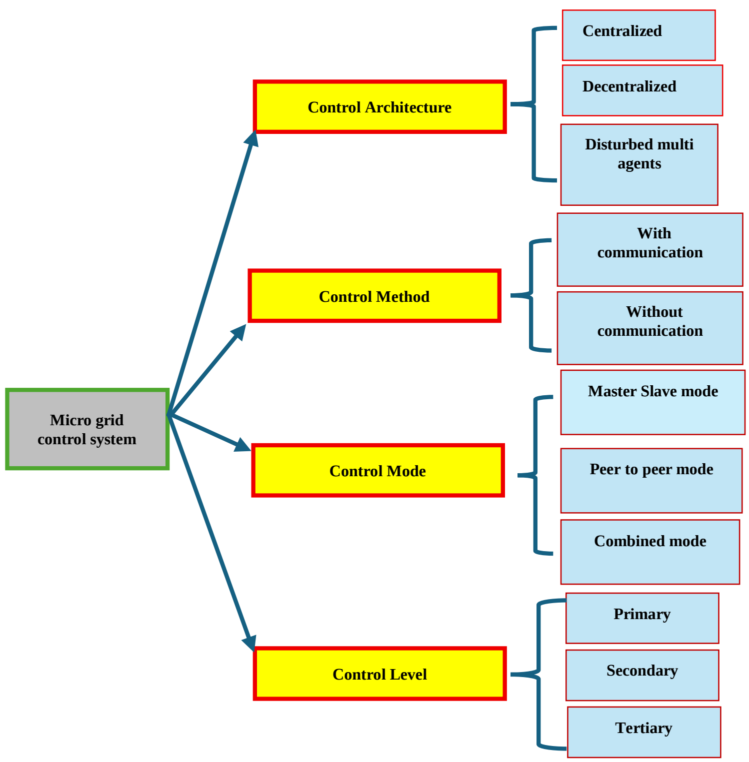


Fig. 7 Multilevel Micro-Grid structure

3.2. Taxonomy of Power Disturbances

Violation in power in micro-grids may be classified as voltage-magnitude, waveform-shape, frequency, and multi-factor complex. Voltage sag, voltage swell, interruption, harmonics, transients, flicker, unbalance, and variation of the frequency are the most frequent cases that are reported in the literature [4, 7, 9, 24].

These groups are common in the general PQ analysis, however when it comes to micro-grids, they are usually varied than in the typical utility system because of renewable intermittency, inverter switching, bidirectional power flow, local protection behaviour and load diversity. Table 3 provides a cursory disturbance taxonomy of the present review.

Table 3. Taxonomy of power disturbances in microgrids and their monitoring implications

SN	Disturbance type	Typical causes in microgrids	Signal characteristics	Monitoring difficulty	Relevance for method selection
01	Voltage sag	Faults, motor starting, sudden load increase, feeder switching	Short-duration reduction in RMS voltage magnitude	Can overlap with transitions and load events; difficult under noisy measurements.	Requires accurate time localization and robust magnitude-sensitive detection
02	Voltage swell	Load rejection, capacitor switching, and abrupt reduction in demand	Short-duration increase in RMS voltage magnitude	Often confused with transient recovery or switching events	Benefits from event segmentation and threshold refinement
03	Interruption	Protection operation, islanding, severe faults, converter shutdown	Near-complete loss of voltage for a finite duration	Easy to identify in severe cases, harder for momentary or partial interruptions	Time-domain and event-based methods are generally effective
04	Harmonics	Inverter switching, nonlinear loads, rectifiers, EV chargers	Spectral distortion at integer multiples of the fundamental frequency	Persistent and often mixed with other events	Frequency-domain and time-frequency approaches are particularly suitable
05	Transients	Switching actions, fault clearance, lightning, converter commutation	Short-duration impulsive or oscillatory waveform distortion	A very short duration requires high sampling and precise localization	High-resolution signal processing is essential
06	Flicker	Rapid load variation, intermittent generation, weak-grid coupling	Repetitive low-frequency voltage fluctuation	May be subtle and prolonged rather than abrupt	Statistical and time-series methods are useful for severity assessment
07	Unbalance	Asymmetrical loading, unequal phase impedances, single-phase DER or faults	Unequal phase magnitudes and/or phase angle displacement	Requires three-phase measurement and phase-coupled interpretation	Three-phase feature extraction is necessary
08	Frequency variation	Power imbalance, poor inertia support, and islanding transitions	Deviation from nominal system frequency	Coupled with control actions and operating mode	Dynamic and time-sequential models are often required
09	Compound events	Simultaneous or sequential occurrence of multiple PQ disturbances	Mixed features across magnitude, spectrum, and duration	Most difficult to classify due to overlapping signatures	Hybrid and deep models may offer advantages if trained on realistic data

