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Implementation of Machine Learning for Power Quality Improvement in DG Systems

[1]Vijayshree G and [2]Sumathi S

[1, 2] Department of Electrical and Electronics Engineering, RNS Institute of Technology, Bangalore, India

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Abstract: The integration of distributed generation (DG) systems, like solar and wind power, presents significant challenges for power quality, including issues with voltage stability, harmonic distortion, and transient disturbances. Traditional power quality solutions often lack flexibility and adaptability, making machine learning (ML) a promising alternative. This review examines how ML models including neural networks, support vector machines, and deep learning architectures can improve power quality by detecting and mitigating disturbances in real time. Key topics covered include step by step real-time implementation strategies, application of ML and artificial for power quality improvement and its advantages. By highlighting recent advances and identifying research gaps, this review offers insights into the future role of ML in maintaining power quality within DG-integrated smart grids.

Keywords: *Power Quality, Distributed Generation, Machine Learning, Deep Learning Algorithm.*

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I. INTRODUCTION

The rapid growth of distributed generation (DG) systems, driven by the adoption of renewable energy sources such as solar photovoltaic (PV) and wind power, has trans- formed the structure of modern power grids. While DG systems are vital for advancing sustainable energy goals, their intermittent and variable nature poses significant challenges to maintaining power quality. Power quality issues such as voltage sags, harmonic distortion, flicker, and transient disturbances have become more prevalent, threatening the stability and reliability of both local and national grid infrastructures. These disturbances can adversely affect sensitive equipment, reduce grid efficiency, and impact end-user satisfaction.

Conventional methods for power quality management of- ten rely on predefined rules and hardware-based solutions like filters and compensators. Although effective to an ex- tent, these methods are typically costly, inflexible, and may struggle to adapt to dynamic grid conditions inherent to DG systems. In this context, machine learning (ML) has emerged as a promising approach for enhancing power quality management. With capabilities in pattern recognition, anomaly detection, and predictive analysis, ML models can offer real-time, adaptive solutions that improve accuracy and reduce response time in handling power quality issues.

This review aims to explore the application of ML techniques in addressing power quality challenges within DG- integrated power systems. It discusses various ML models such as artificial neural networks (ANNs), support vector machines (SVMs), decision trees, and deep learning approaches like convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—and their roles in monitoring, classifying, and mitigating power quality disturbances.

Furthermore, the review examines critical aspects of data preprocessing, feature extraction (e.g., Fourier and wavelet transforms), and real-time deployment to improve model efficacy in complex grid environments. By identifying current advancements, implementation challenges, and research gaps, this review provides insights into how ML can be leveraged for resilient and sustainable power quality solutions in DG-enhanced smart grids. Applying machine learning (ML) for power quality improvement using a Custom Power Device (CPD) involves leveraging predictive algorithms to optimize the operation and control of these devices, ultimately enhancing the stability and efficiency of power delivery. Here’s a step-by-step guide on how you can do this using common ML techniques, including the necessary data preparation and potential algorithms:

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II. STEP-BY-STEP GUIDE TO APPLYING ML FOR POWER QUALITY IMPROVEMENT

A. Understanding the Role of Custom Power Devices (CPDs)

Custom Power Devices like DSTATCOM (Distribution Static Compensator), DVR (Dynamic Voltage Restorer), or UPQC (Unified Power Quality Conditioner) are used to mitigate power quality issues like voltage sags, swells, harmonics, and power factor correction.

➢ *ML can Help in:*

- Predicting disturbances and determining the required compensation.
- Optimizing the control parameters of the CPD for dynamic adaptation.
- Identifying patterns or anomalies in power quality that traditional controllers might miss.

B. Data Collection and Preprocessing

Data collection and preprocessing are crucial steps for power quality improvement. Key parameters like phase currents (Iabc), phase voltages (Vabc), load currents (Is), and load voltages (Vs) are gathered from MATLAB simulations or real-time systems. Preprocessing involves handling missing values, cleaning noise, detecting outliers, and normalizing data. Important features such as RMS values, harmonic distortion, and power metrics (active, reactive, and apparent power) are extracted. The processed data is then labeled for various power quality events (e.g., sags, swells, harmonics) and split into training, validation, and test sets for machine learning, ensuring a robust analysis framework. To apply ML, you need a well-structured dataset with the relevant parameters.

The data can be extracted from:

MATLAB simulation or real-world measurements. Key parameters include:

➢ *Input Features (x):*

- Voltage (source voltage, load voltage)
- Current (source current, load current)
- Power (active power, reactive power)
- Harmonic levels (THD)
- Power factor
- Environmental variables (e.g., temperature, time of day, load type)

➢ *Target Variables (y):*

- Desired voltage level after compensation.
- Desired current waveform.
- Reduction in Total Harmonic Distortion (THD).
- Power factor correction.

