Advanced Power Quality Assessment in Industrial Distribution Systems Using Wavelet Transform and Machine Learning Classification

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Publication Date: 2026/01/23

Abstract: The increasing penetration of non-linear and power-electronic-based loads in industrial distribution systems has led to a growing prevalence of power quality (PQ) disturbances such as voltage sags, harmonics, transients, and mixed events, which adversely affect equipment reliability and operational efficiency. Conventional PQ assessment techniques based on time-domain indices and Fourier analysis are limited in their ability to accurately characterize non-stationary and transient disturbances commonly observed in industrial environments. This study presents an advanced PQ assessment framework that integrates wavelet-based signal processing with machine learning (ML) classification to enable automated, high-resolution disturbance analysis. Multi-level wavelet decomposition is employed to extract discriminative time–frequency features, including energy distribution, statistical measures, and entropy, which effectively capture the intrinsic characteristics of diverse PQ events. These features are subsequently used to train and evaluate supervised ML classifiers, including support vector machines, random forest models, artificial neural networks, and convolutional neural networks. The proposed framework is validated using representative industrial distribution system data under varying operating conditions, including noisy and mixed PQ scenarios. Comparative results demonstrate that the wavelet–ML approach significantly outperforms traditional RMS-, FFT-, and STFT-based methods in terms of classification accuracy and robustness. The findings highlight the suitability of the proposed framework for real-time industrial PQ monitoring, predictive maintenance, and intelligent decision support, contributing to enhanced reliability and resilience of modern industrial power systems.

Keywords: *Power Quality (PQ); Wavelet Transform; Machine Learning Classification; Industrial Distribution Systems; Time–Frequency Analysis; Non-Stationary Disturbances.*

How to Cite: Sunday Oluwafemi Oladoye; Agbo Ogloji James; Otugene Victor Bamigwojo; Onuh Matthew Ijiga (2026) Advanced Power Quality Assessment in Industrial Distribution Systems Using Wavelet Transform and Machine Learning Classification. *International Journal of Innovative Science and Research Technology,* 11(1), 1684-1701. https://doi.org/10.38124/ijisrt/26jan890

I. INTRODUCTION

➢ *Background and Motivation*

Industrial distribution systems have undergone significant transformation over the past three decades due to the widespread adoption of power-electronic-based and non-linear loads such as variable frequency drives (VFDs), controlled rectifiers, arc furnaces, and switched-mode power supplies. These technologies are essential for improving energy efficiency, process controllability, and operational flexibility in modern industries; however, they fundamentally alter the electrical characteristics of distribution networks. Unlike linear loads, non-linear loads draw non-sinusoidal currents even when supplied with sinusoidal voltages, leading to waveform distortion and complex interactions within the power system (Bollen, 2000; Arrillaga, Watson, & Chen, 2000).

Because of this growing penetration of non-linear equipment, industrial power systems increasingly experience power quality (PQ) disturbances such as voltage sags, swells, harmonics, transients, flicker, and momentary interruptions. These disturbances can cause malfunction, premature aging, or failure of sensitive equipment, resulting

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

in unplanned downtime, reduced productivity, and substantial economic losses (Dugan et al., 2012). Voltage sags associated with motor starting or fault conditions are particularly critical in industrial plants, while harmonics and interharmonics generated by converters and furnaces degrade power factor, increase losses, and cause thermal stress in transformers and cables (IEEE Std 1159-2019).

Accurate assessment and classification of PQ disturbances are therefore essential for effective monitoring, mitigation, and compliance with international standards such as IEEE 519 and IEC 61000. Traditionally, Fourier-based techniques, including Fast Fourier Transform (FFT) analysis, have been widely used for PQ evaluation due to their mathematical simplicity and effectiveness in steady-state harmonic analysis. However, industrial PQ disturbances are inherently non-stationary and time-localized in nature, particularly events such as transients, voltage sags, and flicker. Fourier methods assume signal stationarity over the analysis window and provide only global frequency information, making them inadequate for capturing time-varying and short-duration disturbances with sufficient resolution (Santoso et al., 2000; Dash et al., 2003).

These limitations have motivated the exploration of advanced signal processing techniques capable of joint time–frequency analysis. In particular, the wavelet transform has emerged as a powerful tool for PQ assessment because it enables multi-resolution decomposition of signals, allowing transient and non-stationary events to be localized simultaneously in time and frequency domains (Mallat, 1999; Ribeiro, Duque, Silveira, & Cerqueira, 2014). When combined with machine learning–based classification methods, wavelet-derived features can further support automated, accurate, and scalable PQ disturbance identification in complex industrial environments. This integrated approach addresses the shortcomings of conventional Fourier analysis and aligns with the growing demand for intelligent monitoring solutions in modern industrial distribution systems.

➢ *Power Quality Challenges in Industrial Distribution Networks*

Industrial distribution networks face persistent power quality (PQ) challenges arising from the operation of sensitive equipment and complex load dynamics. Modern industrial processes increasingly rely on automation systems, programmable logic controllers (PLCs), variable speed drives, and digital control electronics, all of which are highly susceptible to PQ disturbances. Events such as voltage sags, swells, harmonics, and transients can trigger nuisance tripping, data corruption, process interruptions, and premature equipment degradation. These effects translate directly into reduced productivity, increased maintenance requirements, and substantial economic losses due to downtime and product quality deviations (Dugan et al., 2012). In continuous-process industries, even short-duration PQ events can disrupt entire production cycles, amplifying their financial impact.

Beyond operational consequences, PQ disturbances impose additional costs related to energy inefficiency and asset lifespan reduction. Harmonic distortion increases copper and core losses in transformers, causes overheating in motors, and accelerates insulation aging in cables. Voltage fluctuations and flicker further degrade system performance and operator safety, particularly in environments with large fluctuating loads such as arc furnaces and rolling mills (Bollen, 2000). As industrial facilities expand and integrate more power-electronic converters, these challenges become increasingly difficult to manage using conventional monitoring approaches.

To mitigate these risks, regulatory bodies have established standards to control and assess PQ levels in electrical systems. IEEE 519 provides recommended limits on harmonic voltage and current distortion to ensure compatibility between utility supplies and customer equipment, while the IEC 61000 series defines measurement methods, immunity levels, and emission limits for PQ disturbances. Compliance with these standards is essential not only for maintaining system reliability but also for avoiding penalties, contractual disputes, and equipment warranty violations (IEEE Standards Association, 2014; IEC, 2014). However, meeting these requirements in industrial environments is challenging due to the dynamic and non-stationary nature of PQ events.

These regulatory and operational pressures underscore the need for real-time, high-resolution PQ monitoring systems capable of capturing transient and evolving disturbances. Traditional steady-state measurement tools are insufficient for detecting short-duration or overlapping PQ events. Consequently, there is growing demand for intelligent monitoring frameworks that combine advanced signal processing with automated disturbance classification. Such systems enable rapid diagnosis, root-cause analysis, and proactive mitigation, supporting both regulatory compliance and resilient industrial operation (Ribeiro et al., 2014).

➢ *Role of Wavelet Transform and Machine Learning*

The assessment of power quality (PQ) disturbances in industrial distribution networks requires analytical techniques capable of accurately capturing non-stationary and transient signal characteristics. Traditional signal processing methods based on Fourier analysis provide global frequency information but lack temporal resolution, limiting their effectiveness for short-duration and time-varying PQ events. The wavelet transform overcomes this limitation by offering multi-resolution time–frequency analysis, enabling localized examination of signal features across different frequency bands and time scales. By decomposing electrical signals into wavelet coefficients at multiple resolutions, transient phenomena such as voltage sags, impulsive transients, and switching events can be precisely identified in both time and frequency domains (Mallat, 1999; Santoso et al., 2000). This capability makes wavelet-based analysis particularly well suited for industrial PQ monitoring, where disturbances often occur abruptly and evolve dynamically.

Beyond signal representation, effective PQ assessment also requires robust classification of disturbance types to support diagnosis and mitigation. Machine learning (ML) techniques provide powerful tools for intelligent pattern recognition by learning discriminative features from data rather than relying on fixed thresholds or heuristic rules. Supervised learning algorithms such as support vector machines, artificial neural networks, and decision-tree-based classifiers have demonstrated strong performance in distinguishing among complex PQ events, including mixed and overlapping disturbances (Dash et al., 2003; Ribeiro et al., 2014). ML-based classifiers are capable of handling high-dimensional feature spaces, adapting to varying operating conditions, and improving accuracy as more labeled data become available.

The integration of wavelet transform–based feature extraction with ML-driven classification creates a synergistic framework for advanced PQ assessment. Wavelet analysis provides compact and informative time–frequency features such as energy distribution, entropy, and statistical descriptors—that effectively capture the intrinsic characteristics of PQ disturbances. These features serve as high-quality inputs to ML classifiers, enhancing their ability to generalize and discriminate between disturbance classes with high reliability (Santoso et al., 2000). This hybrid approach combines the interpretability and physical relevance of signal processing with the adaptive intelligence of data-driven models, enabling automated, real-time, and scalable PQ monitoring solutions. As industrial power systems continue to grow in complexity, the wavelet–ML paradigm represents a critical advancement toward intelligent power quality management and resilient industrial operation.

