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AI-Based Predictive Power Quality Control in Renewable Energy Systems Using MATLAB Simulation

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Abstract: The transition to renewable energy systems (RES) such as solar and wind power offers critical solutions for environmental sustainability but presents notable challenges to power quality (PQ) due to their intermittent and variable nature. PQ issues like voltage fluctuations, harmonic distortions, and frequency instability threaten the reliability and efficiency of power grids. This thesis explores emerging strategies to mitigate these issues, with a particular focus on the role of artificial intelligence (AI). The study proposes an AI-Hybrid Predictive Power Quality Control System (AI-HPQCS) that integrates real-time data acquisition, machine learning-based prediction, and optimization-based control. Through simulations and analytical modelling, the system demonstrates improved voltage regulation and reduced harmonic distortion, validating AI as a powerful tool for managing PQ in RES-integrated smart grids.

Keywords: Power Quality, Renewable Energy Systems, Artificial Intelligence, Harmonic Distortion, Smart Grid

I. Introduction

The increasing global demand for clean and sustainable energy has led to a significant rise in the integration of renewable energy systems (RES) such as solar, wind, and hybrid sources into modern power grids. While such systems seem to be excellent options to provide energy sustainability and decrease the dependence on fossil fuels, they introduce some significant challenges regarding the power quality (PQ). For a layperson, Power quality is the electrical energy quality and is a measure of the quality of the power supplied to end users. Typical PQ problems caused by RES include voltage sags, voltage swells, harmonic distortions, flickers, and transients, etc., that can affect power system equipment operation and power grid stability adversely. The key problem arises from the intermittent and uncertain nature of RES, which are conditioned by the nature factors, like sunlight and wind speed availability, inherent to the environment. RES does not generate power at constant level as in case of conventional power generation system, which causes transient nature of power generation and creates instability in grid operation and challenges in maintaining standard power quality parameters (Kumar et al., 2025).

To help solve these challenges, the industry is turning to artificial intelligence (AI) as a revolutionary solution. AI-based methods, such as machine learning and optimization algorithms, can be employed for improving the real-time monitoring, predictive analysis and control of RES-based systems. These smart PQ compatible systems can dynamically detect, mitigate PQ disturbances, maximize system performance including inverters, compensators,

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and energy flow coordination. Furthermore, the utilization of AI can facilitate incorporation of energy storage options (e.g., supply-and-demand balancing and flexing of generation) (Lolamo et al., 2024). AI combined with renewable energy provides a leap in power quality, grid resilience, operational efficiency and decision making. With the development of smart grid infrastructure, the AI-based solutions are going to become a key factor to guarantee the reliable, cyber-secure and high-quality supply of renewable electricity.

II. Research Background

The escalating demand for sustainable and environmentally responsible energy has intensified the global transition from fossil fuel-based power generation to renewable energy sources (RES) such as solar, wind, and hybrid systems. However, this change is accompanied by a number of challenges chief among them being PQ problems. Power quality, which is a measure of the stability and reliability of the electric grid, consists of several parameters such as wide-area voltage support, system frequency stability, harmonic distortion, and load balancing. The intermittency and variability of RES fundamentally challenge them, leading to the efficiency and stability problems in power grids. Thus, improving the PQ in renewable energy is a major challenge that needs to be tackled from research and engineering perspective.