Ensure data is normalized/scaled if using algorithms sensitive to input ranges. You can use Standard Scalar from scikit- learn for normalization in Python.

C. Select a Suitable Machine Learning Algorithm and train the ML model

The choice of ML algorithm depends on the specific task. Here are some common ML techniques that can be applied:

➢ *Supervised Learning: For regression or classification tasks.*

- Linear Regression: To predict the level of compensation required based on input conditions.
- Random Forest / Decision Trees: To predict power quality metrics and optimize CPD operations.
- Support Vector Machines (SVM): To classify disturbances like voltage sags, swells, and harmonics.

➢ *Unsupervised Learning: For anomaly detection and clustering.*

- K-Means Clustering: To group similar types of disturbances and adapt CPD responses.
- Autoencoders (Deep Learning): For detecting anomalies in power quality data that might indicate a need for CPD adjustment.
- Reinforcement Learning (RL): Useful for dynamic adjustment of CPD control actions to maintain optimal power quality in real-time.

D. Model Evaluation

- Use metrics like Mean Squared Error (MSE) for regression tasks or accuracy, precision, recall for classification tasks.
- Cross-validation can be applied to ensure that the model is not over-fitting and performs well on unseen data.
- Analyze feature importance (available with models like Random Forest) to understand which parameters most influence the CPD's performance.

E. Deploying the Model for Real-time Control

- Once trained and evaluated, integrate the model into the CPD's control logic using Python scripts or MATLAB interfaces.
- Use the model's predictions to adjust control parameters like:

(i)Compensation current or voltage levels. (ii)Switching patterns of power electronic converters.
(iii)Real-time adjustment of the control signals (e.g., PWM).

Example: If using a DSTATCOM, the model might predict the amount of reactive power to inject based on current grid conditions, allowing the device to adjust its output accordingly.

F. Feedback Loop for Continuous Improvement

- Implement a feedback loop where the performance of the CPD is monitored, and the model is retrained periodically with new data to adapt to changing conditions.

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- This ensures that the ML model stays up-to-date and accurate in different operating conditions.

III. POWER QUALITY IMPROVEMENT USING MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

The integration of machine learning (ML) and artificial intelligence (AI) into power quality (PQ) management systems is transforming how electrical networks address challenges associated with non-linear loads, disturbances, and in efficiencies [4]. This overview highlights various approaches and methodologies that leverage ML and AI for enhancing power quality.

A. AI-Driven Control Techniques

Recent research has demonstrated the effectiveness of AI- based control methods in managing power quality issues, particularly in systems like Unified Power Quality Conditioners (UPQC). A study evaluated three advanced control techniques—Artificial Neural Network (ANN) Controller, NARMA-L2 Controller, and a PI Controller optimized using the Adaptive Lizard Algorithm. The results indicated that these AI-driven controllers significantly reduce total harmonic distortion (THD), with the ANN Controller performing the best among them [13]. This approach is particularly beneficial for metro rail systems, where maintaining power quality is crucial for operational efficiency.

B. Deep Learning Applications

Deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are increasingly applied to power quality monitoring. These models excel at identifying complex patterns within large datasets, enabling accurate classification of disturbances and anomalies in power systems. They can effectively handle non-linear and non-stationary signals, making them suitable for real-time monitoring applications[11]. The adaptability of deep learning algorithms allows them to improve the reliability of power quality assessments in increasingly complex electrical grids.

C. Machine Learning for Renewable Energy Integration

The integration of renewable energy sources poses unique challenges for power quality due to their intermittent nature. Machine learning methods are employed to preprocess historical load data and analyze features of load time series, facilitating more accurate predictions of energy supply and demand. This predictive capability is essential for optimizing the operation of renewable energy systems while ensuring stability in power distribution networks [10]. Additionally, active power filters controlled by machine learning algorithms can rectify current imbalances and mitigate harmonics effectively [3].

D. Monitoring Techniques Based on Machine Learning

Innovative monitoring methods utilizing machine learning have been proposed for detecting electrical disturbances in low-voltage networks. Techniques such as Multilayer Neural Networks with Multivalued Neurons (MLMVN) and CNNs trained on Short-Time Fourier Transform (STFT) coefficients allow for efficient classification of power quality disturbances with minimal computational effort. These methodologies enhance the ability to monitor and respond to PQ issues dynamically [2].

The application of machine learning and artificial intelligence in power quality improvement is a rapidly evolving field. By employing advanced algorithms and control strategies, electrical systems can achieve greater efficiency, reliability, and adaptability in managing power quality challenges. As these technologies continue to develop, they promise to play an integral role in the future of smart grid technologies and sustainable energy management [8].

