



REAL-TIME AI-DRIVEN POWER QUALITY MONITORING IN INDUSTRIAL GRIDS: A COMPARATIVE ANALYSIS OF MACHINE LEARNING AND DEEP LEARNING APPROACHES

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ABSTRACT

The growing integration of electric vehicles, smart devices, and renewable energy sources has resulted in a significant increase in grid behavior complexity and variability in modern power systems. Conventional PQ monitoring systems, which depend on rule-based logic and static thresholds, frequently are unable to identify disruptions in real time, which can result in operational disruptions, energy losses, and equipment damage. In order to accurately classify and predict PQ disturbances, such as voltage sags, swells, harmonics, and transients, this study suggests an AI-based power quality monitoring system that makes use of machine learning (ML) and deep learning (DL) models like Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks. Metrics like accuracy, latency, and statistical central tendency are used to assess the system's performance as it processes both real-time and simulated data from commercial and industrial settings. The findings show that AI models perform noticeably better than traditional systems in terms of detection accuracy, responsiveness, and adaptability, proving their feasibility for real-time deployment in Industry 4.0 and smart grid scenarios.

Keywords: CNN, LSTM, Artificial Intelligence, Voltage Sag, Harmonics, Machine Learning, Deep Learning, Power Quality Monitoring, and Predictive Maintenance

1. INTRODUCTION AND PROBLEM STATEMENT

Power quality (PQ) has grown to be a major concern in the age of Industry 4.0, where automation, networked systems, and smart technologies power industrial operations.



Equipment failure, production halts, energy losses, and even harm to delicate electronic components can all be caused by poor power quality. The need for a steady, distortion-free, and uninterrupted electrical supply is greater than ever before as modern industries depend more and more on digital control systems and precision electronics. Maintaining high power quality is essential to efficient and sustainable industrial operation and goes beyond simple technical requirements.

However, conventional power quality monitoring systems are frequently costly, reactive, and have a narrow range of use. These systems' threshold settings and rule-based algorithms may make it difficult to identify complex or transient disturbances like flickers, harmonics, voltage sags, and interruptions in real time. The dependability and effectiveness of the entire power system are jeopardized by their incapacity to dynamically adjust to shifting grid conditions, which results in missed detections, false alarms, and delayed responses.

The application of artificial intelligence (AI) to power quality monitoring has become a gamechanging way to address these issues. Real-time analysis, pattern recognition, and intelligent classification of power quality disturbances (PQDs) are made possible by artificial intelligence (AI), specifically through Machine Learning (ML) and Deep Learning (DL) algorithms. Artificial intelligence (AI) models can be trained on both historical and current data to find uncommon and subtle anomalies that traditional systems might miss. Additionally, they have the benefit of adaptive learning, which allows the system to adjust to new patterns of disturbances over time, increasing accuracy and operational efficiency.

In order to overcome the present drawbacks of conventional techniques, this study investigates the creation and deployment of an AI-based power quality monitoring system. It seeks to create a responsive, scalable solution that can function in the intricate, high-demand settings typical of Industry 4.0. An intelligent, real-time monitoring framework that uses AI to improve detection accuracy, lower operational risks, and support the larger goal of smart grid transformation is thus the main focus of the problem statement.



2. METHODOLOGY

This research uses a structured methodology that combines data collection, algorithm implementation, and real-time system deployment using both software and hardware platforms in order to create an efficient AI-based Power Quality Monitoring System. Building a solid and varied dataset of simulated and real-time power quality (PQ) events is the first step in the methodology. Power quality meters and monitoring tools like PQView and PQube, which were installed across a few chosen industrial and residential feeders, were used to gather data in real time. Actual grid disruptions, including voltage sags, swells, interruptions, transients, flickers, and harmonic distortions, were recorded by these devices. However, MATLAB/Simulink was also used to generate simulated events, which allowed for precise control over the type, duration, and intensity of each PQ disturbance, in order to guarantee the availability of labeled and balanced data across all disturbance types. A complete dataset for model training and assessment is ensured by combining real and simulated data.