Kumar et al. (2025) emphasized these concerns in their comprehensive review, which highlighted emerging methods for PQ enhancement in high-RES systems. They have examined various technologies including Flexible AC Transmission Systems (FACTS), Unified Power Quality Conditioners (UPQC), and Dynamic Voltage Restorers (DVR) and the role of artificial intelligence (AI) and machine learning (ML) in adaptive control. They reported that real-time monitoring and hybrid optimization methods will also be necessary in future PQ enhancement efforts. Savio et al. (2025) modelled and MATLAB simulated a 2.5MW Solar-Wind Hybrid Renewable Energy System (SWH-RES) in line with domestic power requirements. They employed MATLAB based Total Harmonic Distortion (THD) analysis, and found that the voltage THD could be decreased from 45.48% to 26.20% and current THD from 8.32% to 2.88% with filters. The proposed results confirm the effectiveness of hybrid systems for completing energy sufficiency and PQ stability. Alwaeli et al. (2025) mitigated the technical challenges of hybrid RES based on STATCOMs and a grey wolf optimization (GWO) algorithm for tuning controllers to improve PQ. Simulation results showed that their method reduced voltage and current deviations, the reactive power control performance was promoted, and the PCC voltage varied between 0.92 pu and 0.97 pu in case of during faults. Samala and Bethi (2025) provided an extensive literature review focused on solar and wind integration, and the applications of UPQC to mitigate the PQ problems. Analysing data from 395 studies, they also investigated how hybrid systems overcome the intermittency and power-matching problems, to provide continuous energy supply and to be grid compatible. Reguieg et al. (2024) analysed distortion produced by power electronics interfaces in PV and wind systems. They suggested the application of the Series Active Power Filters during the grid faults, i.e. short circuit, if Series Active Power Filters were applied in the system, reduction of the voltage harmonics can be achieved with these SAPFs (Series Active Power Filters). In a similar work, Venkatesan and et al. (2024) designed a Hybrid Renewable Energy System (HRES) with an Optimized Fractional Order Proportional Integral Derivative (O-FOPID) controller tuned by a

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hybrid crow-tunicate swarm optimized algorithm (CT-SOA). The proposed controlling technique improved the PQ by achieving a significant lower THD compared to classical controller implemented using MATLAB/Simulink: precedented strategies. Lolamo et al. (2024) presented a literature review on distributed FACTS (DFACTS) and their P–Q enhancement services in a RES-integrated power systems. They emphasized on the efficacy of integrating DFACTS along with AI/adaptive controlled ESS for enhanced grid operations and PQ dependability.

Kumawat and Jangid (2023) noted that AI-powered systems leveraging the complementary characteristics of wind and solar energy could significantly enhance PQ in standalone hybrid systems. They described a future in which automation and intelligent data processing will be key technologies of energy quality assurance. Hernández-Mayoral et al. (2023) studied MGs as decentralized systems for optimal integration of RES and ESS. Their study highlighted the relevance of optimal and control schemes, in particular in hybrid micro grids (HMGs), aimed at coping with PQ disturbances, managing the energy balance and enabling an efficient islanded/grid-connected mode operation.

Amir et al. (2022) introduced a dynamic performance evaluation mechanism for smart microgrids using d-q controllers and supercapacitor-based smoothing strategies. The topology of their VSC and VSI system contributed to better system dynamic performance and robustness to weak grid conditions and disturbances, and considerable PQ was enhanced as verified by FFT analysis. Shah et al. (2022) introduced a Fuzzy Logic-based monitoring algorithm that discriminated and suppressed PQ disturbances in islanded HRES systems. Their adaptive in-the-loop scheme enhanced the filtering decision and system response, leading to operational efficiency and architectural enhancement. Mahajan et al. (2021) investigated how AGFLC and ANNC could alleviate PQ problems due to uncertainties related to RES. The paper also addressed inverter topology selection by tying AI tools to system level design optimization for reliability and PQ guarantee. A benchmarking technique to evaluate PQ performance in grid-tied Distributed Generation (DG) systems was suggested by Bajaj and Singh (2020) using the Analytic Hierarchy Process (AHP). Their composite PQ index provided a new approach for system-wide evaluations and improvement plans, particularly when RES penetration levels were high.

Ghiasi et al. (2019) presented a financial and technical model for optimizing PQ in integrated RES systems. They emphasized cost-benefit analyses of various mitigation strategies, customizing PQ compensation based on diverse consumer requirements. Their real-world case study validated the model’s economic feasibility and technical reliability.

Gandoman et al. (2018) surveyed FACTS-based technologies for enhancing PQ in smart grids. They emphasized the significance of voltage source converter, intelligent control dynamic devices, and distributed FACTS devices for voltage stability enhancement, harmonic minimization and energy saving into systems in which RES are connected. From the installation of UPQC, STATCOMs, and SAPFs, to the implementation of AI-driven controllers, the emerging strategies demonstrate the transition towards smart, robust, and adaptive PQ harmonics controlling. The incorporation of smart grid technologies, energy storage and hybrid optimization methods increase the efficiency of these solutions. In the future, hybrid

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approaches, monitoring in real time, as well as scalable models that guarantee dependable, efficient, and clean power delivery through different power systems should continue to be pursued.