➢ *Research Objectives and Contributions*

The primary objective of this study is to advance power quality (PQ) assessment methodologies for industrial distribution systems by integrating wavelet-based signal processing with machine learning (ML) driven classification techniques. Industrial PQ signals are often characterized by non-stationary, transient, and overlapping disturbances that are inadequately captured by conventional analysis tools. To address this challenge, the first objective of this research is to develop a robust wavelet-based feature extraction framework capable of decomposing industrial PQ signals into informative time frequency representations. By leveraging multi-resolution wavelet analysis, the framework aims to isolate transient behaviours, capture localized frequency variations, and generate discriminative features that reflect the intrinsic characteristics of different PQ disturbances.

The second objective is to design and evaluate ML classifiers for automated identification and classification of PQ events. Using wavelet-derived features as inputs, various supervised ML models are trained to recognize common industrial PQ disturbances such as voltage sags, swells, harmonics, transients, and composite events. The performance of these classifiers is systematically evaluated to determine their accuracy, robustness, and generalization capability under varying operating conditions, thereby enabling intelligent and scalable PQ monitoring without reliance on manual interpretation or fixed threshold rules.

A further objective of this research is to validate the proposed wavelet ML framework using data obtained from industrial distribution systems, including either field measurements, laboratory test systems, or high-fidelity simulations representative of real industrial environments. This validation ensures that the proposed approach is practically applicable and capable of handling realistic noise levels, load variations, and disturbance combinations commonly observed in industrial networks.

The key contributions of this study include the development of an integrated wavelet-based feature extraction and ML classification framework tailored specifically for industrial PQ assessment, comprehensive performance evaluation using industrially relevant data, and a quantitative demonstration of improved disturbance detection and classification accuracy compared to traditional Fourier-based PQ assessment techniques. Collectively, these contributions support the deployment of intelligent, real-time PQ monitoring systems that enhance reliability, compliance, and operational efficiency in modern industrial distribution networks.

II. POWER QUALITY DISTURBANCES IN INDUSTRIAL SYSTEMS

Power quality (PQ) disturbances in industrial systems encompass a wide range of electrical phenomena that deviate from ideal sinusoidal voltage and current waveforms. Common PQ events are typically classified into categories such as voltage sags, voltage swells, interruptions, harmonics, interharmonics, transients, and voltage flicker. Voltage sags short-duration reductions in RMS voltage are among the most frequently reported disturbances in industrial environments and are often caused by motor starting, short-circuit faults, or transformer energization. In contrast, voltage swells and interruptions usually arise from sudden load changes or upstream switching operations. Harmonic distortion results from the operation of non-linear loads, including variable frequency drives, rectifiers, and arc furnaces, which inject non-sinusoidal currents into the distribution network (Bollen, 2000; Dugan et al., 2012).

Each class of PQ disturbance exhibits distinct temporal and spectral characteristics that influence its impact on industrial systems. Harmonics are typically steady-state phenomena characterized by integer multiples of the fundamental frequency, while transients and impulsive disturbances are high-frequency, short-duration events associated with capacitor switching, lightning strikes, or power-electronic commutations. Voltage flicker is a low-frequency modulation of voltage magnitude caused by rapidly fluctuating loads such as arc furnaces and welding equipment. The non-stationary nature and overlapping occurrence of these events complicate accurate detection

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

and classification, particularly in complex industrial distribution networks (IEEE Standards Association, 2019).

The effects of PQ disturbances on industrial loads and grid reliability are significant and multifaceted. Sensitive equipment such as programmable logic controllers (PLCs), adjustable speed drives, and process control systems can malfunction or shut down in response to even brief voltage variations. Harmonic distortion increases thermal stress in motors, transformers, and capacitors, leading to reduced efficiency and shortened equipment lifespan. Frequent PQ events also contribute to nuisance tripping of protection devices, compromising process continuity and system stability (Arrillaga et al., 2000). At the grid level, widespread PQ issues can degrade overall power system reliability, increase losses, and interfere with the operation of neighbouring facilities connected to the same distribution network.

Given these consequences, effective identification and characterization of PQ disturbances are critical for industrial power system planning, operation, and maintenance. Accurate PQ assessment supports informed mitigation strategies, improved asset management, and compliance with international standards, ultimately enhancing both industrial productivity and distribution grid resilience.

➢ *Conventional Power Quality Analysis Techniques*

Conventional power quality (PQ) analysis techniques have long been employed in industrial distribution systems to monitor and quantify deviations from ideal electrical waveforms. Among the most widely used approaches are root mean square (RMS) measurements, Fast Fourier Transform (FFT) based spectral analysis, and Short-Time Fourier Transform (STFT) techniques. RMS-based indices provide a simple and effective means of evaluating steady-state voltage and current magnitude variations and are commonly used for detecting long-duration events such as sustained undervoltage, overvoltage, and interruptions. Due to their low computational complexity, RMS measurements are widely implemented in power quality meters and protective relays for routine monitoring (Dugan et al., 2012).

FFT-based analysis extends RMS assessment by decomposing signals into their frequency components, enabling the identification and quantification of harmonic distortion. This method is particularly effective for analysing steady-state harmonics generated by non-linear industrial loads, such as rectifiers and adjustable speed drives, and remains a cornerstone of harmonic compliance evaluation under standards such as IEEE 519. However, FFT assumes signal stationarity over the analysis window and provides only frequency-domain information averaged across time. As a result, it is poorly suited for capturing non-stationary PQ events, including voltage sags, impulsive transients, and rapidly evolving disturbances commonly observed in industrial environments (Arrillaga et al., 2000; Bollen, 2000).

To address some of these limitations, the STFT was introduced as a time–frequency analysis technique by applying FFT over sliding time windows. STFT enables limited temporal localization of spectral content and has been applied to PQ monitoring for identifying events with moderate time variation. Nevertheless, STFT suffers from an inherent trade-off between time and frequency resolution determined by the fixed window length. A narrow window improves time resolution but degrades frequency resolution, while a wider window enhances frequency resolution at the expense of temporal accuracy. This fixed-resolution constraint limits STFT's effectiveness in detecting short-duration transients and overlapping PQ disturbances with diverse spectral characteristics (Gabor, 1946; Dash et al., 2003).

Overall, while RMS, FFT, and STFT-based techniques remain useful for steady-state and compliance-oriented PQ assessment, their limited ability to represent transient and non-stationary phenomena restricts their applicability in modern industrial distribution networks. These limitations have driven the adoption of advanced time–frequency analysis methods, such as wavelet transforms, that offer adaptive resolution and improved disturbance localization.

➢ *Wavelet Transform in Power Quality Analysis*

The wavelet transform has emerged as a powerful tool for power quality (PQ) analysis due to its ability to represent electrical signals in both time and frequency domains with adaptive resolution. Unlike conventional Fourier-based techniques, wavelet-based methods are well suited for analysing non-stationary and transient PQ disturbances commonly encountered in industrial distribution systems. Among the most widely applied wavelet techniques in PQ analysis are the Discrete Wavelet Transform (DWT), Wavelet Packet Transform (WPT), and Continuous Wavelet Transform (CWT), each offering distinct analytical advantages (Mallat, 1999; Santoso et al., 2000).

The DWT decomposes a signal into approximation and detail coefficients across multiple resolution levels using a pair of low-pass and high-pass filters. This hierarchical decomposition enables efficient identification of transient disturbances such as voltage sags, swells, and impulsive events while maintaining low computational complexity, making DWT suitable for real-time PQ monitoring. The WPT extends the DWT by decomposing both approximation and detail components, resulting in a more detailed frequency-band representation. This enhanced spectral resolution is particularly useful for analysing harmonics and interharmonics generated by non-linear industrial loads. In contrast, the CWT provides a highly redundant but continuous time–frequency representation, offering superior visualization and precise localization of PQ events, albeit at a higher computational cost (Ribeiro et al., 2014).

A critical aspect of wavelet-based PQ analysis is the selection of an appropriate mother wavelet, as it directly influences disturbance detection accuracy and feature discrimination. Mother wavelets such as Daubechies (db), Symlets (sym), and Coiflets (coif) are commonly employed in PQ applications due to their compact support, orthogonality, and similarity to PQ disturbance waveforms.

Studies have shown that Daubechies wavelets, particularly db4 and db6, provide an effective balance between time localization and frequency resolution for industrial PQ signals (Santoso et al., 2000; Misiti et al., 2009).