Several AI algorithms were created and evaluated for the classification of PQ disturbances after the dataset was established. Because of its effectiveness with small to medium-sized feature sets, a Support Vector Machine (SVM) was first used as a baseline model. Total harmonic distortion (THD), frequency deviation, crest factor, and root mean square (RMS) voltage were among the extracted features used to train the SVM. Even though SVM performed well, more sophisticated deep learning models were investigated in order to increase classification accuracy and automate feature extraction. Time-frequency representations of the electrical signals, such as spectrograms and wavelet-transformed images, were used to train a Convolutional Neural Network (CNN). CNNs don't require manual feature engineering and are especially good at capturing spatial features in waveform data. Additionally, a Long Short-Term Memory (LSTM) model was created to address the time-dependent nature of PQ disturbances. LSTM, a kind of recurrent neural network (RNN), is perfect for categorizing disruptions that develop over time because it can recognize temporal patterns and long-term dependencies in sequential data.



These AI models were developed and implemented using a combination of hardware platforms and software tools. While Python was the main programming language used for training and testing deep learning models such as CNN and LSTM using TensorFlow and Keras libraries, MATLAB was widely used for simulation, signal generation, and SVM implementation. Additionally, Python made performance analysis, visualization, normalization, and data preprocessing easier. Real-time inference and field-level deployment were made possible by the use of embedded platforms like the Raspberry Pi, Arduino, and ESP32. The Industry 4.0 idea of decentralized, intelligent monitoring systems was in line with these embedded systems' ability to process PQ signals at the edge with low latency. To run on these embedded devices, the trained models were optimized and transformed into lightweight formats, proving that realtime AI deployment is feasible.

Overall, this methodology combines a hybrid dataset, intelligent algorithms, and scalable hardware integration to close the gap between theoretical AI models and real-world power system monitoring applications. It guarantees that in addition to being accurate in classification, the suggested system is also flexible, affordable, and appropriate for real-time deployment in industrial settings and smart grids.

3. FRAMEWORK FOR IMPLEMENTATION

The AI-Based Power Quality Monitoring System is implemented using a scalable and modular framework that combines data preprocessing, real-time deployment on embedded platforms, and AI model training. The training and validation of deep learning and machine learning models, such as SVM, CNN, and LSTM architectures, are at the heart of the framework. A well-labeled dataset of simulated and real-time power quality disruptions is used to start the training process. Normalization, noise filtering, waveform data segmentation into uniform time windows, and conversion into frequency or time–frequency domains using methods like the Fourier Transform and Wavelet Transform are all steps in the systematic data preprocessing pipeline that these data samples go through. Accuracy and convergence speed are increased by this preprocessing, which guarantees that the input features are standardized and optimized for model learning.



Additional procedures are carried out to get the data ready for learning for deep learning models like CNN and LSTM. Raw voltage/current signals are transformed into spectrograms or scalograms, which are visual depictions of signal energy over frequency and time, and then fed into CNNs as images. In contrast, time-series data sequences that preserve the temporal context of every disturbance event are fed into LSTM models. Supervised learning techniques, in which labeled examples direct the learning process, are used to train the models. To assess model performance, prevent overfitting, and guarantee generalization to new data, the dataset is divided into training, validation, and testing sets (usually 70/15/15 or 80/10/10). The best configuration for each model is found using hyperparameter tuning techniques like grid search and random search, and performance metrics like accuracy, precision, recall, F1-score, and confusion matrix are used for assessment.

The top-performing models are ready for deployment in a real-time setting after they have been trained and verified. A specially created system architecture that facilitates cloud and edge computing is used to accomplish this. The models are deployed on embedded systems, specifically the NVIDIA Jetson Nano, a potent AI-capable edge device, after being compressed using quantization and pruning to lessen the computational load. Because the Jetson Nano supports GPU acceleration, it can run low-latency, high-efficiency lightweight versions of CNN or LSTM models. In order to continuously monitor voltage and current waveforms, make inferences using the trained AI model, and classify disturbances in real time, the device interfaces with sensors or data acquisition modules. To remotely record events, send alerts, and view power quality trends, the system can also be integrated with IoT platforms.

