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Power Quality Management for Solar-Based Microgrids Using Integrated Artificial Intelligence and Internet of Things Technologies

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Abstract
Demand for solar-based microgrid systems is increasing in remote and rural areas due to their simple installation and operation flexibility. Power quality issues arise in the solar supply system because of the switching of inverters, nonlinear loads, and fluctuation in solar irradiance. This study proposes an integrated artificial intelligence and Internet of Things-based smart power quality management system for a solar microgrid. A MATLAB simulation model of a 20 kW solar microgrid is developed, incorporating a DC–DC boost converter and a maximum power point tracking system for improving the power conversion efficiency. An IoT monitoring system continuously monitors real-time data of supply voltage, current, power factor, and total harmonic distortion. These measures are processed using an artificial neural network- long short-term memory-based intelligent controller to detect power quality disturbances by analyzing the sensor data and making quick control decisions. The proposed MATLAB Simulink microgrid model is validated through hardware-in-the-loop testing on the Typhoon hardware-in-the-loop platform. The experimental results of hardware-in-the-loop demonstrate a 70% total harmonic distortion reduction (to 3%), power factor (0.99), and settling time less than 50 ms that is under irradiance/load dynamics, outperforming baselines and meeting IEEE 519/1547 standards. Hardware-in-the-loop results show less than 5% deviation, demonstrating suitability for deployment.

Keywords- Solar microgrid, Power quality management, Artificial intelligence and Internet of Things, Artificial neural network-long short-term memory, Hardware-in-the-loop validation, Total harmonic distortion.

1. Introduction

The demand for solar power generation has increased because of growing awareness of clean, sustainable, and reliable electricity. These systems are particularly suitable for supplying power to rural areas, remote areas, educational and commercial campuses, and small industries and simultaneously reducing dependence on conventional fossil-fuel-based power generation systems. These systems provide significant environmental benefits by reducing greenhouse gas emissions and minimizing dependence on fossil fuel–based power generation. Consequently, solar microgrids have become an important component of modern smart grid architectures and sustainable energy strategies (Ratnakaran et al., 2023).

Although solar-based microgrids have benefits, they have several operational issues that influence the stability of the system and the quality of power. The non-uniformity of solar irradiance and the switching of power electronic converters and nonlinear loads tend to cause voltage variation, harmonic distortion, and reduced power factor. These issues with power quality may cause a substantial decrease in the efficiency of loads connected to them, increase system losses, and decrease the overall reliability of the microgrids (Das et al., 2022). Thus, the solar microgrid systems need to be monitored and controlled with the help of effective strategies to provide stable operation and adequate levels of power quality.

Over the past few years, there has been a lot of interest in the use of advanced digital technologies like artificial intelligence and the Internet of Things to enhance the performance and reliability of renewable energy systems. The Internet of Things allows real-time control of important electrical parameters, such as voltage, current, frequency, and power factor, with interconnected sensors and communication networks. Constant monitoring enables the operators of the system to identify abnormal conditions and react promptly to power quality disruptions. Simultaneously, artificial intelligence methods offer intelligent data analysis features, which can forecast system behavior, detect faults, and create the best control actions (Nair et al., 2022). Likewise, Sumana et al. (2022) proposed and validated a photovoltaic (PV) based unified power quality conditioner (UPQC) in a typical micro-grid environment with the help of an adaptive neuro-fuzzy inference system (ANFIS) controller. Their findings showed better voltage regulation and harmonic compensation, but did not include the monitoring of IoT or deep learning based adaptive control under dynamic operating conditions.

Artificial intelligence techniques that have been extensively applied in the power systems field include artificial neural networks, deep learning models, and hybrid machine learning algorithms. These methods can handle the nonlinear change in load, dynamics of systems, and uncertainties associated with renewable energy production. Among them, the combined effect of artificial neural networks and long short-term memory networks has shown promising results in analyzing the time-series data and predicting the dynamic behavior of systems. By combining AI-based control algorithms with IoT-enabled monitoring systems, it is easy to develop automatic intelligent microgrid platforms that can operate and make adaptive decisions (Mir et al., 2025).