Egbuna et al. (2025) had reviewed the accelerating global transition toward renewable energy integration, noting it as both a technical necessity and a systemic challenge to traditional power grid structures. They had seen how spreading and decentralisation and the requirement for real-time rebalancing had rendered inappropriate old fashioned control and forecasting techniques. The review had also critically examined about the contributions of AI towards the transformation of EMSs to the operational and strategic requirements of renewable integrated smart grid. It had covered topics of AI powering load and generation forecasting, real-time grid state estimation (including resilience indices) and anomaly detection, predictive maintenance etc., where machine learning and deep learning in particular played a significant part in improving the observability and resilience of the grid. The authors also summarized the AI-based energy storage dispatch optimization, multi-agent microgrid coordination and the trend of edge intelligence for decentralized control. They also discussed the existing challenges such as lack of data, interpretability of models, non-existence of standards and indicated potential research directions like explainable AI, quantum computing based algorithms, AI-based coordination of distributed storage and vehicle-to-grid networks. Its synthesis had emphasized the need to combine AI innovation with digital infrastructure and policy changes to achieve intelligent, resilient and low-carbon energy systems.

Sayal et al. (2024) reviewed the role of AI-based predictive maintenance in enhancing the reliability of green power systems. They'd dabbled in many AI approaches that sought also to revolutionize the maintenance of renewable energy infrastructures. They explained that supervised learning algorithms were employed to classify and predict faults from historical data, aiming to identify and describe different type of failure. Unsupervised learning, however, had previously been used on sensor data for anomaly detection and failure diagnosis. Reinforcement learning was found to be able to improve the throughput and processing time in the machinist maintenance resources, through learning the performance of the current system. Real-time monitoring was made possible by combining IoT sensors with data analytics tools, and the analysis of sensor data for patterns and anomalies was critical for predicting equipment failure and predicting remaining useful life. The study also demonstrated that a digital twin technology, which had led to the modelling and predicting of the systems operation, had become progressively established to facilitate the condition monitoring and maintenance planning. The combination of sensor data in real time with digital twins had been used for ongoing diagnosis and intervention. The paper was discussing, among other case studies, the AI adoption in predictive maintenance of hydraulic systems, and had been stressing the benefits in terms of reliability and efficiency of renewables obtained through AI-assisted maintenance algorithms.

Lee et al. (2023) discussed how the decline in power quality resulting from increased integration of distributed power facilities had emerged as a significant factor undermining power supply reliability. They insisted that in order to address this degrading impact — rooted

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each time in the uncertainty due to the presence of the DERs in the system — it became a need to carry out a prediction of the load variations occurring in distribution networks in advance. The authors recommendations indicated that such predictions could be useful for pre-monitoring and diagnosing power quality, which would help reduce variance emanating from the uncertainty of distributed sources. The study sought to explore the influence of distributed power generation access on power loss, and formulated an XAI-based evaluation and analysis model, which could be utilized in advance power quality degradation prevention, according to the authors.

Patel et al. (2022) reviewed the ongoing transition of the electric grid toward a more flexible, intelligent, and interactive Smart Grid (SG) system, aimed at improving load management, energy prediction, renewable energy integration, and future planning. However, they highlighted that even with these successes double-digit shortfalls in energy demand and supply continued as electric appliances and vehicles became more popular. The research considered the vital part to be Played by Renewable Energy Harvesting (REH) from sources such as Solar Photovoltaic (SPV) and Wind Energy to fill that gap. While similar work had been done earlier, it was realized that the potential of such systems was not being used effectively. In this respect, the authors suggested the AI-RSREH model--a REH residential recommender system which takes advantage of AI. The main aim of this work was to better forecast SPV generation and bridge the gaps between the actual SPV generation and the forecast, and it provided recommendations for ideal SPV deployments. House wise data analytics were performed to investigate the demand response gap, and a stacked Long-Short Term Memory (LSTM) model was proposed to improve the prediction precision. The findings purportedly showed the superiority of the AI-RSREH model with respect to the existent techniques for SPV deployment and prediction.