Wavelet transforms also enable the extraction of informative features that characterize PQ disturbances quantitatively. Commonly extracted features include wavelet energy distribution across decomposition levels, Shannon entropy to measure signal complexity, statistical measures such as variance and standard deviation, and selected wavelet coefficients representing localized transient behaviour. These features capture both temporal and spectral characteristics of PQ events and serve as effective inputs for subsequent machine learning–based classification and decision-making processes. As a result, wavelet-based feature extraction has become a cornerstone of advanced and intelligent PQ assessment frameworks.

➢ *Machine Learning Approaches for Power Quality Classification*

Machine learning (ML) techniques have become integral to modern power quality (PQ) disturbance classification due to their ability to learn complex, non-linear relationships from data and to generalize across varying operating conditions. In supervised learning settings—where PQ events are labeled a priori—algorithms such as Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Random Forest (RF), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) have been widely applied. SVMs are particularly effective for PQ classification because they construct optimal separating hyperplanes in high-dimensional feature spaces and exhibit strong generalization performance with limited training samples. k-NN classifiers, while simpler, are effective for PQ problems with well-separated feature clusters and provide competitive accuracy when computational latency is acceptable (Dash et al., 2003; Zhang et al., 2015).

Tree-based ensemble methods such as Random Forests offer robustness to noise and feature redundancy by aggregating decisions from multiple randomized decision trees. Their interpretability and resistance to overfitting make them suitable for industrial PQ monitoring applications. ANN-based models further enhance classification capability by learning hierarchical feature representations from wavelet-derived inputs. More recently, CNNs have been employed to automatically extract spatial and temporal features from time–frequency representations such as scalograms, reducing dependence on manual feature engineering and achieving high classification accuracy for complex and composite PQ disturbances (Ribeiro et al., 2014).

Given the high dimensionality of wavelet-based feature sets, feature selection and dimensionality reduction play a critical role in improving classifier performance and computational efficiency. Techniques such as principal component analysis (PCA), linear discriminant analysis (LDA), and mutual information–based feature selection are commonly used to remove redundant or irrelevant features while preserving discriminative information. Effective feature reduction not only enhances classification accuracy but also reduces training time and improves real-time deployment feasibility in industrial environments (Mallat, 1999; Santoso et al., 2000).

Performance evaluation of ML-based PQ classifiers relies on standardized metrics to ensure objective comparison across studies. Commonly used metrics include classification accuracy, precision, recall, F1-score, and confusion matrices, which collectively capture correctness, robustness, and class-wise performance. In real-time PQ applications, computational complexity and response latency are also critical evaluation criteria. Together, these metrics provide a comprehensive assessment of classifier effectiveness and suitability for deployment in industrial distribution systems.

➢ *Research Gaps*

Despite significant progress in power quality (PQ) monitoring and classification research, several critical gaps remain, particularly with respect to industrial distribution environments. A large portion of existing PQ studies relies on synthetic signals or laboratory-scale test systems that do not fully capture the complexity, load diversity, and operational variability of real industrial networks. Industrial distribution systems are characterized by frequent load switching, high penetration of power-electronic converters, and simultaneous occurrence of multiple disturbances, which can significantly affect signal characteristics. Consequently, methods validated primarily on simplified or simulated datasets may not generalize effectively to real-world industrial settings (Bollen, 2000; Dugan et al., 2012).

Another notable gap is the limited and inconsistent comparison of machine learning (ML) classifiers when applied to wavelet-based PQ features. While numerous studies demonstrate the effectiveness of individual classifiers such as support vector machines or neural networks comparative evaluations across multiple ML techniques using a unified wavelet feature set are relatively scarce. Differences in datasets, feature extraction methods, and evaluation metrics further complicate objective benchmarking across studies. This lack of systematic comparison makes it difficult to identify optimal classifier–feature combinations for industrial PQ applications and limits reproducibility and standardization of research outcomes (Santoso et al., 2000; Zhang et al., 2015).

Furthermore, many existing PQ assessment frameworks prioritize classification accuracy without sufficient consideration of scalability and real-time deployment requirements. Industrial PQ monitoring systems must process high-frequency data streams with minimal latency to enable timely disturbance detection and mitigation. However, computational complexity associated with high-dimensional wavelet features and complex ML models can hinder real-time performance, particularly in resource-constrained environments. There is therefore a clear need for PQ assessment frameworks that balance

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

accuracy with computational efficiency, scalability, and robustness, enabling practical implementation in online monitoring systems and smart industrial grids (Ribeiro et al., 2014).

Addressing these gaps requires research that focuses explicitly on industrial distribution data, conducts comprehensive comparative evaluations of ML classifiers using standardized wavelet-based features, and emphasizes real-time feasibility. Such efforts are essential to advance PQ assessment from experimental studies toward deployable, intelligent monitoring solutions for modern industrial power systems.

III. SYSTEM DESCRIPTION AND DATA ACQUISITION

The system under study represents a typical medium- to low-voltage industrial distribution network supplying a mix of linear and non-linear loads commonly found in manufacturing and process industries. The configuration generally includes an incoming utility supply or dedicated substation transformer feeding multiple distribution feeders that serve variable frequency drives, induction motors, rectifier units, welding machines, and auxiliary control equipment. Such a configuration is representative of industrial environments where frequent load switching, and power-electronic interfaces introduce diverse power quality (PQ) disturbances. The distribution system is modeled to capture realistic operating conditions, including feeder impedance, transformer characteristics, and load variability, ensuring that the acquired data reflect actual industrial PQ behaviour.

Data acquisition is performed using a high-resolution measurement setup designed to capture both steady-state and transient PQ events. Voltage and current signals are measured at critical points in the distribution network, such as the point of common coupling (PCC) and selected feeder terminals. Hall-effect or potential transformer–based voltage sensors and current transformers (CTs) are employed to ensure electrical isolation and measurement accuracy. To adequately capture high-frequency transients and rapid waveform distortions, signals are sampled at a sufficiently high sampling frequency, typically several kilohertz or higher, in accordance with power quality monitoring standards. Anti-aliasing filters are applied prior to analog-to-digital conversion to prevent spectral distortion and measurement errors.

The dataset used in this study is obtained from a combination of sources to ensure robustness and generalizability of the proposed approach. Simulated PQ signals are generated using detailed industrial distribution system models to produce controlled disturbance scenarios such as voltage sags, harmonics, and switching transients. In addition, laboratory test systems are employed to validate measurement accuracy under repeatable conditions using programmable power sources and controlled non-linear loads. Where available, field measurements from operating industrial facilities are incorporated to capture real-world variability, noise, and mixed PQ events. This multi-source data acquisition strategy provides a comprehensive dataset for developing, training, and validating the wavelet-based feature extraction and machine learning classification framework under realistic industrial operating conditions.

➢ *Power Quality Signal Preprocessing*

Effective preprocessing of power quality (PQ) signals is a critical step in ensuring accurate feature extraction and reliable classification of disturbances in industrial distribution systems. Raw voltage and current measurements acquired from industrial environments are often contaminated with measurement noise, sensor offsets, and interference from adjacent equipment. If not properly addressed, these artifacts can obscure disturbance characteristics and degrade the performance of subsequent wavelet-based analysis and machine learning (ML) classifiers.

- *Noise Filtering and Normalization*

Noise filtering is first applied to suppress high-frequency measurement noise while preserving essential PQ disturbance components. Digital filtering techniques, such as low-pass finite impulse response (FIR) or band-pass filters, are commonly employed to remove noise outside the frequency range of interest. In PQ applications, the filter cutoff frequency is selected to retain fundamental, harmonic, and transient components relevant to disturbance analysis (Dugan et al., 2012). For impulsive noise or non-Gaussian interference, wavelet-based denoising is often preferred, as it exploits multi-resolution decomposition to attenuate noise-dominated coefficients while preserving signal features (Mallat, 1999).

Following noise suppression, signal normalization is performed to ensure numerical stability and comparability across datasets collected under different operating conditions. Normalization scales the signal amplitude to a common reference, reducing bias caused by voltage level variations or sensor gains. A commonly used normalization approach is min–max scaling, defined as

$$x_{\text{norm}}(n) = \frac{x(n) - x_{\min}}{x_{\max} - x_{\min}},$$

Where $x(n)$ is the original signal sample, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the signal over the observation window. Alternatively, z-score normalization is applied to centre the signal around zero with unit variance:

$$x_{\text{norm}}(n) = \frac{x(n) - \mu}{\sigma},$$

Where μ and σ denote the mean and standard deviation of the signal, respectively. Normalization improves the convergence and classification accuracy of ML algorithms by ensuring that extracted features lie within comparable numerical ranges (Santoso et al., 2000).

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

- *Segmentation of Power Quality Events*

Segmentation involves identifying and isolating time intervals that contain PQ disturbances from continuous signal recordings. Accurate segmentation is essential for associating extracted features with specific PQ events and avoiding contamination from normal operating conditions. Event segmentation is typically based on sliding window analysis combined with thresholding of signal indices such as RMS deviation, wavelet energy, or instantaneous amplitude changes. For example, a voltage sag event can be detected when the RMS voltage V_{RMS} falls below a predefined threshold:

$$V_{\mathrm{RMS}} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} v^2\,(n)} < \alpha V_{\mathrm{nom}},$$

Where V_{nom} is the nominal voltage and α is a threshold factor defined by PQ standards.