IV. ADVANTAGES OF USING DEEP LEARNING FOR POWER QUALITY MONITORING IN MODERN GRIDS

Deep learning (DL) techniques are increasingly being adopted for power quality (PQ) monitoring in modern electrical grids due to their ability to effectively analyze complex and high-dimensional data[16]. Here are the key advantages of utilizing deep learning in this context:

A. Handling Nonlinear and Non-Stationary Signals

Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), excel at processing nonlinear and non-stationary signals. This capability is crucial for accurately identifying and classifying power quality disturbances that do not follow predictable patterns, which traditional monitoring methods often struggle with[1].

B. Automatic Feature Extraction

One of the significant benefits of deep learning is its ability to automatically extract relevant features from raw data. This reduces the need for manual feature engineering, allowing models to learn directly from the data without extensive preprocessing. This feature extraction capability is particularly beneficial in environments where the nature of disturbances may vary widely [5].

C. Real-Time Monitoring and Anomaly Detection

Deep learning algorithms can be optimized for real-time classification of power quality events, enabling quick detection and response to disturbances. This is essential for maintaining the reliability and security of modern power systems, especially as they become more complex with the integration of renewable energy sources [9].

D. Robustness to Noise

Deep learning models have shown resilience against noisy data, which is common in power quality measurements. By employing techniques such as deep auto-encoders and hybrid models that combine DL with traditional signal processing methods, these models can

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effectively filter out noise and improve classification accuracy [6].

E. Scalability

Deep learning frameworks are inherently scalable, allowing them to handle large datasets typical of modern power systems. As data availability increases with smart grid technologies, deep learning can leverage this information to improve model performance continuously [15].

F. Predictive Capabilities

Using architectures like LSTM networks, deep learning can predict future power quality conditions based on historical data trends. This predictive capability aids in proactive maintenance and operational planning, minimizing the impact of potential disturbances before they occur [14].

G. Integration with Smart Grid Technologies

Deep learning models can be integrated into smart grid systems for enhanced decision-making processes. They facilitate advanced applications such as demand response management and automated fault detection, which are crucial for optimizing grid operations [7].

The integration of deep learning into power quality monitoring systems offers significant advantages over traditional methods, including improved accuracy, efficiency, and adapt- ability to changing conditions in modern electrical grids. As these technologies continue to evolve, they hold the potential to enhance the overall reliability and performance of power systems globally [12].

V. CONCLUSION

The implementation of ML and artificial intelligence in PQ improvement is the most recent research domain. By using advanced algorithms and control strategies, electrical systems can achieve greater efficiency, reliability, and adaptability in managing PQ challenges. As these technologies continue to develop, they promise to play an integral role in the future of smart grid technologies and sustainable energy management. The integration of deep learning into power quality monitoring systems offers significant advantages over traditional methods, including improved accuracy, efficiency, and adaptability to changing conditions in modern electrical grids. As these technologies continue to evolve, they hold the potential to enhance the overall reliability and performance of power systems globally. While deep learning holds significant promise for enhancing power quality monitoring, addressing these challenges is crucial for its successful implementation in modern electrical grids. Ongoing research focused on improving data availability, model interpretability, robustness, and integration with existing systems will be vital for leveraging the full potential of deep learning in this field. Addressing the lack of novelty in deep learning applications for power quality requires a multifaceted approach that includes fostering collaboration, enhancing transparency, developing robust datasets, and exploring innovative learning techniques. By implementing these strategies, researchers can drive forward the application of deep learning in power quality monitoring, ultimately leading to improved reliability and efficiency in modern electrical grids.

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Vijayshree G is an Assistant Professor in Department of Electrical Engi- neering, RNS Institute of Technology, Bangalore, India. She completed her Ph.D. in power system engineering from VTU. She has done her M.Tech. with first rank from Ghousia College of Engineering Ramnagar affiliated to VTU in 2012 and her B.E. first class in 2007 from DBIT, Bangalore affiliated to VTU. She has overall experience of 13 years. She is familiar with software like MATLAB, KEIL, E-Tap Software, and PSIM. Her areas of interest are power electronics, power systems and renewable sources.

Sumathi Srinivasan is a Professor in Department of Electrical and Electronic Engineering, RNS Institute of Technology, Bangalore, India. She completed her Ph.D. from VTU. She has done her M.Tech. from UVCE, Bangalore. She is working as Dean and Professor, Department of EEE, RNSIT, Bangalore. Her areas of interest are power system voltage stability, AI applications for power system analysis, and FACTS controllers.