Voltage sag and swell are one of the most researched phenomena due to their direct dependence on the susceptibility of equipment and the continuity of the process. Nevertheless, in micro-grids, such events are not necessarily due to traditional upstream grid faults; they can also arise due to source intermittency, control reconfiguration, or sudden local power imbalance. Harmonics and transients are also significant since the penetration of power electronic interfaces causes waveform distortion to be a natural monitoring issue and not an infrequent anomaly. Similarly, imbalance and frequency deviation gain a greater role in islanded or weakly supported micro-grids, where local generation and imbalanced loads can quickly influence system stability [9, 13, 17]. The most important thing is that the disturbance categories can't be defined by the waveform label only. The implications of each event class to sensing requirements, feature representation, and classifier design differ. An example is that RMS-based voltage events can be well represented using time-domain analysis or hybrid threshold-based analysis, but harmonics and transients are typically analyzed using frequency-selective or time-frequency analysis. Likewise, imbalance and frequency deviation require phase-sensitive or time-sensitive models instead of single-signal pattern recognition. It is this event-to-method connection that will be the focus of the critical synthesis that will be carried out later in the paper.

3.3. Detection and Monitoring Implications

Not only are the disturbances in PQ in micro-grids difficult to detect due to their variety, but they also tend to be nonstationary, noisy, and operationally coupled. A number of sources of complexity are recurrently found in the literature. To begin with, nonlinear loads and converter-based interfaces introduce distortion of waveforms even when operating normally, which decreases the separability of normal and abnormal states. Second, fluctuation due to renewable intermittency presents fluctuation signatures that can be similar or obscure short-duration PQ events. Third, several events can happen in series or in parallel and create compound disturbances whose characteristics intersect both in time and frequency space. Fourth, the apparent structure of the disturbance can be distorted by measurement noise, the sparse sensor location, and sampling resolution variations, and classifier robustness may be compromised [7, 9, 24].

Another problem is the real-time demands of real-world monitoring. In the laboratory, numerous techniques have been shown to perform well with offline feature extraction, curated data, or computationally expensive classifiers. In working micro-grids, however, detection pipelines need to be tradeoffs between speed, interpretability and robustness. High classification accuracy cannot be used solely as an event detector when it is too slow or has unrealistic preprocessing, or when it cannot survive topology changes and unknown operating regimes. This is especially true in islanded systems, when reconfiguring the network, or when operating on weak-grid conditions, when timely disturbance detection is directly connected to protection coordination and response to control.

These limitations have a direct impact on the choice of methods. The signal-processing-based approaches are still useful when the localization of events, their interpretability, and low-data-rate operation are in focus. Traditional methods of monitoring also have a practical significance in cases when simplicity of implementation and deterministic response are needed. Machine-learning methods are appealing when feature separability is learnable using representative labeled data, particularly in identifying multiclass disturbance. Deep-learning and hybrid models provide further flexibility in nonlinear patterns and compound events, but their usefulness in practice requires high data realism, computational budget and extrapolation across operating conditions. Based on this, there is no single best type of method that can be considered as universally the best; it is a matter of disturbance characteristics, quality of measurements, phase configuration, and deployment constraints.

Overall, the micro-grid setting changes the nature of the PQ disturbance analysis as a traditional signal classification problem into a system-aware monitoring problem. The type of disturbance, the architectural context, the hierarchy of control, and the data conditions are the factors that collectively define the complexity of detection, as well as the suitability of the analytical approach. This contextual knowledge is critical in the critical interpretation of the literature. Based on that, the following section summarizes the literature under review using a comparative framework to assess traditional methods, signal-processing models, machine-learning models, deep-learning models, and hybrid methods in terms of their reported performance and real-world applicability.

4. Comparative Review of Detection and Classification Techniques

The body of work on the subject of power quality disturbance monitoring in micro-grids has developed to focus on more data-driven and hybrid analysis schemes than the traditional waveform-based inspection. This development is not only algorithmic, but it is indicative of the increased complexity of micro-grid operation, the nonstationary nature of disturbance signals, and the necessity to balance the accuracy of detection with interpretability, computational efficiency, and deployability. The available literature can be broadly categorized into three: signal-processing and traditional monitoring techniques, machine-learning and deep-learning models, and hybrid systems that combine feature engineering with intelligent classifiers [7-11, 21, 24, 32]. Instead of comparing these techniques separately, this section will compare them based on the kind of information they utilize, the conditions of data they work best in, their major limitations, and how well they are applicable in real-time micro-grid monitoring.