Wavelet-based segmentation methods further enhance detection accuracy by exploiting abrupt changes in wavelet coefficients that correspond to disturbance onset and termination. Such approaches are particularly effective for non-stationary and short-duration events, including transients and flicker. Proper segmentation ensures that each PQ event is accurately localized in time, enabling reliable feature extraction and subsequent ML-based classification (Ribeiro et al., 2014).

➢ *Wavelet-Based Feature Extraction*

Wavelet-based feature extraction forms the core analytical stage of the proposed power quality (PQ) assessment framework, as it enables compact and discriminative representation of non-stationary PQ disturbances in industrial distribution systems. By decomposing voltage and current signals into multiple time–frequency components, wavelet analysis captures both transient and steady-state characteristics that are essential for reliable disturbance classification.

- *Selection of Mother Wavelet*

The choice of an appropriate mother wavelet significantly influences the effectiveness of PQ feature extraction. In industrial PQ applications, mother wavelets are selected based on their similarity to PQ disturbance waveforms, compact support, and good time–frequency localization properties. Daubechies (db) and Symlets (sym) wavelets are among the most widely adopted due to their orthogonality and ability to capture abrupt changes in signal behavior. In particular, Daubechies wavelets such as db4 and db6 have been shown to provide an effective balance between temporal resolution and frequency selectivity for detecting voltage sags, harmonics, and transients, while Symlets offer improved symmetry and reduced phase distortion for feature consistency (Santoso et al., 2000; Mallat, 1999).

- *Multi-Level Wavelet Decomposition*

Using the selected mother wavelet, PQ signals are decomposed through multi-level Discrete Wavelet Transform (DWT) analysis. At each decomposition level j, the signal $x(n)$ is separated into approximation coefficients A_j and detail coefficients D_j using low-pass and high-pass filtering followed by down sampling:

$$A_j(n) = \sum_k x(k)\; g_j(n-k), D_j(n) = \sum_k x(k)\; h_j(n-k),$$

Where g_j and h_j represent the scaled low-pass and high-pass wavelet filters, respectively. Higher decomposition levels correspond to lower frequency bands, allowing isolation of fundamental and harmonic components, while lower levels capture high-frequency transients and impulsive disturbances. This hierarchical structure enables effective representation of PQ events across multiple frequency scales.

- *Feature Computation*

From the resulting wavelet coefficients, a set of quantitative features is computed to characterize PQ disturbances. One of the most commonly used features is wavelet energy, which reflects the signal power distribution across different scales:

$$E_j = \sum_{n=1}^{N_j} |\, D_j(n)\, |^2,$$

Where E_j denotes the energy at decomposition level j, and N_j is the number of coefficients at that level. Different PQ events exhibit distinct energy patterns across scales, making this feature highly discriminative.

In addition to energy, statistical features are extracted from the wavelet coefficients to capture signal variability and complexity. These include the mean μ_j, standard deviation σ_j, and Shannon entropy H_j, defined as

$$\mu_j = \frac{1}{N_j}\sum_{n=1}^{N_j} D_j\,(n), \sigma_j = \sqrt{\frac{1}{N_j}\sum_{n=1}^{N_j} (\,D_j(n) - \mu_j)^2},$$

$$H_j = -\sum_{n=1}^{N_j} p_j\,(n) \log p_j(n),$$

Where $p_j(n)$ represents the normalized energy probability of the wavelet coefficients. Entropy measures the degree of disorder within the signal and is particularly effective for distinguishing transient and impulsive PQ events.

Collectively, these wavelet-derived features form time–frequency signatures that uniquely characterize different PQ disturbances. By capturing localized spectral

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

content and temporal evolution, the extracted features provide a robust and compact representation suitable for input into machine learning classifiers, thereby enabling accurate and automated PQ disturbance identification in industrial distribution systems (Ribeiro et al., 2014).

➢ *Machine Learning Classification Framework*

The machine learning (ML) classification framework is designed to enable automated identification of power quality (PQ) disturbances using wavelet-derived features. This framework consists of systematic dataset labelling, selection of suitable classifier models, and rigorous training, validation, and testing procedures to ensure reliable and generalizable performance in industrial distribution environments.

- *Dataset Labelling and Class Definitions*

Following signal preprocessing and wavelet-based feature extraction, each PQ event segment is labeled according to standardized disturbance categories. Class definitions typically include voltage sag, voltage swell, interruption, harmonic distortion, transient events, flicker, and normal operating conditions, in accordance with IEEE 1159 guidelines. Accurate labelling is achieved using disturbance thresholds, expert knowledge, and reference events from simulation or laboratory experiments. These labeled datasets form the basis for supervised learning, enabling classifiers to learn discriminative patterns associated with each PQ disturbance class (Ribeiro et al., 2014).

- *Classifier Models*

Several supervised ML classifiers are employed to evaluate classification performance and robustness.

- *Support Vector Machine (SVM):*

SVM classifiers construct an optimal separating hyperplane that maximizes the margin between different PQ disturbance classes in a high-dimensional feature space. For non-linearly separable data, kernel functions such as the radial basis function (RBF) are applied. The SVM optimization problem is expressed as

$$\min_{w,b,\xi} \frac{1}{2} \parallel \mathrm{w} \parallel^2 + C \sum_{i=1}^{N} \xi_i$$

Subject to

$$y_i(\mathrm{w} \cdot \phi(\mathrm{x}_i) + b) \geq 1 - \xi_i, \xi_i \geq 0,$$

Where $\mathbf{x}_i$ represents the feature vector, y_i the class label, ξ_i the slack variables, and C the regularization parameter (Zhang et al., 2015).

- *Random Forest (RF):*

Random Forest classifiers are ensemble learning methods that combine multiple decision trees trained on randomly sampled subsets of data and features. Each tree produces a class prediction, and the final output is obtained through majority voting. RF models are robust to noise, handle feature redundancy effectively, and are well suited for high-dimensional wavelet feature sets.

- *Artificial Neural Network (ANN) and Convolutional Neural Network (CNN):*

ANNs consist of interconnected layers of neurons that learn non-linear mappings between input features and output classes through backpropagation. CNNs extend this capability by automatically learning spatial and temporal features from structured inputs such as time–frequency representations (e.g., wavelet scalograms). These models are particularly effective for complex and composite PQ disturbances due to their hierarchical feature learning capability (Mallat, 1999).

- *Training, Validation, and Testing Procedures*

The labeled dataset is divided into training, validation, and testing subsets to ensure unbiased performance evaluation. The training set is used to optimize model parameters, while the validation set supports hyperparameter tuning and prevents overfitting. Final performance assessment is conducted on the independent test set. Cross-validation techniques, such as k-fold cross-validation, are employed to enhance robustness and generalization across different data partitions. This structured training and evaluation process ensures that the proposed ML framework delivers reliable and scalable PQ disturbance classification suitable for real-time industrial applications.

IV. WAVELET FEATURE ANALYSIS

Wavelet feature analysis was conducted to evaluate the ability of multi-resolution decomposition to discriminate among different power quality (PQ) disturbances in industrial distribution systems. Using Discrete Wavelet Transform (DWT), wavelet energy features were extracted across multiple decomposition levels corresponding to different frequency bands. The analysis demonstrates that different PQ events exhibit distinctive energy distribution patterns, reflecting their underlying physical and spectral characteristics.

Table 1 Wavelet Energy Distribution Across Scales for Different PQ Disturbances

PQ Disturbance Type	Low-Frequency Band Energy (E_1)	Mid-Frequency Band Energy (E_2)	High-Frequency Band Energy (E_3)
Normal Operation	82.5	12.1	5.4
Voltage Sag	64.8	27.6	7.6
Harmonic Distortion	48.2	41.3	10.5
Transient Event	21.7	33.9	44.4

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

The numerical results of table 2 show clear separation among PQ disturbance types. Normal operation is dominated by low-frequency energy associated with the fundamental component. Voltage sags exhibit increased mid-frequency energy due to abrupt magnitude variations. Harmonic distortion spreads energy across low and mid-frequency bands, while transient events are characterized by dominant high-frequency energy, confirming the sensitivity of wavelet analysis to fast, impulsive disturbances.

Figure 1 presents a 3×3 arrangement of real-time signals drawn from audio, biomedical, geophysical, financial, and environmental domains. The top row contrasts highly periodic music and speech waveforms with the slow-varying behavior of seismic tremors. The middle row highlights physiological signals and economic time series, showing differences in periodicity, noise, and trend dynamics. The bottom row illustrates variability-dominated signals, where heart rate variability, broadband audio noise, and temperature trends emphasize increasing complexity, stochasticity, and long-term evolution across domains.