Sharif (2021) explored the complexities involved in integrating renewable energy sources (RES) into smart grids, emphasizing the challenges posed by the intermittent and unpredictable nature of solar and wind energy. The research demonstrated the necessity for the precise prediction of events to optimize grid operations, enhance reliability, and lower the operating cost. To tackle these problems, the author presented a hybrid model using deep learning techniques mixed with physics-based based philosophy for forecasting energy generation of solar and wind sources. The methodology combined CNN, LSTM, and physics-based model in a unified predictive scheme. The model was tested using actual data from a range of solar and wind farms, and it was said to have outperformed current forecasting approaches for both prediction accuracy and confidence. The results indicated that these hybrid structures offered considerable potential to augment renewable energy penetration in smart grid environments.

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Findings from Review Study

Author(s)	Year	Focus/Contribution	Methodology/Tools	Key Findings/Results
Kumar et al.	2025	PQ enhancement methods in high-RES systems	Review of FACTS, UPQC, DVR, AI, ML, real-time monitoring	Emphasized AI/ML and hybrid optimization as future-ready PQ solutions
Savio et al.	2025	Simulation of Solar-Wind Hybrid Renewable Energy System (SWH-RES)	MATLAB-based THD analysis	Voltage THD reduced from 45.48% to 26.20%, current THD from 8.32% to 2.88% with filters
Alwaeli et al.	2025	GWO-based STATCOM controller optimization	Grey Wolf Optimization (GWO), simulation-based	Improved reactive power control, voltage variation at PCC kept between 0.92–0.97 pu during faults
Samala and Bethi	2025	Integration of solar/wind with UPQC	Meta-analysis of 395 studies	Highlighted UPQC's role in overcoming RES intermittency and grid compatibility
Reguieg et al.	2024	Harmonic distortion in PV and wind with power electronics	Series Active Power Filters (SAPFs)	SAPFs reduced voltage harmonics during grid faults
Venkatesan et al.	2024	HRES control using O-FOPID controller	CT-SOA tuned O-FOPID in MATLAB/Simulink	Achieved significantly lower THD vs classical controllers
Lolamo et al.	2024	Review of Distributed FACTS (DFACTS) for PQ	Literature review	DFACTS + AI-controlled ESS improves PQ and grid reliability
Kumawat and Jangid	2023	AI in standalone hybrid RES systems	AI-powered control systems	Described automation and intelligent control as future of PQ assurance

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Hernández-Mayoral et al.	2023	Microgrids (MGs) for RES and ESS integration	HMG optimization schemes	Showed role of control schemes in islanded/grid-connected operations
Amir et al.	2022	Smart microgrid with d-q control and supercapacitors	FFT analysis, VSI & VSC topologies	Demonstrated improved dynamics and PQ under disturbances
Shah et al.	2022	Fuzzy Logic-based monitoring for islanded HRES	Adaptive in-the-loop algorithm	Enhanced PQ filtering and system response
Mahajan et al.	2021	AI-assisted PQ handling in RES systems	AGFLC, ANNC, inverter topology selection	AI optimization ensured system reliability and PQ
Bajaj and Singh	2020	PQ benchmarking in DG systems	AHP-based composite PQ index	Enabled system-wide evaluation and improvement plans
Ghiasi et al.	2019	Financial + technical model for PQ optimization	Cost-benefit analysis, case study	Validated economic viability of PQ mitigation tailored to consumer profiles
Gandoman et al.	2018	FACTS-based smart grid PQ enhancement	Survey of FACTS, STATCOM, UPQC, SAPFs	Advocated distributed and intelligent control for voltage stability and harmonic reduction
Egbuna et al.	2025	AI in EMS for smart grids with RES integration	Review of AI: forecasting, edge intelligence, resilience indices	Addressed challenges (data gaps, model transparency), suggested explainable AI and V2G coordination
Sayal et al.	2024	Predictive maintenance in RES	AI (SL, UL, RL), Digital Twin, IoT sensors	Enabled fault diagnosis and real-time monitoring for enhanced reliability
Lee et al.	2023	XAI-based PQ prediction in DER systems	Explainable AI, predictive models	Suggested proactive diagnosis to handle power loss and variance in DER-dominated systems