4.1. Signal Processing and Traditional Monitoring

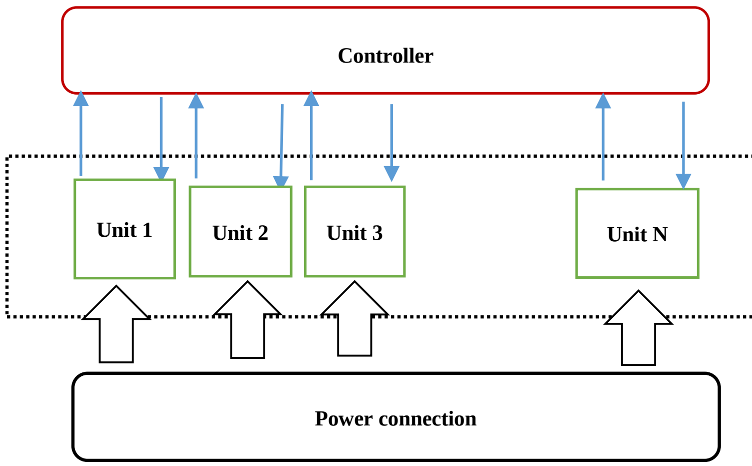
Signal-processing and traditional monitoring methods are still fundamental in the analysis of power disturbances due to their physical interpretability and capability to use limited labeled data. The traditional monitoring layer is composed of waveform analysis, fault recording, event detection algorithms and phasor-based monitoring, and the principal analytical layer of feature extraction is composed of Fourier-based, wavelet-based, Stockwell-transform-based and Hilbert-based methods [7, 8, 24]. Practically, these techniques are frequently used as the initial step of a detection pipeline, in which case they transform raw voltage or current data into discriminative representations to be thresholded or classified.

Waveform analysis and fault recording are especially effective when the main goal is to localize events, achieve time resolution, or diagnose events. They are strong in terms of maintaining temporal fidelity and engineering interpretation of voltage sags, swells, interruptions and short transients. Likewise, monitoring with PMU can increase situational awareness by using synchronized measurements of many nodes, particularly where disturbance propagation and control interaction need to be viewed at the system level. These techniques are, however, highly reliant on sensor location, availability of communication, and data resolution and tend to be less effective in the presence of disturbances that overlap, develop slowly or manifest themselves in noisy converter-dominated locations.

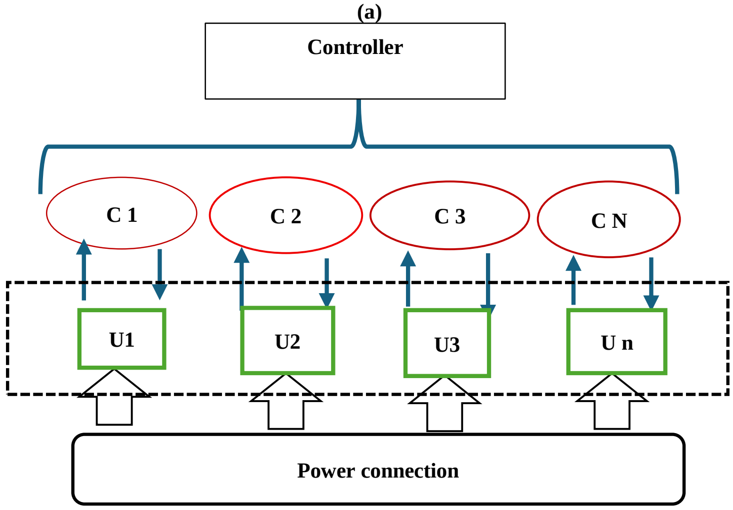
The Fast Fourier Transform (FFT) is still suitable when the harmonic analysis is required to be stationary, and its utility reduces with nonstationary or short events of PQ. In comparison, the Discrete Wavelet Transform (DWT) and the Stockwell Transform (ST) offer superior localization of the time-frequency, and thus they are still among the most commonly used front-end methods of PQ disturbance classification [7-10, 23, 49, 52]. Wavelet methods are especially useful in sharp changes in waveforms and multi-scale transients, whereas the Stockwell transform can provide more detailed time-frequency resolution and has demonstrated high performance in multiclass PQ event detection.

Other useful methods include Hilbert transform and related forms of analysis, which can also be used to characterize instantaneous amplitude and frequency, but with a generally lower discriminative ability than combined transform-classifier systems.

Conventionally and signal-processing approaches are appealing in a deployment context where interpretability, deterministic response, and limited-data operation are important. They are particularly useful where operators need to know the exact content of frequency, the time of events or alarm logic that is rule-based. They are mostly limited by the fact that they tend to rely on handcrafted features and fine-tuned thresholds, which expose them to compound perturbations, waveform fluctuations, and domain changes under varying micro-grid conditions. The centralized and decentralized monitoring views of such architectures are shown in Figure 8(a) and Figure 8(b), which are also applicable when taking into consideration the practical positioning of measurement, analysis, and control functions.



