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Power Quality Event Detection and Classification using Novel Techniques: A Review

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ABSTRACT

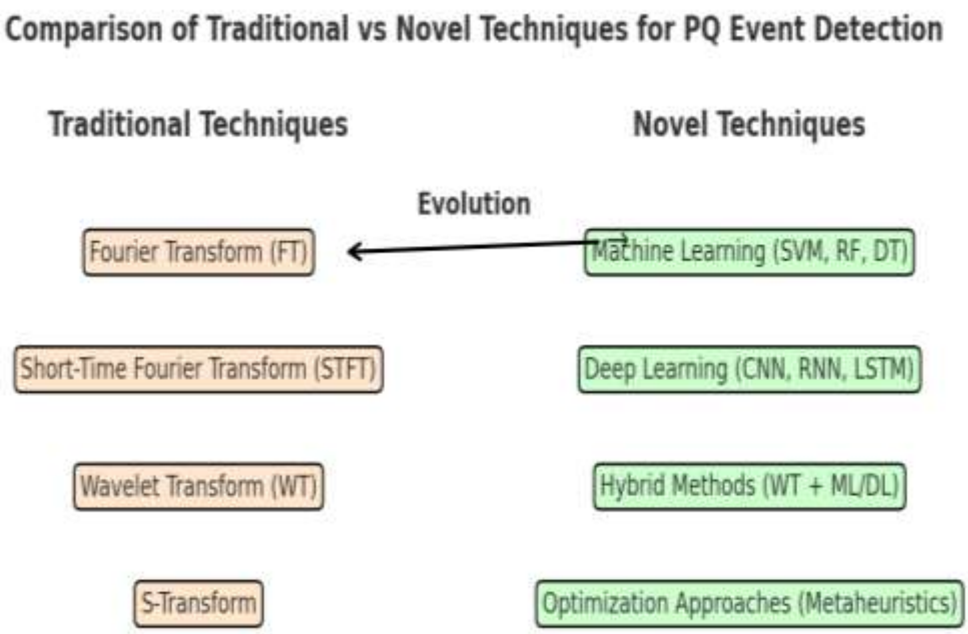
Power quality (PQ) has become a significant concern in modern electrical systems due to the widespread use of nonlinear loads, sensitive electronic equipment, and renewable energy integration. Disturbances such as voltage sags, swells, harmonics, transients, and interruptions degrade system performance and reliability. Traditional detection and classification methods, including Fourier transform, wavelet transform, and S-transform, offer foundational approaches but face challenges in real-time adaptability, noise robustness, and complex event recognition. Recent advancements in machine learning (ML) and deep learning (DL) have enabled more accurate, automated, and intelligent PQ monitoring. This review highlights the evolution of PQ detection and classification techniques, focusing on novel hybrid methods, optimization frameworks, and data-driven strategies. Strengths, limitations, and comparative performance of different techniques are analyzed. Finally, research gaps and potential future directions are identified, paving the way for next-generation, robust PQ monitoring systems.

1. INTRODUCTION

Power quality issues have gained significant importance in modern power systems due to the integration of distributed generation, renewable energy sources, and the increasing dependency on sensitive electronic devices. Power quality disturbances can result in equipment malfunction, data loss, increased system losses, and customer dissatisfaction. As such, reliable detection and classification of PQ events are crucial.

Traditional PQ event detection methods rely on signal processing techniques such as Fourier transform, wavelet transform, and S-transform. While these methods provide valuable insights, they often struggle with overlapping disturbances, noise, and real-time implementation. Recent advancements in machine learning (ML), deep learning (DL), and hybrid optimization approaches offer promising alternatives that enhance detection accuracy and robustness.

This paper provides a comprehensive review of PQ event detection and classification, presenting both traditional and novel techniques, comparative analysis, existing challenges, and future research directions.



2. TRADITIONAL APPROACHES FOR PQ EVENT DETECTION

Traditional approaches for PQ event detection and classification largely rely on signal processing and feature extraction techniques.