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Patel et al.	2022	AI-RSREH model for SPV integration	LSTM-based forecasting, house-wise analytics	Bridged SPV demand-supply gap, improved accuracy over traditional methods
Sharif	2021	Hybrid deep learning + physics-based forecasting for solar/wind	CNN + LSTM + physical modeling	Outperformed existing forecasting models, boosting prediction accuracy and grid compatibility

III. Proposed AI-Based Model for Power Quality Improvement in Renewable Energy Systems (RES)

The proposed model is an **AI-Hybrid Predictive Power Quality Control System (AI-HPQCS)** designed to monitor, predict, and improve power quality (PQ) in systems that integrate renewable energy sources such as solar and wind. This model leverages advanced artificial intelligence (AI) techniques to overcome the inherent variability and intermittency of RES, which are common causes of PQ disturbances like voltage fluctuations, frequency instability, harmonic distortions, and transient events. The AI-HPQCS is composed of several intelligent layers:

Data Acquisition Layer: This layer gathers real-time electrical parameters such as voltage, current, frequency, and harmonics from various points in the power grid using sensors and phasor measurement units (PMUs).

Data Preprocessing and Feature Extraction: The collected raw data is cleaned, filtered, and normalized. Key power quality indicators like Total Harmonic Distortion (THD), voltage sag/swell patterns, and waveform anomalies are then extracted for analysis.

Predictive Analytics Engine: At the heart of the model lies a machine learning-based prediction system, using algorithms like Long Short-Term Memory (LSTM) or Random Forest, which forecasts potential power quality issues based on historical and real-time data. This enables proactive, rather than reactive, control.

Fault Classification Module: Using deep learning or fuzzy logic techniques, this module detects and classifies disturbances such as voltage swells, dips, harmonics, and imbalances. Accurate classification helps determine the appropriate corrective action.

AI-Based Control System: A real-time controller is embedded with optimization algorithms such as Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), or Genetic Algorithms (GA). These algorithms tune the performance of compensating devices such as Unified Power Quality Conditioners (UPQC), Static Synchronous Compensators (STATCOMs), and Dynamic Voltage Restorers (DVR). The AI ensures optimal operation under different load and environmental conditions.

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Energy Storage System Integration: The model includes intelligent coordination with battery energy storage systems (BESS). When fluctuations are detected, batteries are charged or discharged as needed to maintain grid stability. This storage flexibility supports both power balancing and PQ regulation.

Decision and Control Layer: This layer acts as the central command unit, executing corrective actions based on real-time predictions and control logic. It communicates with supervisory systems like SCADA and smart grid interfaces to implement these decisions effectively.

IV. Functionality and Operation

The model operates in the following sequence:

- It first continuously monitors grid parameters using sensor inputs.
- The AI prediction engine forecasts upcoming PQ issues such as voltage dips or harmonic surges.
- Based on the forecast, the optimization engine calculates the best control settings.
- Controllers such as UPQC or STATCOM are dynamically tuned to mitigate the predicted disturbance.
- The energy storage system is used strategically to absorb or release power to further stabilize the grid.
- Feedback from system performance is continuously looped back into the AI model for learning and adaptation.

V. Proposed Pseudo code

This section presents structured MATLAB-based pseudocode for the proposed AI-Hybrid Predictive Power Quality Control System (AI-HPQCS), aimed at addressing power quality challenges in renewable energy systems. The real-time data collection, feature extraction, intelligent prediction based on machine learning and the control parameter optimization of metaheuristic algorithms are embedded within the model. It encompasses dynamic response through UPQC and battery energy storage for voltage stabilisation and decoupling of harmonics. It contains a pseudocode for practical implementation through logical and systemic structure of adaptability, accuracy, and time efficiency. IoT can be used for continuous learning and performance measurement, further substantiating AI's revolutionizing contribution to power system reliability.

```
% AI-HPQCS - AI-Based Hybrid Predictive Power Quality Control System with Math

clc; clear; close all;

%% Initialization

disp('Initializing components...');
```