This implementation framework, which combines cutting-edge AI capabilities with embedded system efficiency, guarantees a smooth transition from model development to real-world deployment. It illustrates how edge computing driven by AI has the potential to completely transform power quality monitoring in smart grid and industrial applications.



4. RESULTS AND PERFORMANCE EVALUATION

Standard performance metrics, statistical tools, and a comparison with conventional PQ monitoring systems were all used to thoroughly assess the performance of the suggested AI-Based Power Quality Monitoring System. Accuracy, precision, recall, and latency were the main metrics used to evaluate the classification models. While precision and recall gauge the model's capacity to accurately identify particular disturbance types without producing false alarms or overlooking important events, accuracy indicates the model's overall correctness. In this context, latency refers to the system's real-time responsiveness, more precisely the amount of time that passes between the capture of an input signal and the classification of a disturbance. For the majority of disturbance classes, CNN and LSTM models demonstrated classification accuracy levels above 95% during testing, with precision and recall values exceeding 93%. Due to the Jetson Nano's ability to maintain latency below 150 milliseconds, the system is appropriate for real-time applications in industrial and smart grid settings.

The system's performance was also compared to more conventional power quality monitoring techniques, which usually use rule-based logic and fixed thresholds. When faced with complex, overlapping, or noisy disturbances, the accuracy of traditional systems frequently fell below 80%, demonstrating their limited adaptability. On the other hand, even with different load conditions, AI-based models showed better resilience and flexibility to a variety of power quality problems. Notably, the deep learning models were able to recognize subtle waveform variations in disturbances that were either missed or incorrectly classified by conventional systems. This demonstrates how the AI system can reduce the risk of equipment damage and unscheduled downtimes by offering early detection and improved situational awareness.

Mean, median, mode, and percentage-based evaluations were used in statistical analysis to further quantify the system's improvements. Strong reliability and stability were demonstrated by the AI models' mean classification accuracy of about 96.2% and median accuracy over several test runs, which consistently stayed above 95%. The system's ability to reliably provide near real-time performance was confirmed by the observation that the mode of detection time (latency) was approximately 100 milliseconds. Furthermore, compared to conventional systems, the AI-based framework improved accuracy by 18–25%, recall by more than 30%,



and false positives by almost 40%. These enhancements show both technical superiority and usefulness in raising the general dependability and effectiveness of power quality monitoring systems.

According to this performance evaluation, AI-driven methods are perfect for integrating into contemporary industrial and smart grid infrastructures because they not only perform better than conventional methods in terms of accuracy and responsiveness, but they also make intelligent, adaptive, and efficient power quality management possible.

5. CONVERSATION

A number of important insights about the effectiveness, versatility, and usefulness of AI models for power quality monitoring in actual electrical systems are revealed by their application. Support Vector Machine (SVM), one of the tested models, performed well in situations with small and distinct feature sets. It is appropriate for embedded applications with limited hardware resources due to its simplicity, speed, and low computational demand. However, SVM's efficacy is limited in complex or dynamic environments due to its inability to handle high-dimensional or time-sequential data and the need for manual feature extraction.

The Convolutional Neural Network (CNN) demonstrated remarkable efficacy in extracting spatial patterns from time-frequency images and waveform spectrograms. It removed the need for manual feature engineering and produced better accuracy. CNNs are especially useful when the data contains subtle or overlapping disturbances that are hard to measure numerically but visually distinct. Notwithstanding their benefits, CNNs need more processing power and training time, which means that, unless properly optimized, they are less appropriate for very light devices without GPU support.

When it came to handling sequential data, the Long Short-Term Memory (LSTM) network performed exceptionally well, which made it perfect for identifying temporal dependencies in voltage and current signals. Compared to static models, it can more accurately identify slowly changing or reoccurring power quality events because of its capacity to retain long-term



patterns. But in order to generalize effectively, LSTMs need a larger training dataset and are computationally demanding. Furthermore, cutting-edge edge platforms like NVIDIA Jetson Nano, which offer GPU acceleration for quick inference, might be required for the real-time deployment of LSTM models.