- Fourier Transform (FT): Effective for steady-state signals but limited in time-frequency resolution.
- Short-Time Fourier Transform (STFT): Provides localized frequency information but fixed window limits adaptability.
- Wavelet Transform (WT): Superior time-frequency resolution; widely used for transient detection.
- S-transform: Combines benefits of STFT and WT, effective for disturbance localization.

Limitations of these methods include sensitivity to noise, difficulty handling compound disturbances, and challenges in real-time implementation.

3. NOVEL TECHNIQUES FOR PQ EVENT DETECTION AND CLASSIFICATION

Recent research leverages artificial intelligence (AI), machine learning (ML), and deep learning (DL) to overcome the shortcomings of traditional techniques.

- Machine Learning Models: SVM, decision trees, random forests for supervised classification.
- Deep Learning Models: CNNs, RNNs, LSTMs for raw signal learning and handling sequential dependencies.
- Hybrid Methods: Combination of wavelet features with ML/DL classifiers.
- Optimization Approaches: Use of metaheuristic algorithms for feature selection and parameter tuning.

These novel techniques improve classification accuracy, robustness to noise, and adaptability to real-time PQ monitoring.

4. COMPARATIVE ANALYSIS OF TECHNIQUES

Method	Strengths	Limitations	Applications
Fourier/STFT	Good for periodic disturbances	Poor time-frequency resolution	Harmonics, steady signals
Wavelet Transform	Excellent for transients, multi-resolution	Computationally intensive	Sags, swells, transients
S-Transform	Time-frequency localization	Complex, high computation	Localization of mixed PQ events
Machine Learning	High classification accuracy with features	Feature extraction required	Basic PQ event classification
Deep Learning	Automatic feature learning, robust	High computational cost, data hungry	Complex, compound PQ events
Hybrid/Optimization	Improved accuracy, adaptive	Complex design	Real-time PQ monitoring

5. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite significant advancements, several gaps exist:

- Lack of large-scale, real-world benchmark datasets.
- Need for lightweight, real-time DL models.
- Limited interpretability of black-box AI models.
- Scalability challenges for large grid-wide PQ monitoring.

Future research directions include:

- Development of synthetic dataset generators and open-source repositories.
- Transfer learning and federated learning approaches for PQ classification.
- Explainable AI (XAI) for greater trust in ML/DL models.
- Integration of PQ monitoring with IoT and edge computing.
- Exploring graph neural networks (GNNs) for distributed PQ analysis.

6. CONCLUSION

Power quality monitoring has become increasingly important in modern power systems due to the widespread use of sensitive electronic devices, integration of renewable energy sources, and the emergence of smart grids. Traditional approaches such as Fourier analysis, wavelet transform, and S-transform have laid the foundation for PQ event detection and classification. While effective in certain scenarios, these methods face significant limitations in terms of noise sensitivity, real-time capability, and adaptability to complex disturbances. Recent advancements in signal processing, machine learning (ML), and deep learning (DL) have substantially improved the accuracy, robustness, and scalability of PQ monitoring systems. ML-based models such as SVMs and decision trees, when combined with advanced feature extraction techniques, have demonstrated reliable classification of common disturbances. Deep learning approaches, particularly CNNs, RNNs, and hybrid CNN–LSTM architectures, have further enhanced the ability to handle overlapping and compound events. Moreover, hybrid and optimization-based frameworks provide a promising balance between accuracy and computational efficiency, making them attractive for real-time applications.

Despite these advancements, several challenges remain, including the lack of standardized real-world datasets, the need for scalable real-time deployment, and the limited interpretability of black-box models. Addressing these issues requires future research efforts focused on lightweight DL architectures, transfer and federated learning, explainable AI, and graph-based models for grid-wide event detection.

In summary, the evolution of PQ event detection and classification reflects a transition from conventional signal analysis to intelligent, data-driven solutions. By bridging current research gaps and leveraging emerging technologies, future PQ monitoring systems can achieve high levels of accuracy, adaptability, and scalability, ultimately contributing to the reliability and resilience of next-generation power systems.

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