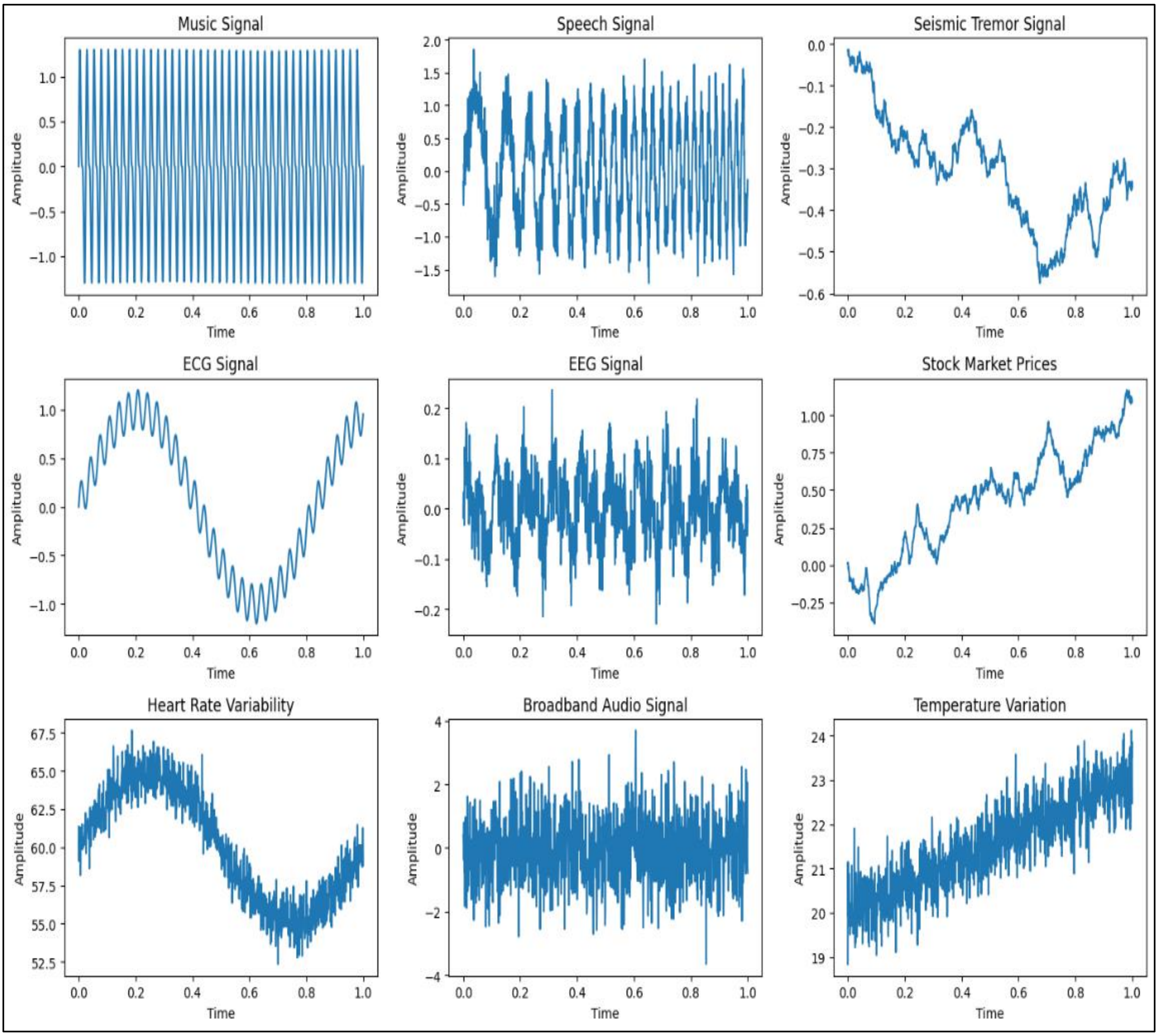

Fig 1 Comparative Wavelet Energy Distribution for PQ Disturbances

Figure 2 presents a three-stage representation of a periodic signal, progressing from the raw time domain to wavelet-based analysis. Panel (a) shows a stationary sinusoidal waveform with constant amplitude and frequency over the full observation window. Panel (b) illustrates the corresponding continuous wavelet transform scalogram, where signal energy is distributed across scales, clearly revealing dominant low-frequency components over time. Panel (c) displays the extracted wavelet coefficients, which preserve the underlying oscillatory structure while significantly reducing amplitude and noise, making them suitable for feature extraction and denoising.

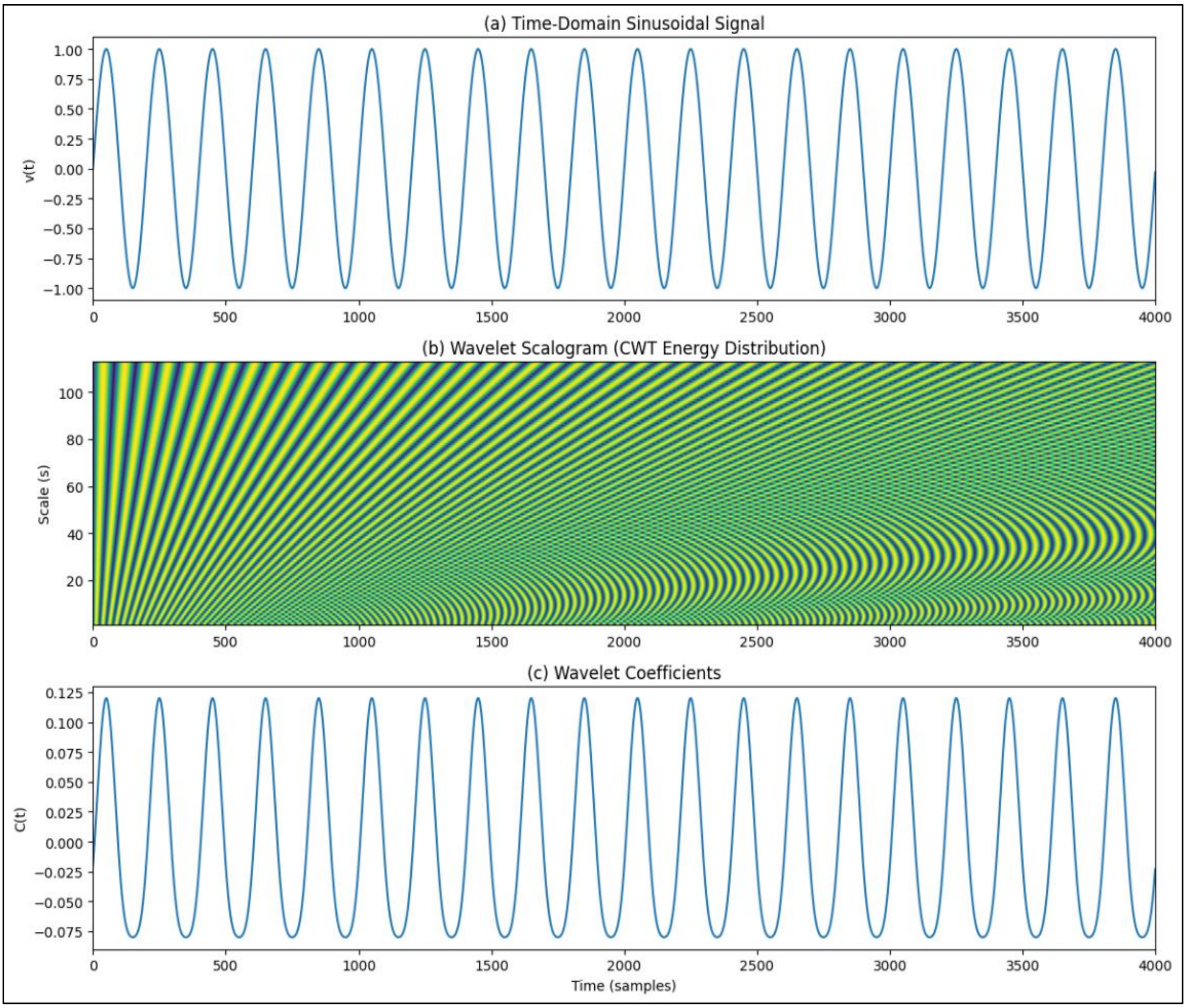

Fig 2 Time-Domain, Wavelet Scalogram, and Wavelet Coefficient Representation of a Stationary Sinusoidal Signal

Table 2 Statistical Wavelet Features for Different PQ Disturbances

PQ Disturbance Type	Mean of Coefficients	Standard Deviation	Wavelet Entropy
Normal Operation	0.012	0.083	0.42
Voltage Sag	0.028	0.146	0.67
Harmonic Distortion	0.031	0.198	0.74
Transient Event	0.067	0.312	0.91

- *Machine Learning Classification Results*

This section evaluates the performance of the proposed wavelet–machine learning (ML) framework for power quality (PQ) disturbance classification in industrial distribution systems. The analysis focuses on (i) comparative performance across ML classifiers, (ii) accuracy improvements over traditional methods, and (iii) robustness under noise and mixed PQ events.