Although several studies have explored the use of AI techniques for microgrid control and power quality improvement, many existing approaches rely primarily on simulation-based analysis without real-time validation. Moreover, the integration of AI-based predictive control with IoT-enabled monitoring frameworks for real-time power quality management in solar microgrids remains an active research area. Therefore, there is a need for intelligent control architectures that combine real-time sensing, data-driven analysis, and practical validation to ensure reliable operation under varying environmental and load conditions.

This paper focuses on the power quality management system of a 20 kW solar-based microgrid using the integrated AI–IoT smart system. In this integrated system, IoT has different kinds of sensors, monitoring the various output quantities continuously, whereas ANN-LSTM algorithms read the sensor data and make fast control decisions. This solar system is connected with a DC–DC boost converter with MPPT (maximum power point tracker) for the boosting of power level as well as increasing the capture of sun radiation. The main objective of the intelligent system is to reduce total harmonic distortion, maintain voltage stability, improve power factor, and enhance overall power quality under different operating conditions.

The effectiveness of the proposed approach is validated using hardware-in-the-loop experimentation on the Typhoon hardware-in-the-loop platform, which provides a realistic environment for testing power electronic control systems. The proposed intelligent framework aims to reduce harmonic distortion, improve power factor, maintain voltage stability, and enhance the overall reliability of solar-based microgrid systems under varying irradiance and load conditions.

1.1 Key Contributions

- Development of an AI–IoT integrated power quality management framework for a 20 kW solar microgrid.
- AI-IoT integrated system reducing THD by 70 %, achieving power factor = 0.99, and validated via Typhoon HIL
- Closed-loop control meeting IEEE 519/1547 standards under dynamics with less than 5% HIL-simulation deviation

The paper is organized as follows: Literature reviews and identified research gaps are shown in Section 2. Section 3 demonstrates the methodology in detail. Section 4 presents the MATLAB/Simulink implementation and performance evaluation of the proposed AI–IoT-based solar microgrid. It includes the simulation model, closed-loop operation, and detailed performance analyses presented in Sections 4.1.1–4.1.4 under various operating conditions. Section 5 discusses simulation results and HIL-validated results. Finally, Section 6 concludes the paper by summarizing the key findings, limitations, and future research directions.

2. Literature Review

The fast adoption of renewable energy in microgrids has posed new problems concerning the quality of power, reliability, and smart control. It has been demonstrated that advanced AI methods can be highly effective in improving the performance of power quality in microgrids by enhancing harmonics, voltage instability, and disturbance mitigation, as illustrated by intelligent unified power quality conditioners and optimized neural network-based controllers (Das et al., 2022; Ratnakaran et al., 2023). It has also been reported that AI-based microgrid systems can improve stability, effective power sharing, and system reliability, which makes AI a promising tool in modern power quality improvement (Nair et al., 2022).

Recent literature emphasizes that AI can be used together with the IoT to enhance monitoring and maintenance in solar-based systems, which will allow predictive diagnostics, optimization of operational efficiency, and enhanced reliability of the system (Singh et al., 2024; Mir et al., 2025). The methods of machine learning have also been used to make correct predictions and manage energy efficiently, which indirectly leads to the enhancement of power quality by improving load balancing and reducing uncertainty in distributed generation systems (Srilakshmi et al., 2023).

The quality of power analysis in renewable microgrids has also developed with sophisticated signal processing techniques, including multi-signal discrete wavelet transform, which allows accurate detection and classification of PQ disturbances (Eluri & Naik, 2022; Singh et al., 2023). Adaptive and intelligent controllers have also become a major strategy, with intelligent energy management proving to improve the quality of power and operating performance in grid-connected microgrids (Rani et al., 2021; Tabassum et al., 2024).