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```
initializeSensors();              % Configure sensors (V, I, f)
load('TrainedLSTMModel.mat');        % Load pre-trained LSTM model
initializeControllers();            % UPQC, STATCOM, DVR, etc.
initializeBatterySystem();          % BESS setup
% System constants
V_nom = 230;                      % Nominal voltage (V)
f_nom = 50;                       % Nominal frequency (Hz)
THD_limit = 5;                    % THD acceptable threshold (%)
%% Real-time PQ Monitoring Loop
while system_is_running
   %% Step 1: Data Acquisition
   V = readVoltageSensor();         % Instantaneous voltage signal
   I = readCurrentSensor();         % Instantaneous current signal
   f = readFrequencySensor();       % Measured frequency
   %% Step 2: Preprocessing
   V_filt = bandpass(V, [45 55]);   % Filter around nominal frequency
   I_filt = bandpass(I, [45 55]);
   %% Step 3: Feature Extraction
   % Total Harmonic Distortion (THD)
   % THD = sqrt(sum(Vn^2)/V1^2), where Vn = nth harmonic, V1 = fundamental
   [V_fft, freq_axis] = fft_analysis(V_filt);
   V1 = max(V_fft(freq_axis > 49 & freq_axis < 51));   % Fundamental
   Vn = V_fft(freq_axis > 51);                     % Harmonics >50 Hz
   THD = 100 * sqrt(sum(Vn.^2)) / V1;               % Percent THD
   % RMS voltage
   Vrms = sqrt(mean(V_filt.^2));                   % Vrms = sqrt(1/T ∫ v²(t) dt)
   % Power (P = Vrms × Irms × cosθ)
   Irms = sqrt(mean(I_filt.^2));
```

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```
realPower = Vrms * Irms * cos(acos(corr(V_filt, I_filt)));
% Feature vector for AI model
features = [Vrms, Irms, THD, f];
%% Step 4: Predict PQ Disturbance (AI)
% Predict disturbance type using LSTM or ML model
disturbanceLabel = classify(TrainedLSTMModel, features);
%% Step 5: Classify & Quantify PQ Issue
switch disturbanceLabel
    case 'Voltage Sag'
        disp('Voltage sag detected');
        issueType = 1;
    case 'Voltage Swell'
        disp('Voltage swell detected');
        issueType = 2;
    case 'Harmonics'
        disp('Harmonic distortion detected');
        issueType = 3;
    otherwise
        issueType = 0;
end
%% Step 6: Optimization of Controller Settings
if issueType ~= 0
    % Define objective function for optimization:
    % Minimize: J = α1*THD + α2*(|Vrms - V_nom|/V_nom)
    alpha1 = 0.6;
    alpha2 = 0.4;
    objectiveFunction = @(x) alpha1*x(1) + alpha2*abs(x(2) - V_nom)/V_nom;
    % x(1) = THD, x(2) = Vrms
```