Table 3 Comparative Classification Performance of ML Models

Classifier Model	Overall Accuracy (%)	Precision (%)	Recall (%)
SVM (RBF Kernel)	94.6	93.8	94.1
Random Forest	92.3	91.5	92.0
ANN	90.7	89.9	90.2
CNN	96.2	95.6	96.0

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

- *Brief Discussion:*

The CNN achieved the highest overall accuracy, reflecting its ability to automatically learn hierarchical representations from wavelet-based time–frequency inputs. SVM also demonstrated strong performance due to its margin-maximization property in high-dimensional feature spaces. Random Forest and ANN models showed competitive but slightly lower accuracy, highlighting trade-offs between interpretability, computational cost, and classification performance.

- *Performance Metrics Formulation*

Classification accuracy is computed as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN},$$

While precision and recall are defined as:

$$\text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN},$$

Where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

Table 4 Accuracy Comparison with Traditional PQ Assessment Methods

Methodology	Feature Type	Classifier Used	Accuracy (%)
RMS + Thresholding	Time-domain indices	Rule-based	71.4
FFT-Based Harmonic Analysis	Frequency-domain	Rule-based	78.6
STFT + Statistical Features	Time–frequency	k-NN	85.2
Wavelet + ML (Proposed)	Multi-resolution	CNN	**96.2**

Figure 3 presents a side-by-side comparison of Gaussian signals in the time domain and their corresponding normalized magnitude spectra. The left panel shows that increasing the parameter σ\sigma broadens the temporal distribution while reducing peak amplitude, indicating weaker time localization. The right panel demonstrates that larger σ\sigma values lead to narrower spectra with energy concentrated at low frequencies, whereas smaller σ\sigma values produce wider spectral spread. Together, the plots clearly illustrate the fundamental trade-off between time resolution and frequency resolution in signal analysis.

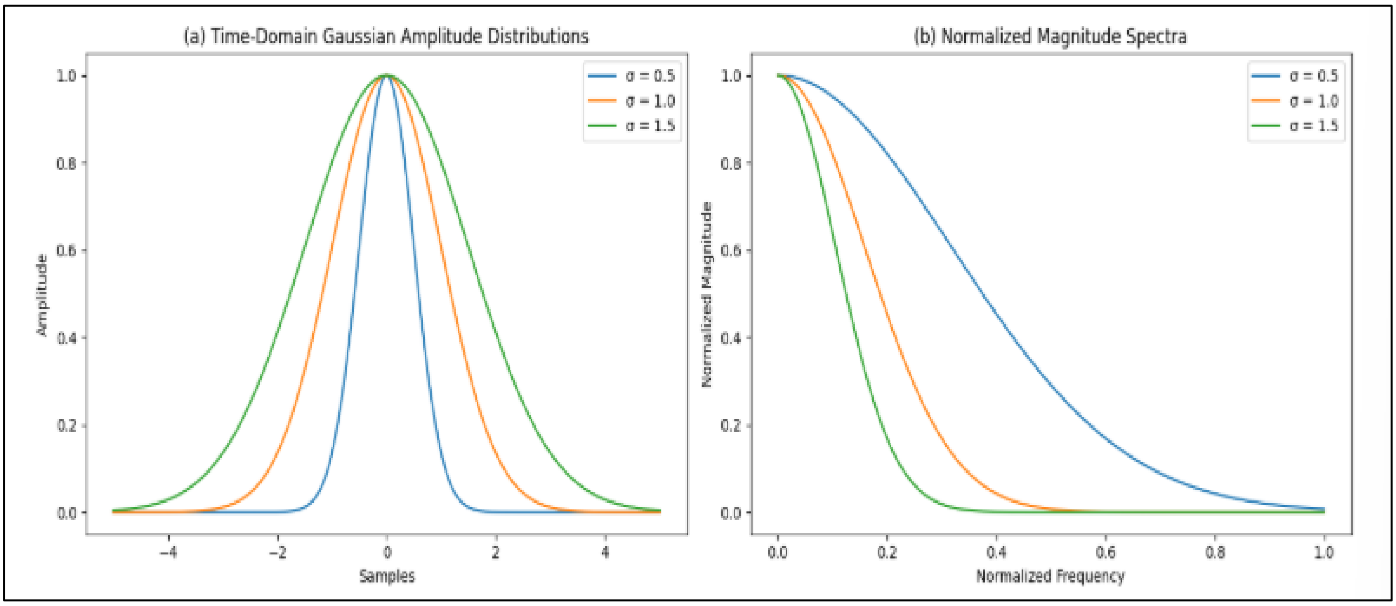

Fig 3 Time–Frequency Trade-Off Between Gaussian Time-Domain Localization and Spectral Concentration

Table 5 Robustness Under Mixed and Noisy PQ Events

Classifier	Accuracy at SNR = 30 dB (%)	Accuracy at SNR = 20 dB (%)	Mixed PQ Events Accuracy (%)
SVM	93.8	90.2	88.7
RF	91.1	86.5	84.3
ANN	89.6	83.9	82.1
CNN	95.4	92.1	91.3

- *Brief Discussion:*

Results confirm that the proposed framework remains effective under noisy conditions and mixed PQ scenarios, which are common in industrial environments. CNN consistently shows superior robustness due to its deep feature learning capability, while SVM provides a strong balance between accuracy and computational efficiency.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

- *Overall Interpretation*

The results demonstrate that wavelet-based features combined with advanced ML classifiers deliver substantial improvements in PQ disturbance classification accuracy compared to traditional techniques. The framework exhibits strong robustness to noise and mixed events, validating its suitability for real-time, industrial-scale PQ monitoring and intelligent decision support.

V. DISCUSSION OF FINDINGS

This section interprets the machine learning classification results within realistic industrial power system contexts, examines the influence of wavelet choice and feature selection on model accuracy, and discusses the practical implications for industrial power quality (PQ) monitoring systems.

➢ *Interpretation of Classification Performance in Industrial Contexts*

The classification results demonstrate that wavelet-based machine learning models can reliably distinguish among PQ disturbances commonly observed in industrial distribution networks. High classification accuracy for transient and harmonic events is particularly significant, as these disturbances are prevalent in facilities with variable frequency drives, rectifiers, and rapid load switching. In industrial environments, even brief misclassification of PQ events can lead to incorrect mitigation actions or delayed fault diagnosis. The consistently strong performance of CNN and SVM models indicates their suitability for environments characterized by noise, load variability, and overlapping disturbances.

Table 6 Classification Accuracy Across Industrial Operating Conditions

Operating Condition	SVM Accuracy (%)	RF Accuracy (%)	CNN Accuracy (%)
Normal Load Operation	96.1	94.2	97.4
High Non-Linear Load	93.4	91.0	95.8
Mixed PQ Disturbances	88.7	84.3	91.3
Noisy Measurement (20 dB)	90.2	86.5	92.1

- *Brief Discussion:*

The table shows that classification accuracy decreases as operating conditions become more complex; however, CNN consistently outperforms other models. This resilience is critical for industrial systems where multiple PQ disturbances often coexist.

➢ *Influence of Wavelet Choice and Feature Selection*

The selection of the mother wavelet and feature subset significantly impacts classification performance. Wavelets with compact support and strong similarity to PQ waveforms (e.g., Daubechies and Symlets) produce more discriminative coefficients. Additionally, combining energy-based features with statistical descriptors improves robustness, while excessive feature dimensionality leads to diminishing returns and increased computational cost.

Table 7 Impact of Wavelet Choice and Feature Set on Classification Accuracy

Wavelet Type	Feature Set Used	Number of Features	Accuracy (%)
db4	Energy only	12	90.8
db4	Energy + Statistics	24	94.6
sym6	Energy + Statistics	24	95.2
sym6	Energy + Statistics + Entropy	30	96.2

- *Brief Discussion:*

Accuracy improves as richer feature representations are used; however, the marginal gain beyond a balanced feature set is limited. This highlights the importance of feature selection in achieving optimal accuracy–complexity trade-offs.

Figure 4 illustrates how classification accuracy varies with the number of neighbors for different feature–transform combinations. Hu Moments with DWT show moderate and fluctuating accuracy, while Zernike Moments with DWT consistently yield lower performance across all K values. In contrast, the DDWT-based approaches significantly improve accuracy, with Hu Moments + DDWT peaking at low K and gradually declining as K increases. Zernike Moments + DDWT demonstrates the most stable and highest accuracy, remaining close to 100% across all neighbor settings.