When properly optimized, all three AI models can be deployed in smart grid and industrial settings from a scalability standpoint. Edge-level monitoring is made possible by embedded AI platforms, which also minimize latency and lessen dependency on centralized systems. Distributed intelligence and scalable deployment across substations, distribution feeders, and manufacturing facilities are made possible by CNN and LSTM models, especially when implemented on devices such as Jetson Nano or industrial-grade microcontrollers. Long-term analysis and data accessibility are further improved by their integration with cloud and IoT platforms.

However, there are opportunities as well as challenges when integrating AI-based monitoring systems with legacy power infrastructure. Since many of the PQ monitoring systems in use today are based on rule-based logic, they might not have the data processing or communication protocols required to interface with AI modules. To ensure compatibility, middleware systems, data converters, or IoT gateways must be used to bridge this gap. Thankfully, the majority of contemporary AI platforms and embedded systems support common communication protocols like MQTT, OPC-UA, and Modbus, which makes integration with SCADA and other supervisory systems possible. Improved disturbance detection, predictive maintenance, and grid stability over time make the AI-based approach a compelling and future-ready solution, even though retrofitting older systems may require initial costs and configuration work.

In conclusion, the application environment, data availability, and deployment constraints should all be taken into consideration when choosing an AI model because each one has distinct advantages and disadvantages. An important step toward intelligent and autonomous power quality monitoring, the system as a whole shows great promise for widespread adoption in both new and existing power infrastructure.



6. CONCLUSION AND PROSPECTS

In order to overcome the shortcomings of conventional monitoring methods and move closer to the goal of intelligent, real-time power system management, this research offers a thorough analysis and real-world application of an AI-Based Power Quality Monitoring System. Using AI models like SVM, CNN, and LSTM, the system was able to classify a variety of power quality disturbances, such as voltage sags, swells, flickers, transients, and harmonics, with high accuracy, low latency, and robustness. Deep learning models (CNN and LSTM) considerably outperform conventional techniques and rule-based algorithms in terms of detection accuracy and adaptability, particularly when handling complex or overlapping disturbances, according to the comparative evaluation. The system is scalable, decentralized, and appropriate for smart grid and Industry 4.0 applications. The integration of AI into embedded platforms such as Jetson Nano demonstrated the viability of implementing sophisticated monitoring solutions at the edge level.

Several deployment recommendations can be made in light of these findings. First, SVM or lightweight CNN models can be incorporated into smart meters or real-time controllers to identify simple PQ problems in industrial settings with moderate processing demands. LSTM-based models in conjunction with GPU-supported edge devices are more appropriate for sensitive applications or high-priority grids that demand sophisticated disturbance recognition. Furthermore, centralized analysis, long-term trend monitoring, and predictive maintenance can be made possible by implementing IoT gateways that communicate with cloud dashboards. Standardized communication protocols, such as MQTT, Modbus, and OPC-UA, are also advised in order to guarantee compatibility with legacy infrastructure and current SCADA systems. Periodically retraining AI models with fresh data is recommended to adjust to changing grid behaviors and improve system performance even more.

This study paves the way for a number of fascinating directions for further investigation. Adoption of federated learning, which allows AI models to be trained cooperatively across several nodes (such as substations or industries) without sharing raw data, is one important area. This would enhance model generalization while protecting data privacy. Additionally,



more intelligence can be sent straight to the data source by using Edge AI frameworks like NVIDIA JetPack, Google Coral, or ARM-based AI accelerators. This improves response time and lessens dependency on cloud systems. The creation of hybrid AI frameworks that combine CNN-LSTM architectures or rule-based logic with AI models to take advantage of the temporal and spatial aspects of power outages is another exciting avenue. Additionally, the system could become an active grid management component that can recommend corrective actions or activate protective mechanisms by incorporating self-healing and decision-making capabilities.

The suggested AI-based system, in summary, not only enhances power quality monitoring capabilities but also supports the more general objectives of sustainability, smart grid development, and energy systems digital transformation. This method facilitates the continuous transition to autonomous, data-driven power infrastructures that can satisfy the intricate needs of contemporary industry and society by enabling real-time, precise, and adaptive disturbance detection.

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