Subsequent reviews note that contemporary photovoltaic systems are becoming more dependent on AI, remote-control features, and cyber-security, which is a definite technological change to intelligent PQ-aware smart systems (Hafidz et al., 2023; Joshua et al., 2024). General studies of microgrid architectures reveal that disturbances in power quality, complexity of control, and protection coordination are significant issues requiring sophisticated mitigation methods (Alagusundari et al., 2025).

Real-time IoT-based monitoring is crucial in enhancing the reliability of microgrids by allowing timely identification of PQ problems and the provision of corrective measures by improving protective systems (Votava et al., 2025). In addition, IoT combined with smart adaptive control methods has been known to greatly enhance the real-time PQ correction capacity, which facilitates the functioning of smart grids with minimal distortions and greater voltage regulation (Ghoshal & Tripathy, 2024).

A thorough bibliometric survey of AI implementation in solar-assisted greenhouse systems, with a focus on IoT-AI integration, which has the potential to achieve energy efficiency and microclimate control by predictive maintenance and MPC presented by Das et al. (2022). The authors of Wazirali et al. (2023) give a state-of-the-art review on ANN, ML, and DL methods of energy and load forecasting in microgrids on short, medium, and long-term horizons.

An example of a systematic review writing on the use of AI in solving power quality challenges in the distribution system can be seen in (Dehaghani et al., 2025; Villagran et al., 2025), in which different AI-related mechanisms like machine learning and neural networks were evaluated to enhance voltage stability and harmonic mitigation. It was investigated that solar-based microgrids can be enhanced in terms of quality of power and in terms of reducing voltage and current distortions, and proposed intelligent algorithms as the means of achieving this goal (Reguieg et al., 2025). The article Singh et al. (2025) highlights the latest developments in the field of modern power system management, such as smart grid automation, artificial intelligence, IoT-based monitoring, renewable energy integration, and intelligent control methods for transmission and distribution systems. In a similar way, Zulu et al. (2025) developed PQ improvement in PV/wind smart grids based on the artificial neural network and AI-based inverter control.

The authors of Zahid et al. (2026) give a thorough analysis of AI-based methods of PQ optimization in microgrids and outline new tendencies and future problems. The implementation and operation of hybrid renewable energy sources within microgrids with the help of AI, were described with a focus on predictive energy management and optimization of the system. An analysis of the performance of an AI controller of a PV-battery-connected UPQC is presented in Srilakshmi et al. (2023), with better voltage regulation and harmonic suppression.

In article Nijanthan & Bharathi (2025), a hybrid solar system model including the use of AI-based predictive control was suggested, and it was explained how this model is efficient in forecasting and scheduling power. An overview of various techniques of compensation in microgrids was presented in Khan et al. (2026) through a scoping review on improving PQ with the help of unified power quality conditioners (UPQC) in microgrids. In Sahoo et al. (2025), determination of precision PQ control of grid-integrated microgrids was investigated through advanced mathematical methods involving the use of the matrix pencil method.

A deep reinforcement learning (DRL) based controller presented by Sravani & Sobhan (2025) for a solar PV integrated UPQC that reduced THD and dynamic response compared to PI controller. The study, however, did not take into account the IoT-based monitoring and ANN–LSTM-based adaptive control for intelligent operation of the microgrid. Authors of Brahmane & Deshmukh (2023) proposed AI-based systems of energy management of renewable sources were designed so that they could work stably because they are distributed optimally. The article Călin et al. (2024), covers a review on the enabling technologies of AI-driven microgrids and their future. In Bhardwaj et al. (2024), AI-based energy management systems have been suggested to achieve renewable integration and load balancing in microgrid optimization.