(a)



(b)

Fig. 8 (a) Centralized control process, and (b) Decentralized controlled process.

4.2. Machine Learning, Deep Learning, and Hybrid Techniques

Machine learning techniques were proposed to minimize the use of manually set thresholds and enhance differentiation between various PQ event categories. Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), boosting-based models, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and ensemble or hybrid models are the principal groups of intelligent classifiers in the reviewed literature [12, 16, 24, 26, 33, 34].

The idea of the traditional analysis to the monitoring with the help of AI is represented in Figure 9.

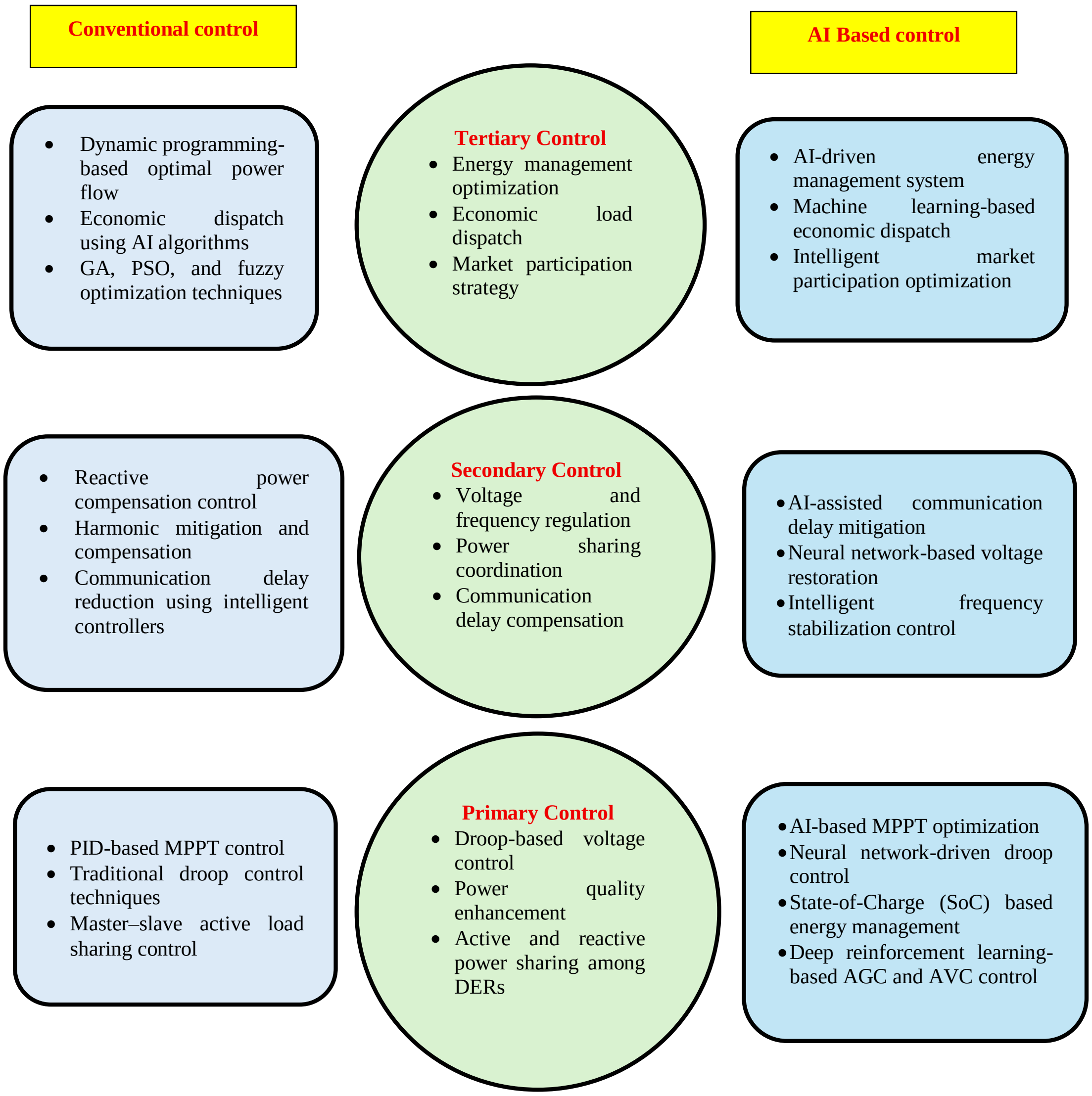


Fig. 9 Conventional vs. AI control approaches

The SVM-based methods are also competitive when the training data are small, but the extraction is robust. They are effective in high-dimensional feature space and are also common in pipelines constructed on wavelet, Stockwell, entropy-based or image-derived descriptors [10, 12, 44].