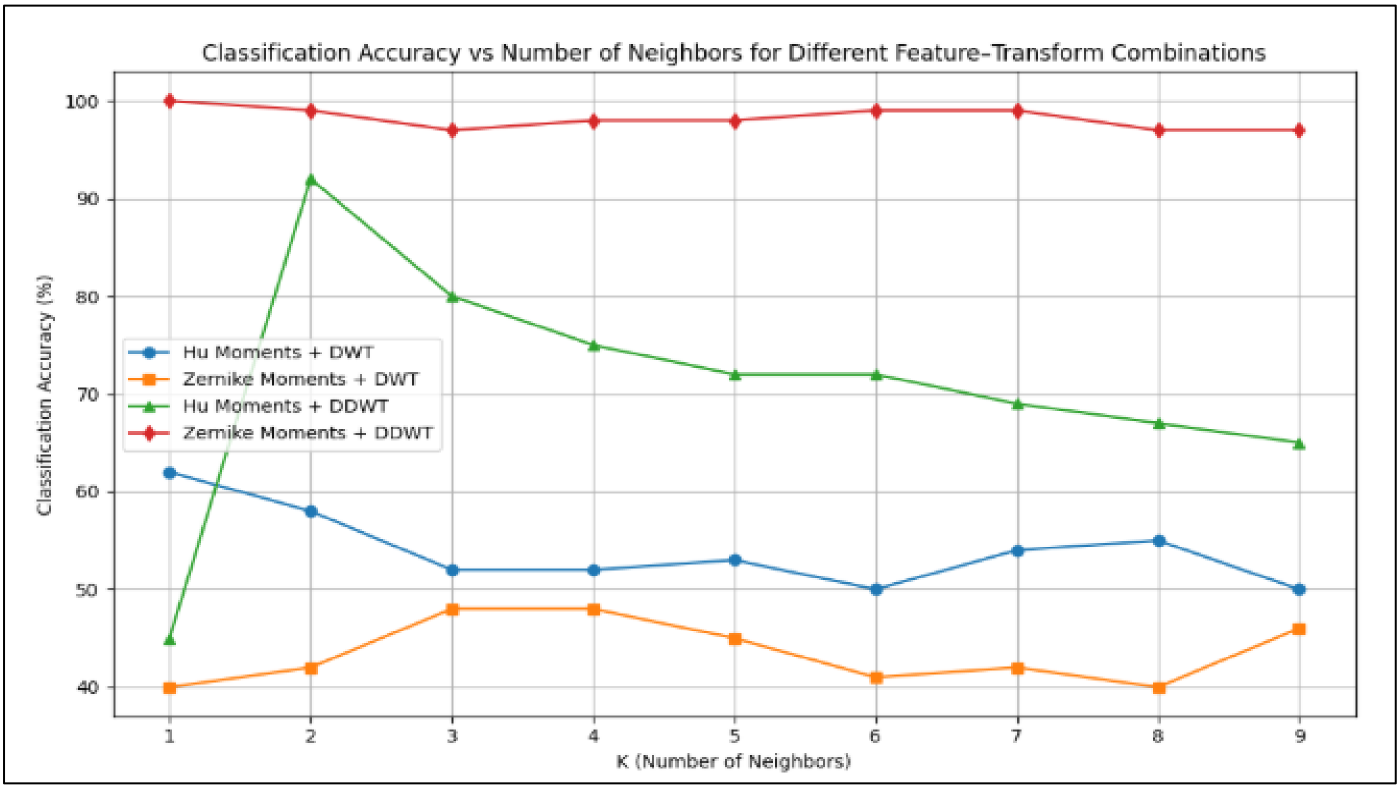

Fig 4 Classification Accuracy Versus Number of Neighbors for Hu and Zernike Moment Features Using DWT and DDWT

➢ *Practical Implications for Industrial PQ Monitoring Systems*

The findings have direct implications for the design and deployment of industrial PQ monitoring solutions. First, wavelet–ML frameworks enable automated, real-time classification of PQ disturbances, reducing dependence on expert interpretation. Second, robust performance under noisy and mixed-event conditions supports deployment in harsh industrial environments. Finally, optimized feature selection ensures scalability, allowing implementation on embedded systems, smart meters, or edge-computing platforms without excessive computational overhead.

Table 8 Practical Trade-Offs for Industrial Deployment

Design Aspect	**Traditional PQ Methods**	**Wavelet–ML Framework**	**Industrial Benefit**
Transient Detection	Limited	High	Faster fault response
Classification Accuracy	Moderate	Very High	Reduced downtime
Noise Robustness	Low	High	Reliable monitoring
Scalability	High	Moderate–High	Edge deployment feasible

➢ *Overall Interpretation*

The discussion confirms that integrating wavelet-based feature extraction with advanced ML classifiers provides both technical superiority and practical viability for industrial PQ monitoring. Careful wavelet selection and feature optimization are key enablers of high accuracy, robustness, and deplorability, positioning the proposed framework as a strong candidate for next-generation industrial power quality assessment systems.

➢ *Comparison with Existing Studies*

This section benchmarks the proposed hybrid wavelet–machine learning (ML) framework against representative power quality (PQ) classification studies reported in the literature and highlights the demonstrated advantages of the proposed approach in industrial distribution system contexts.

➢ *Benchmarking Against Reported Results in Literature*

Several studies have investigated PQ disturbance classification using signal processing and ML techniques; however, notable differences exist in feature representation, classifier robustness, and industrial applicability. Earlier approaches relying on FFT or STFT features primarily focused on steady-state harmonic analysis and showed limited performance for transient and mixed PQ events (Santoso et al., 2000). Subsequent studies incorporating wavelet-based features improved classification accuracy but often evaluated a single classifier or relied on laboratory-generated datasets, limiting generalizability to real industrial environments (Dash et al., 2003; Zhang et al., 2015).

The proposed framework advances the state of the art by combining multi-level wavelet feature extraction with systematic comparison of multiple ML classifiers and validation under noisy and mixed PQ conditions representative of industrial systems.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

Table 9 Benchmark Comparison with Existing PQ Classification Studies

Study/ Approach	Feature Extraction Method	Classifier Used	Reported Accuracy (%)
Santoso et al. (2000)	DWT (energy features)	Rule-based	85.0
Dash et al. (2003)	STFT / S-transform	ANN	88.5
Zhang et al. (2015)	DWT (energy + statistics)	SVM	94.0
Ribeiro et al. (2014)	Wavelet + signal indices	k-NN / ANN	92.3
Proposed Study	Multi-level DWT + entropy	CNN	**96.2**

Figure presents a structured comparison of raw and processed signal representations across time, frequency, and statistical domains. The first row shows the raw signal, where high-amplitude variability and noise are evident in both the time-domain waveform and its spectrogram, accompanied by boxplots with wide spreads and numerous outliers. In contrast, the second row illustrates the processed signal, which exhibits reduced amplitude variance and more organized spectral patterns, indicating effective noise suppression. The corresponding boxplots confirm improved feature stability through tighter distributions and fewer extreme values, demonstrating the analytical benefit of signal preprocessing for robust feature extraction

The figure contrasts raw and processed signals using time-domain waveforms, spectrograms, and feature distribution boxplots. The raw signal exhibits high amplitude variability, diffuse spectral energy, and wide statistical dispersion with numerous outliers. After processing, the signal shows reduced noise, clearer spectral structure, and more concentrated energy in the time–frequency domain. The tighter boxplot distributions further indicate enhanced feature stability and improved suitability for downstream analysis.