A list of extensive sources regarding the application of AI in power systems is provided in Singh et al. (2023), and it presents both theoretical and practical grounding. Some of the earlier studies, like Nguyen (2022) provided the groundwork of power quality enhancement and optimal control in grid-connected solar PV systems, which is the reason behind the current developments made by AIs. **Table 1** presents the summary of related studies on artificial intelligence and Internet of Things- based microgrid power quality management.

Table 1. Comparative analysis of existing studies with methodologies, applications, and key findings.

Author / Year	Method / Technology	Application	Key contribution
Ratnakaran et al. (2023)	Neural network controlled UPQC	PV microgrid power quality improvement	Proposed artificial ecosystem optimized neural network controller to improve voltage regulation and harmonic mitigation
Das et al. (2022)	Artificial intelligence techniques	Hybrid renewable microgrid	Demonstrated AI-based techniques for power quality enhancement and harmonic reduction
Nair et al. (2022)	AI-based microgrid control	Smart microgrid system	Developed intelligent control for power sharing and power quality improvement
Mir et al. 2025	AI-IoT integration	Solar energy systems	Integrated AI with IoT for predictive maintenance and system monitoring
Singh et al. (2024)	Machine learning energy forecasting	Grid-connected microgrid	Improved energy forecasting and system management using machine learning
Hafidz et al. (2023)	IoT-based monitoring system	Microgrid PQ monitoring	Developed IoT-based portable power quality monitoring system
Tabassum et al. (2024)	IoT and adaptive neuro-fuzzy system	Smart grid PQ improvement	Real-time power quality enhancement using IoT and ANFIS
Eluri & Naik (2022)	Adaptive fuzzy logic controller	Grid integrated microgrid	Enhanced power quality and energy management using fuzzy control
Joshua et al. (2024)	Machine learning based PQ control	Solar microgrid	Demonstrated ML techniques for harmonic mitigation and system stability
Zulu et al. (2025)	Artificial neural network control	PV/Wind smart grid	Improved harmonic suppression and voltage stability using ANN
Reguieg et al. (2025)	Optimization-based PQ and energy management	PV-battery microgrid	Integrated power quality improvement with energy management
Zahid et al. (2026)	AI-driven optimization methods	Microgrid PQ control	Review of AI techniques for power quality improvement
Talaat et al. (2023)	AI-based renewable microgrid control	Hybrid renewable energy systems	Demonstrated AI-based energy management and microgrid integration
Sahoo et al. (2025)	Matrix pencil technique	Grid-integrated microgrid	Precise control strategy for power quality enhancement

Based on the literature reviewed, it can be concluded that AI-IoT technologies are important in enhancing monitoring, forecasting, and control of microgrids, which eventually results in improved performance in terms of power quality. However, the majority of current literature focuses on either AI-based control methods or IoT-based monitoring separately. Comprehensive integration of AI-IoT for coordinated real-time power quality management in practical solar-based microgrid systems, particularly around realistic power levels such as 20 kW, remains relatively underexplored. This article addresses this research gap by developing an AI–IoT-enabled system for power quality improvement in solar microgrids, focusing on harmonic reduction, voltage stability, and reliable operation.

2.1 Research Gap

1) Most existing studies focus either on AI-based control or IoT-based monitoring alone, but so far, no research has concentrated on the combined use of AI-IoT for managing power quality in solar microgrids.
2) Limited research demonstrates real-time power quality enhancement using integrated AI–IoT platforms in practical microgrid environments.
3) Very few works validate solutions on realistic mid-scale solar microgrids (~20 kW) with comprehensive evaluation of THD, voltage profile, and power factor.
4) Existing approaches lack a unified, intelligent, and communication-enabled framework, with limited HIL validation in 20 kW solar microgrids; most remain MATLAB-only.
5) Existing studies lack a comprehensive assessment of dynamic operating conditions to ensure THD ≈ 3% and a power factor of 0.99 in compliance with IEEE 519 standards.