Their primary weaknesses are due to the choice of the kernel, sensitivity of the parameters, and the decrease in flexibility in case of highly nonlinear event boundaries or multiclass and compound-event conditions.

Decision trees are easy to interpret and have low computational costs, whereas random forest and boosting models are stronger and more nonlinear in their discrimination capabilities. They can work well with structured statistical characteristics, though their performance is still largely determined by the quality of the extracted feature set and the representativeness of the training data [4, 38, 46, 47].

Neural-network-based approaches, especially CNN and LSTM structures, have gained a lot of interest due to the fact that they do not require manual feature engineering and can also learn more sophisticated spatial or temporal signatures directly off of raw signals or transformed representations.

CNN-based methods are effective when PQ signals are transformed into images, spectrograms, or scalograms, and multiple studies have demonstrated that time-frequency maps can be very effective as inputs to a network [12, 16, 33, 34, 37, 42].

The use of LSTM-based methods is especially effective with temporally related signals, like islanding transitions, time-varying harmonic signatures, and sequential PQ event streams [17, 43]. The generalized deep-learning representation, which is generally used in such studies, is illustrated in the Figure 10.

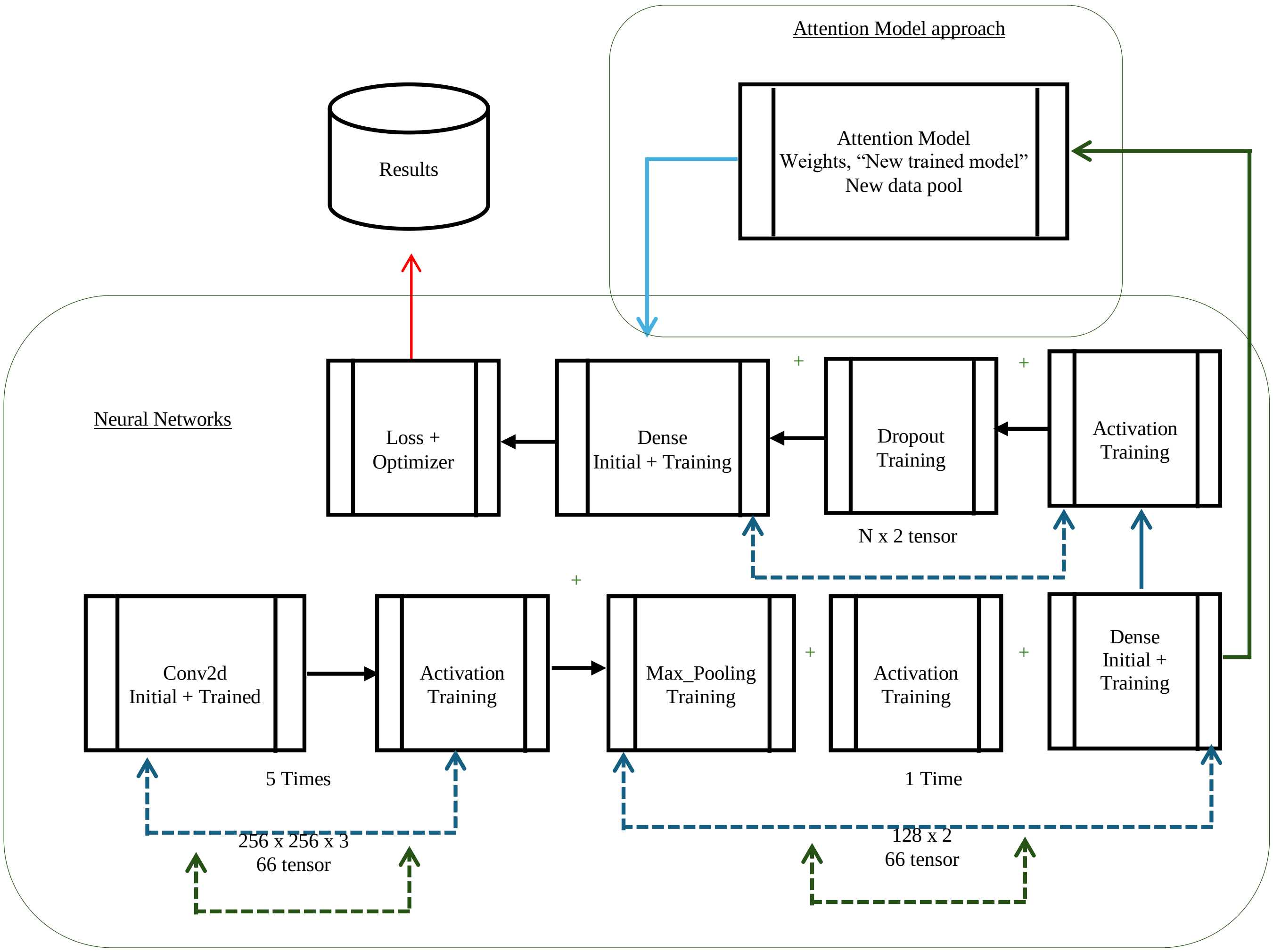


Fig. 10 Generalized CNN model

Deep-learning models are not always better, even though they are predictive. They are most beneficial in situations where large and heterogeneous datasets are present, when feature boundaries are extremely nonlinear and when compound or time-varying events need to be identified.