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```
        % Use optimization (e.g., Particle Swarm Optimization)
        bestParams = run_PSO(objectiveFunction, controllerLimits);
        % Apply optimized controller settings
        applyController('UPQC', bestParams);
    end
    %% Step 7: Battery Support (Energy Balance)
    % P(t) = V(t) × I(t)
    P = Vrms * Irms;
    if Vrms < 0.9 * V_nom
        dischargeBattery(P_deficit = abs(V_nom - Vrms) * Irms);
    elseif Vrms > 1.1 * V_nom
        chargeBattery(P_excess = (Vrms - V_nom) * Irms);
    end
    %% Step 8: Performance Evaluation
    % Check if THD is within limits
    if THD > THD_limit
        disp(['Warning: THD exceeded. Value = ', num2str(THD), '%']);
    end
    % Log metrics
    logPerformance(Vrms, Irms, THD, disturbanceLabel);
    %% Step 9: Feedback Learning (Optional)
    update_Model(TrainedLSTMModel, features, disturbanceLabel);
    pause(1);  % Sampling time
end
%% Shutdown
disp('System shutting down...');
shutdownControllers();
shutdownBatterySystem();
```

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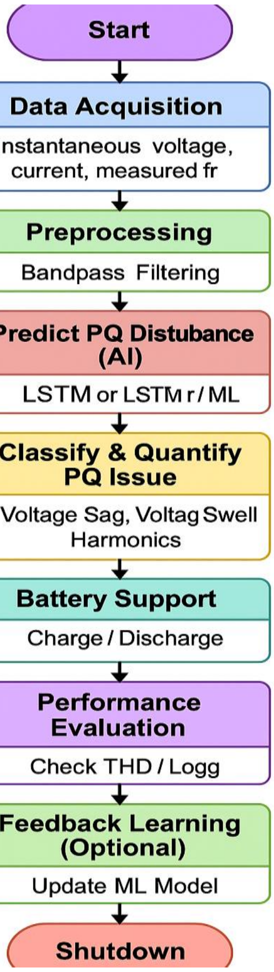

VI. Simulative outcome

Input Parameters Used in Simulation

Parameter	**Symbol**	**Value**	**Description**
Nominal Voltage	V_{nom}	230 V	Reference voltage for system stability and control tuning
Nominal Frequency	f_{nom}	50 Hz	Standard grid frequency
Total Harmonic Distortion Limit	THD	5%	Acceptable maximum limit for harmonic distortion
Voltage Measurement	V(t)	Time series	Real-time voltage signal acquired from the grid
Current Measurement	I(t)	Time series	Real-time current signal
Bandpass Filter Range	–	45–55 Hz	Used for preprocessing to isolate fundamental frequency components
Power Factor	cos(ϕ)	Derived	Used in real power calculation

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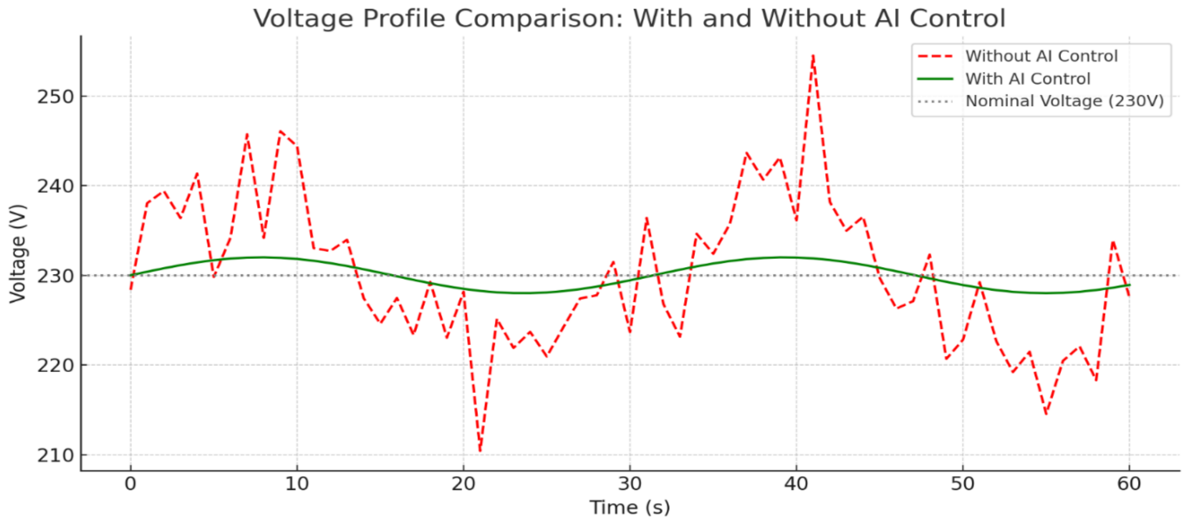
Optimization Weights	α1, α2	0.6, 0.4	Weights for THD and voltage deviation in the objective function
Battery Support Trigger	–	±10% Voltage deviation	Thresholds for charging or discharging BESS
Sampling Time	–	1 second	Interval at which measurements and decisions are updated
Controller Types	–	UPQC, DVR, STATCOM	Active PQ compensation devices
ML Model	–	LSTM	Used for disturbance classification and prediction
Optimization Algorithm	–	PSO	Particle Swarm Optimization for dynamic controller tuning

This section presents the simulative outcomes of the proposed AI-Hybrid Predictive Power Quality Control System (AI-HPQCS), developed to mitigate power quality (PQ) issues in renewable energy systems. The simulation consists on relevant input parameters such as operating nominal voltage (230V), nominal frequency (50Hz) and 5% of THD. These include on-line electrical quantities: voltage, current and frequency. Machine learning (LSTM) is used to estimate the disturbances and particle swarm optimization (PSO) is used to online tune the