3. Methodology

The proposed methodology develops an AI–IoT integrated power quality management system for a solar-based microgrid. A MATLAB simulation model is developed for a 20 kW solar system along with a hybrid AI-based controller that utilizes IoT measurements to enhance voltage quality, maintain near-unity power factor, and minimize THD at the point of common coupling.

3.1 Solar Microgrid with AI–IoT

Figure 1 presents the overall architecture of the proposed AI–IoT integrated solar-based microgrid with a power quality management system. As shown in **Figure 1**, the 20 kW solar PV array connects to a DC–DC boost converter managed by an MPPT controller. This controller regulates the duty cycle to maximize power extraction and ensure a stable DC link voltage for the downstream converter. The DC output is fed to a three-phase five-level inverter, which converts the DC power into AC and injects it into the microgrid at the point of common coupling (PCC). The PCC supplies power to various connected AC loads, ensuring reliable energy distribution within the microgrid (Nair et al., 2022).

At the point of common coupling, sensors grouped within the IoT sensing layer continuously measure voltage, current, active and reactive power, power factor, and total harmonic distortion (THD). These sensors digitize the data and transmit the parameters over a communication network to a remote or local AI-based power quality controller (Eluri & Naik, 2022). The AI controller analyzes real-time data of the power supply and assesses power quality issues. Accordingly, it produces optimal control commands, including the modulation index and reactive power reference for the five-level inverter. Updated references for the MPPT/boost converter are also optional, a close loop system that enhance voltage regulation, reduces harmonics, and maintains near-unity power factor in the solar microgrid.

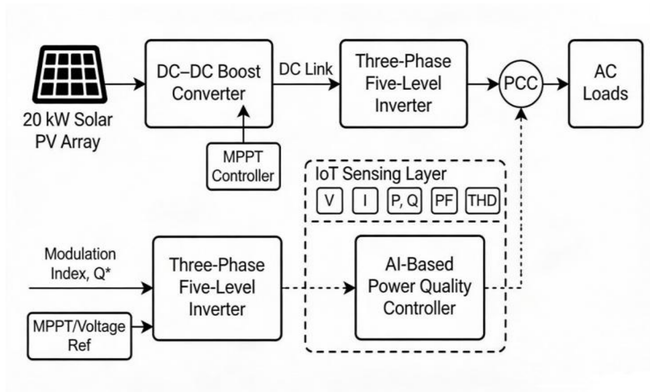

Figure 1. Architecture of solar-based microgrid with integrated AI–IoT.

3.2 PV Array and Boost Converter with MPPT

Figure 2 illustrates the PV array interfaced with the DC–DC boost converter and MPPT controller subsystem. The 20 kW solar PV array generates variable DC voltage VPV and current IPV depending on solar irradiance and temperature, which feeds into the DC–DC boost converter (Nguyen, 2022).

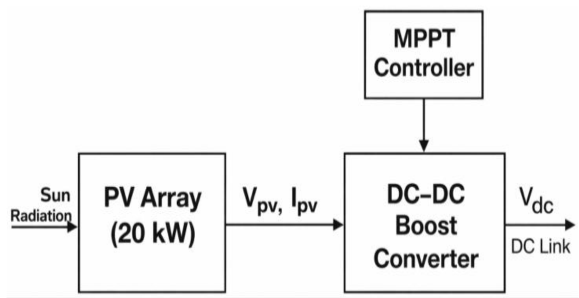

Figure 2. Interfacing of PV array with boost converter and MPPT.

By adjusting the converter's duty cycle, the MPPT controller continuously tracks the maximum power point using algorithms like Perturb & Observe (P&O), ensuring maximum power extraction regardless of environmental variations. The boost converter steps up VPV to a stable DC link voltage V_{dc} suitable for the downstream five-level inverter. Solar microgrid parameters are shown in the **Table 2**.

Table 2. Typical parameter values for 20 kW system.