Their drawbacks are also significant: they are expensive to compute, require more training data, are susceptible to dataset bias, less interpretable, and have poor reproducibility in the case of inadequately reported model design and pre-processing [19-21, 24]. Furthermore, most of the claimed high-accuracy performance is achieved on simulated or hand-crafted datasets, which might not be representative of actual microgrid variability.

Hybrid methods are trying to trade off the interpretability of signal processing and the predictive power of AI models. Common ones are DWT-ANN, ST-SVM, CNN models driven by time-frequency maps, CNN-SVM hybrids, and ensemble deep-learning systems [6, 10, 16, 31, 43, 48, 49, 50, 52]. Such methods commonly perform better than either purely conventional or purely shallow-learning models since they provide focused signal representations and flexible classifiers.

The ability to deal with noisy or overlapping events also seems to be more in the capability of hybrid methods when the feature transformation stage is selected well. Nevertheless, the observed performance improvement is usually achieved at the expense of increased complexity of implementation, increased parameter-tuning load, and decreased cross-dataset and cross-operating condition reproducibility.

In order to prevent redundant method-by-method descriptions, the representative studies that have been reviewed in the present paper are summarized in Table 4. [Appendix]

4.3. Comparative Synthesis Across Studies

The literature reviewed presents three general trends. To begin with, transform-based representations are still central even in AI-oriented research. Most of the high-performing classifiers do not act directly on raw waveforms, but rather on time-frequency decompositions, scalograms, statistical descriptors, or engineered coefficients that render disturbances more separable [7, 8, 10, 16, 23, 37, 49, 52]. This implies that the representation of features is at least as significant as the classifier itself. Second, the reported accuracy is a poor foundation of judging deployment preparedness. A number of studies claim extremely high classification accuracy, especially on simulated data and benchmark signal sets, but have little evidence on inference latency, hardware requirements, model robustness to noise, or cross-operating-mode transferability [24, 32, 42, 43]. In this regard, methods that seem to have lower peak accuracy can be more feasible when they are interpretable, data-hungry, and computationally simpler.

Third, there is no one best method class that fits every disturbance situation. Traditional and transform-based algorithms are also useful in interpretable localization and low-data conditions.

Machine-learning techniques are effective when handcrafted features that are well-separated exist. Deep-learning models are beneficial in nonlinear patterns of complex nature and sequential or image-based representations, but tend to need more extensive and varied datasets.

Hybrid approaches now provide the most balanced performance profile, especially when strong noise and multiclass discrimination resistance are needed, but their complexity is still a hindrance to reproducibility and embedded implementation.

Based on this, the literature is increasingly suggesting a unified perspective of PQ monitoring in microgrids: effective systems will probably need multi-stage pipelines that integrate robust sensing, disturbance-aware signal representation, data-efficient learning, and deployment-sensitive model design.

These comparative results also explain why the key unsolved problems in the field are not only algorithmic; they are directly related to data realism, variability in operations, and system-level deployment limitations.

5. Critical Synthesis, Research Gaps, and Research Roadmap

The literature shows that there has been a lot of advancement in the detection and classification of PQ disturbance, but it also shows a steady discrepancy between reported laboratory performance and deployment-ready monitoring capability.

A more publication-ready research-gap discussion thus needs to be consolidated with a few evidence-based themes and not a lengthy list of generic limitations. According to the comparative review in Section IV, it is possible to identify five key gap themes.

5.1. Domination of Synthetic Data and Weak Field Validation.

A high percentage of the reported outcomes are achieved with simulated or artificially generated PQ signals, frequently in controlled parameter conditions [10, 36, 38, 42, 53].

Even though these datasets are valuable in early-stage benchmarking, they do not comprehensively model micro-grid operating variability, converter noise, topology variations, communication disruptions, and three-phase interaction. Therefore, good results on artificial data do not necessarily mean that it can be trusted in the field.

5.2. Poor Management of Compound and Overlapping Disturbances

The identification of simultaneous or sequential disturbances in compounds is still relatively immature, whereas most studies are still centered on isolated events like sag, swell, harmonics, or interruption [10, 24, 32].

It is a major drawback since real-world micro-grid conditions can combine mixed signatures due to renewable intermittency, control measures and nonlinear load dynamics.