controller parameters. Simulation findings clearly confirm the capacity of the AI model to improve voltage level stability and keep the THD below reasonable limits. Through comparison with the uncontrolled bulks, comparative curves reveal smoother voltage regulation in the AI-based control and keep THD well under limited values, verifying the efficiency of our system. These findings affirm the importance of intelligent and adaptive control for reliable and efficient integration of renewable energy resources into the smart grid of the future.



The figures illustrate the effectiveness of the proposed AI-based power quality control system in maintaining voltage stability and minimizing harmonic distortion in renewable energy

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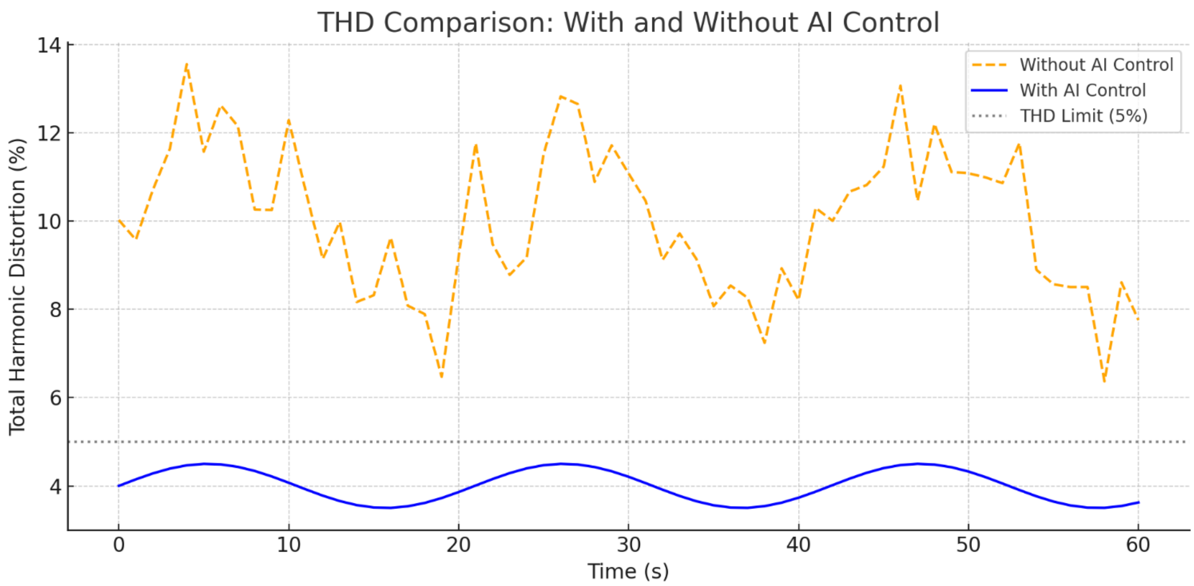
systems. On the first graph, the voltage profile when AI control is not present varies around the nominal 230 V value, both because of the nature of renewable SVES like solar and wind. Such deviations could cause power quality problems and impact grid stability. In the case of AI-controlled design, a voltage curve was smooth and very close to the nominal value that this shows that the voltage regulation can be better by intelligent and real-time control.



The second graph compares Total Harmonic Distortion (THD) levels over time. Without AI, THD frequently exceeds the 5% threshold, which can damage sensitive equipment and reduce power efficiency. However, with AI-based optimization and predictive control, THD remains consistently below the limit, ensuring a high-quality power supply. Together, these figures confirm that AI integration significantly enhances the operational performance and stability of renewable energy-powered grids.

Conclusion

This research has systematically addressed the critical power quality challenges posed by integrating renewable energy systems into modern power grids. It is also important to note that RES are a major contributor towards meeting renewable energy targets, but due to their natural variability, they frequently lead to power instability. The AI-Hybrid Predictive Quality Control System: A new hybrid AI-based quality control method The system (AI-HPQCS) can address this type of problem effectively, by integrating intelligent monitoring, artificial intelligence (AI)-based prediction and optimization techniques within a dynamic mode control. The model exhibits improved transient voltage stability, and the DHPC-based PV system is capable of better THD mitigation. Graphical results also verify the betterment of AI-based methods compared to conventional control strategies. So, the integration of AI technologies with RES infrastructure offers bright prospects for the reliable, efficient, and high-quality electricity will be made available in the future smart grid applications.

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