Parameter	Symbol	Typical value
PV Array Power	-	20 kW
PV Voltage Range	V_{PV}	200–600 V
DC Link Voltage	V_{dc}	800 V
Boost Inductor	L	2 mH
Output Capacitor	C	500 µF
Switching Frequency	f_s	10–20 kHz

PV current of PV array for the standard single-diode equivalent model is given as follows:

$$I = I_{ph} - I_0\left[\exp\left(\frac{V+IR_s}{\eta\,V_t}\right) - 1\right] - \frac{V+IR_s}{R_{sh}} \quad (1)$$

where, I_{ph} - PV current, I_0 - diode saturation current, R_s, R_{sh} -series and shunt resistances(Ω), η- ideality factor, and V_t - thermal voltage.

For a step-up DC–DC boost converter in continuous conduction mode, voltage conversion ratio is given as

$$V_{dc} = \frac{V_{PV}}{1-D} \quad (2)$$

Inductor current relation and inductor voltage balance is given as

$$L\frac{dI_L}{dt} = V_{PV} - (1-D)V_{dc} \quad (3)$$

Output capacitor dynamics (with load R) is given as

$$C\frac{dV_{dc}}{dt} = (1-D)I_L - \frac{V_{dc}}{R_{eq}} \quad (4)$$

where, V_{dc}- DC link/output voltage, D- Duty cycle ($0 < D < 1$), controlled by MPPT, L- Boost inductor (H), typically 1–10 mH for 20 kW system, C-Output capacitor (F), typically 100–1000 µF, I_L-Inductor current (A) and R_{eq} Equivalent load resistance at DC link (Ω).

3.3 Five-Level Multilevel Inverter with L Filter

The stable DC link voltage Vdc (typically 800 V from the boost converter) feeds the three-phase five-level cascaded H-bridge (CHB) inverter, which generates multilevel AC output voltages for reduced harmonic distortion when interfacing with the microgrid at the point of common coupling (PCC) (Dehaghani et al., 2025). **Figure 3** shows the three-phase five-level inverter interfacing the DC link and microgrid PCC.

Each phase consists of two full H-bridge cells (8 switches per phase total), producing five distinct output voltage levels per phase: $+V_{dc}$, $+V_{dc}/2$, 0, $-V_{dc}/2$, and $-V_{dc}$. The inverter output passes through an LC-filter (L_f = 3mH, C_f = 150µF, R_d = 0.5 Ω damping) to attenuate high-frequency harmonics before connecting to PCC and supplying AC loads.

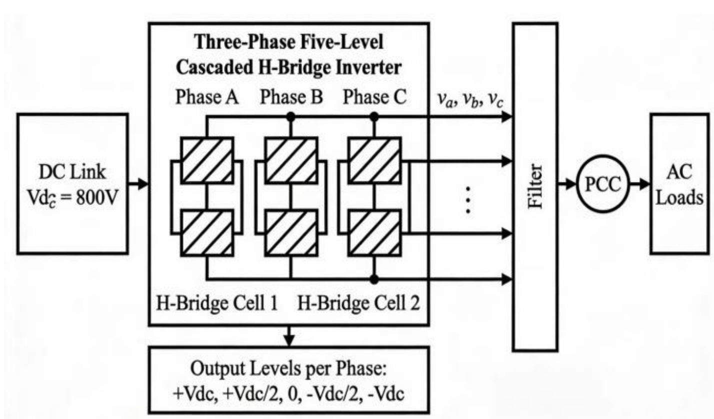

Figure 3. Three-phase five-level inverter interfacing the DC link with microgrid PCC.

Inverter output voltage per phase of the five-level cascaded H-bridge (CHB) inverter equals the sum of two H-bridge cells, producing discrete levels: ±800 V, ±400 V, and 0 V from individual 400 V DC sources ($V_{dc}/2 = 400$ V).