5.3. Deploying Ability is Not Considered Important as Compared to Accuracy

Accuracy, F1-score, RMSE, or other predictive measures are much more frequently reported in the literature than latency, memory requirement, computational complexity, or embedded implementation feasibility [24, 32, 43]. Consequently, numerous approaches seem to work well in a classification viewpoint but are not well defined in terms of real-time monitoring, edge deployment, or controller integration.

5.4. Poor Strength and Extrapolation

Some methods are good on fixed data, but offer little evidence of robustness to noise, unknown operating conditions, domain shift, or different network structures [16, 36, 37, 48].

This brings up the issue of model transferability to other micro-grid configurations and load-generation regimes.

5.5. Low Interpretability and Reproducibility

The more complex the model, the less interpretable it is. Most AI-based approaches are black-box classifiers, and a number of studies do not include much information about preprocessing, hyperparameter optimization, dataset splitting, or real-time execution conditions [21, 24, 32]. This undermines reproducibility and limits practical confidence in safety-critical monitoring settings. These themes and their implications are summarized in Table 5.

Table 5. Evidence-Based research gaps and future roadmap for Micro-Grid-Oriented PQ monitoring

SN	Gap theme	Evidence from the reviewed literature	Practical implication	Research direction
01	G1. Synthetic-data dominance and weak field validation	Many high-performing studies rely on MATLAB/Simulink or fabricated datasets rather than sustained field measurements [10, 36, 38, 42, 53]	Reported accuracy may overestimate practical performance	Build curated real-world benchmark datasets with micro-grid annotations, sensor metadata, and operating-mode labels
02	G2. Weak handling of compound and overlapping disturbances	Most methods target single-event classification; compound-event recognition is less mature [10, 24, 32]	Real disturbances may be misclassified when signatures overlap	Develop compound-event datasets, multi-label classifiers, and sequence-aware detection frameworks
03	G3. Accuracy prioritized over deployability	Latency, memory, and edge feasibility are rarely reported alongside predictive metrics [24, 32, 43]	Methods may be impractical for online protection or controller support	Evaluate computational cost, edge inference time, and hardware-aware model compression
04	G4. Limited robustness and generalization	Noise immunity and domain transfer are inconsistently validated across studies [16, 36, 37, 48]	Models may degrade under field noise, topology change, or unseen scenarios	Use domain adaptation, robust training, transfer learning, and uncertainty-aware inference
05	G5. Limited interpretability and reproducibility	Many AI models are black-box and not fully specified experimentally [21, 24, 32]	Reduced operator trust and weak repeatability	Adopt explainable AI, transparent reporting protocols, and open evaluation pipelines.

According to these gaps, there are six directions that present the most promising roadmap for the field research. To begin with, real-time edge deployment must be a major evaluation focus and not a minor implementation observation.

Second, self-supervised and transfer learning may result in the reduction of the current dependence on expensive labelled PQ datasets.

Third, sensor fusion and fusion with various sources, i.e. a mixture of waveform, phasor and contextual operational data, is anticipated to increase the interpretation of disturbances in distributed micro-grids. Fourth, it is necessary to add explainable AI to increase trust, operator approval, and the standard of diagnosis.

Fifth, uniformly labelled disturbance, noise settings, and train-test protocols, as standardized benchmark datasets, would be advantageous to the field. Finally, the three-phase and compound-disturbance data should be given more consideration, because they are more realistic conditions of micro-grid operations.

In conclusion, even the marginal improvements in the classification accuracy will not be the most important future input in this area. It will rest upon methods that are not only accurate in the presence of realistic noise, but can be interpreted in a way that can be useful in the engineering field and are efficient enough to be implemented online, and tested on operationally representative three-phase micro-grid data.

6. Conclusion

This review has analyzed the literature on power quality disturbance detection and classification in micro-grid systems with the aim of revealing the most popular types of disturbances, the most popular methods of analysis, the most significant obstacles to real-world implementation, and the most promising areas of future research. The analyzed literature demonstrates that the most commonly studied classes of disturbances are voltage sags, swells, harmonics, interruptions, and transients, whereas relatively less systematic consideration is paid to the disturbances caused by compounds, three-phase disturbances, and operating-mode-dependent disturbances.

In the literature, the signal-processing techniques of wavelet transform, Stockwell transform, and other time-frequency techniques remain in the center stage since they offer physically realistic representations of signals to be used in disturbance analysis. Simultaneously, machine-learning, deep-learning, and hybrid frameworks are taking over recent research, as they have a greater multiclass discrimination capacity and can learn complicated nonlinear disturbance patterns. Specifically, CNN-, LSTM-, and ensemble-based models have demonstrated good classification capabilities with the help of appropriate feature representations and an adequate variety of datasets.Nevertheless, the comparative synthesis also shows that there are some limitations that are constant. Many of the published literature is based on simulated or highly controlled data, undermining faith in generalization to the real field. Performance is usually reported in terms of accuracy-based measures, and less systematically in terms of robustness to noise, computational complexity, interpretability, and the ability to deploy the system in real time. Moreover, most models are not adequately tested in three-phase operating conditions, disturbances by compounds, and topology or mode changes, which are typical of realistic micro-grids.