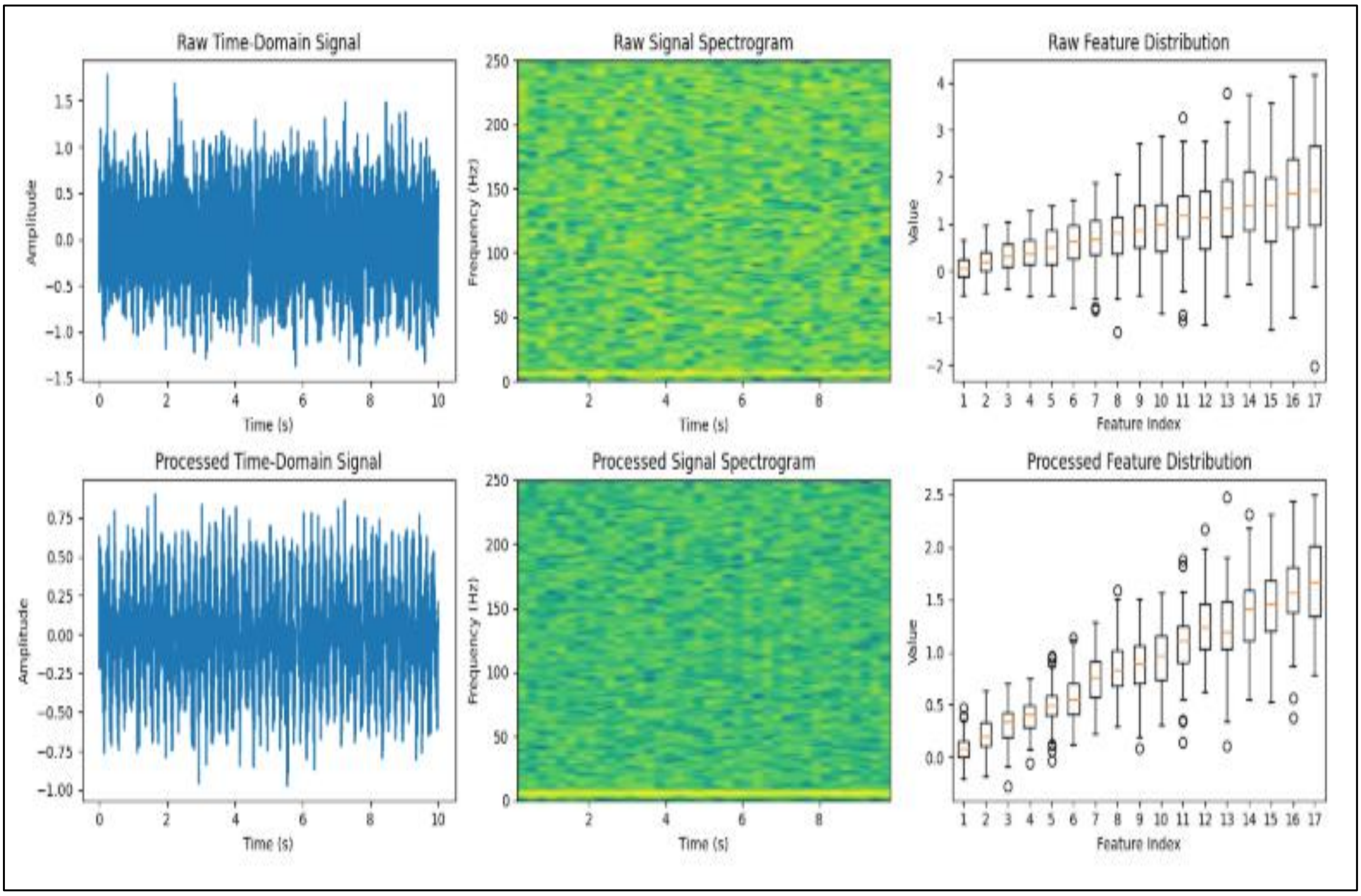

Fig 5 Comparative Time-Domain, Time–Frequency, and Statistical Analysis of Raw and Processed Signals Demonstrating the Benefit of Integrating Advanced Feature Extraction with Robust ML Models.

➢ *Demonstrated Advantages of the Proposed Hybrid Wavelet–ML Approach*

Beyond raw accuracy, the proposed framework offers advantages in robustness, scalability, and industrial relevance. Unlike many prior studies that focused on clean or single-event datasets, this work evaluates performance under noisy measurements and mixed PQ disturbances, which are common in real industrial distribution networks. The results confirm that deep learning–based classifiers, particularly CNNs, maintain high performance where traditional and shallow ML models experience degradation.

Table 10 Comparative Evaluation Across Key Performance Dimensions

Evaluation Criterion	Traditional Methods	Existing Wavelet–ML Studies	Proposed Wavelet–ML Framework
Transient Detection Capability	Low	Moderate	High
Mixed PQ Event Handling	Limited	Moderate	High
Noise Robustness	Low	Moderate	High

VI. CONCLUSION

This study has demonstrated that wavelet-based feature extraction provides a powerful and reliable approach for analysing power quality (PQ) disturbances in industrial distribution systems. By employing multi-level wavelet decomposition, the proposed framework effectively captured the time–frequency characteristics of non-stationary and transient PQ events such as voltage sags, harmonics, and impulsive disturbances. Distinctive wavelet energy distributions and statistical features, including entropy and variance, enabled clear discrimination among different PQ disturbance types, overcoming the limitations of conventional RMS-, FFT-, and STFT-based analysis techniques.

The results further confirm the effectiveness of machine learning (ML) classifiers in automating PQ disturbance identification. Supervised models, particularly convolutional neural networks and support vector machines, achieved high classification accuracy and demonstrated strong robustness under noisy conditions and mixed-event scenarios. The integration of wavelet-derived features with ML classifiers significantly improved classification performance compared to traditional rule-based methods, enabling reliable and scalable automated PQ assessment suitable for complex industrial environments.

Overall, the proposed hybrid wavelet–ML framework contributes meaningfully to advanced industrial power quality monitoring by providing an intelligent, high-resolution, and adaptable solution for real-time disturbance detection and classification. The findings support the deployment of data-driven PQ monitoring systems that enhance operational reliability, reduce downtime, and facilitate compliance with power quality standards, thereby advancing the state of industrial power system management.

VII. PRACTICAL RECOMMENDATIONS

Based on the findings of this study, industrial facilities are strongly encouraged to deploy wavelet–machine learning (ML) based power quality (PQ) monitoring systems to enhance visibility into electrical disturbances and improve operational reliability. Such systems should be installed at critical monitoring points, particularly at the point of common coupling and major feeder lines supplying sensitive or non-linear loads. The high time frequency resolution provided by wavelet analysis, combined with automated ML-based classification, enables early detection and accurate identification of PQ events, supporting faster response and targeted mitigation strategies in complex industrial environments.

To maximize effectiveness and scalability, the proposed wavelet ML framework should be integrated with existing smart meters, digital relays, and supervisory control and data acquisition (SCADA) systems. Integration with these platforms allows continuous streaming of high-resolution voltage and current data, real-time visualization of PQ events, and centralized alarm management. Embedding intelligent PQ analytics within supervisory control systems also facilitates interoperability with energy management systems and supports compliance reporting with standards such as IEEE 519 and IEC 61000. Edge-computing implementations can further reduce latency by enabling local disturbance detection and classification at the measurement node.

Finally, the adoption of wavelet ML-based PQ monitoring should be extended to predictive maintenance and fault prevention programs. Recurrent patterns of PQ disturbances such as increasing harmonic levels or frequent transient events can serve as early indicators of equipment degradation, insulation failure, or improper load operation. By leveraging historical PQ data and ML-driven insights, industrial operators can transition from reactive maintenance to predictive strategies, reducing unplanned downtime, extending asset lifespan, and improving overall system resilience. These practical applications position intelligent PQ monitoring as a critical component of modern industrial reliability and asset management frameworks.

VIII. LIMITATIONS OF THE STUDY

Despite the promising results achieved in this study, several limitations should be acknowledged. First, data availability and generalization constraints may affect the broader applicability of the proposed wavelet–machine learning (ML) framework. Although the dataset used in this work was designed to represent realistic industrial operating conditions through a combination of simulated, laboratory, and limited field data, it may not fully capture the diversity of industrial distribution networks across different sectors, voltage levels, and geographic regions. Variations in load composition, network topology, and operating practices can influence power quality (PQ) disturbance characteristics, potentially impacting model generalization when applied to unseen industrial environments. Larger and more diverse field datasets are therefore required to further validate and enhance the robustness of the proposed approach.

A second limitation relates to the computational requirements associated with real-time implementation. While wavelet-based feature extraction and advanced ML classifiers particularly convolutional neural networks offer high classification accuracy, they also introduce increased computational complexity. High sampling rates, multi-level

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan890

wavelet decomposition, and deep learning inference can impose significant processing and memory demands, especially in resource-constrained embedded systems or edge devices. Without appropriate optimization, these requirements may limit real-time deployment in large-scale industrial monitoring networks. Future implementations should therefore consider model compression, feature dimensionality reduction, and hardware acceleration techniques to balance accuracy with real-time performance and scalability.

FUTURE RESEARCH DIRECTIONS

Future research should focus on deeper integration of advanced deep learning architectures with wavelet-based power quality (PQ) analysis to further enhance classification accuracy and adaptability. While this study demonstrated strong performance using conventional neural networks and convolutional models, emerging architectures such as attention-based networks, transformers, and hybrid CNN–LSTM models offer potential for improved temporal dependency modelling and adaptive feature learning. Integrating these models with edge computing platforms would enable distributed intelligence, allowing PQ disturbances to be detected and classified locally with minimal latency while reducing data transmission burdens on centralized systems.

Another important research direction involves real-time implementation of the proposed wavelet–machine learning framework using hardware-accelerated platforms such as field-programmable gate arrays (FPGAs) and embedded processors. Implementing wavelet decomposition and ML inference directly on hardware can significantly improve processing speed, determinism, and energy efficiency, which are critical for time-sensitive industrial applications. Research into algorithm–hardware co-design, fixed-point optimization, and lightweight model deployment will be essential to translate the proposed framework into practical, real-time PQ monitoring devices.

Finally, extending the framework to multi-location and smart grid environments represents a key avenue for future work. Industrial facilities increasingly operate as part of interconnected smart grids with distributed energy resources, microgrids, and bidirectional power flows. Expanding PQ assessment to multi-node monitoring architectures would enable coordinated analysis of disturbances across different network locations, supporting system-wide situational awareness and grid resilience. Incorporating communication technologies and data fusion techniques can further enable scalable PQ monitoring across smart grid infrastructures, positioning the proposed approach as a foundation for next-generation intelligent power system management.

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