More accurate classifiers are not the most urgent research requirement, but the development of strong, understandable, computationally effective, and realistic micro-grid-scale monitoring systems. Further work in this direction will require the standard benchmark data, more attention to real-time and edge-compatible implementation, explainable AI mechanisms, and learning models that can be adjusted to various operating conditions.

In total, this review is a systematic review of the field, which links disturbance taxonomy, data analysis methods, data properties, and analysis limitations in a single framework. Its practical significance enables scientists and practitioners to establish what methodologically mature techniques are, what are experimentally constrained, and where additional effort is most needed to establish power quality monitoring of the contemporary micro-grid systems that is reliable and saleable.

Conflicts of Interest

The authors declare no conflict of interest.

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Table 4. Comparative review of representative techniques for power quality disturbance detection and classification

SN	Ref.	Year	Disturbance type(s)	Feature extraction/ representation	Classifier/ model	Dataset source	Synthetic/ real / hybrid	Single-phase / three-phase	Noise scenario	Metrics reported	Best result	Main limitation	Real-time suitability
01	[6]	2022	Multiple electrical PQ disturbances	DWT coefficients with statistical descriptors	ANN	Fabricated disturbance signals (200 samples)	Synthetic	NR	NR	Accuracy, confusion matrix	96% accuracy	Small fabricated dataset; feature unpredictability	Moderate
02	[10]	2021	Single and double PQ disturbances	Stockwell transform features	SVM	Modeled PQ disturbance signals	Synthetic	NR	NR	lassification accurac	High classification performance reported	Engineered -feature dependence	Moderate
03	[12]	2019	Online PQ disturbance detection	Smart-meter signal features	One-class SVM	Smart meter data	Real / online	NR	NR	Accuracy	89% accuracy	Limited multiclass flexibility; event overlap remains challenging	Promising
04	[16]	2022	PQ disturbances in SPV -integrated systems	CWT scalograms and deep image features	CNN + NCA + SVM	SPV-connected power system signals	Hybrid/ experimental	NR	NR	MSE, RMSE	MSE = 0.012; RMSE = 0.018	Complex acquisition and multi-stage pipeline	Moderate
05	[17]	2022	Islanding-related PQ anomaly / harmonic distortion	Voltage-current harmonic distortion sequences	Multi-LSTM	PCC measurements in a microgrid setting	Experimental / microgrid-oriented	NR	NR	Error/loss	Error loss = 0.06	Power mismatch may degrade performance	Promising

06	[36]	2021	PQ disturbance classes	Time-series coefficients	CNN-GRU	Synthetic disturbance data with noise levels	Synthetic	NR	Multiple noise levels	Accuracy, sensitivity, specificity, precision, F1-score	98.44% accuracy	Strong dependence on synthetic data	High (claimed)
07	[37]	2021	PQ disturbance classes	S-transform time-frequency signals	CNN	Continuous-time PQ signals	Synthetic / NR	NR	SNR-based analysis	Classification accuracy, SNR	High performance reported	Transform and network increase computational burden	Moderate
08	[38]	2021	Sag, swell, harmonics, flicker, PQI-related events	Voltage-based handcrafted features	Bagging and boosting methods	MATLAB/Simulink custom dataset	Synthetic	NR	NR	Sensitivity, specificity, accuracy, F1-score	~95–97% accuracy range	Simulation-heavy validation	Moderate
09	[42]	2022	Sag, swell, harmonics and related PQ classes	Visual attention-based signal representation	Attention-guided neural classifier	MATLAB/ Simulink	Synthetic	NR	NR	Accuracy, confusion matrix, ROC/AUC	99.8% accuracy	Data demand and high computational complexity	Moderate to low on edge platforms
10	[43]	2022	Automated PQ disturbance signals: sag/swell, THD, PF-related prediction	Temporal sequence features	Ensemble deep learning / LSTM-based framework	Indian distribution system data	Real	NR	Real operating data	RMSE, MAE, MAPE	RMSE = 0.012; MAE = 0.008; MAPE = 0.005	Limited interpretability; overfitting risk	Promising
11	[48]	2022	PQ disturbances in SOFC-PV-based DG	Hybrid feature-classifier pipeline	Hybrid machine-learning model	Distributed-generation setting	Hybrid	NR	High-noise scenario emphasized	Classification accuracy	High noise immunity reported	Tuning burden; deployment detail limited	Promising

NR: not clearly reported in the source study.