For two series cells per phase voltage is given as

$$V_{an}(t) = V_{H1}(t) + V_{H2}(t) \tag{5}$$

where, $V_{Hi}(t) \in \{+V_{dc}/2, 0, -V_{dc}/2\}$, yielding 5 levels and $V_{an} \in \{+V_{dc}, +V_{dc}/2, 0, -V_{dc}/2, -V_{dc}\}$ =+800, +400, 0, −400, −800 V}

Selective harmonic elimination PWM selects the switching angles α_1, α_2, α_3, and α_4 (where $0 < \alpha_1 < \alpha_2 < \alpha_3 < \alpha_4 < \pi/2$) to achieve the desired fundamental voltage V_1 while eliminating the 5th and 7th harmonics. V_1 is given as

$$V_1 = \frac{4V_{dc}}{\pi}(\cos\propto_1 + \cos\propto_2 + \cos\propto_3 + \cos\propto_4) = M.\frac{V_{dc}}{2} \tag{6}$$

THD expression is given as follows (fundamental component approximation)

$$\mathrm{THD} = \frac{\sqrt{\sum_{h=2}^{\infty} V_h^2}}{V_1} * 100\% \tag{7}$$

where, M- modulation index, V_1-RMS amplitude of the fundamental (1st harmonic) component of the voltage waveform (typically 50/60 Hz frequency) and V_h-RMS amplitude of the hth harmonic component where h = 2,3,4,…(2nd harmonic = 100/120 Hz, 3rd = 150/180 Hz, etc.

A five-level topology reduces lower-order harmonics (5th, 7th), achieving THD < 5% at modulation indices near 1. Switching Strategy (Level-Shifted PWM): In this work, 4 triangular carriers per phase, vertically shifted, are considered and then compare with single sinusoidal reference to generate 8 gate pulses, and the last used carrier frequency f_c = 10–20 kHz. **Table 3** shows the typical parameters taken for the 20 kW solar system.

Table 3. Typical parameters of the boost converter and LC filter.

Parameter	Symbol	Typical value
DC Link Voltage	V_{dc}	800 V
Output Voltage (line-line RMS)	V_L	400 V
Filter Inductance	L_f	3 mH
Filter Resistance	R_d	0.5 Ω
Switching Frequency	f_c	15 kHz
Modulation Index	M	0.8

3.4 IoT-Based Monitoring and Intelligent Control System

This section describes the integrated Internet of Things and artificial intelligence-based monitoring and control system used for improving power quality in the solar microgrid. The IoT framework collects real-time electrical parameters such as voltage, current, power factor, and total harmonic distortion from different points of the microgrid system. These measurements are transmitted to the central processing unit, where artificial intelligence algorithms analyze the data and generate appropriate control signals for maintaining stable system operation.

3.4.1 IoT-Based Monitoring

The Internet of Things monitoring system consists of distributed sensors installed at different points in the solar microgrid to measure key electrical parameters. The sensors constantly measure and monitor voltage, current, power factor, and harmonic distortion and send the information to the monitoring platform via communication modules. This real-time data collection allows the ongoing monitoring of the system performance and the intelligent controller to identify the abnormal operating conditions. The data obtained are then analyzed using artificial intelligence algorithms to detect power quality disruptions and implement corrective measures.

3.4.2 Artificial Neural Network Modelling

Artificial neural networks are popular in power system for the applications of the modeling of nonlinear systems and pattern recognition. The ANN that will be used in this study will have an input layer, one or more hidden layers, and an output layer. The microgrid system provides real-time measurements to the input layer, such as voltage, current, power factor, and total harmonic distortion. The inputs are processed by the hidden neurons with weighted connections and nonlinear activation functions.

The output of each neuron is calculated as

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{8}$$

where, x_i - input signals, w_i - connection weights, b -bias value, f - activation function, and y - neuron output.

ANN is trained through supervised learning to reduce the difference between the predicted and real system outputs. The weights are optimized with the help of optimization algorithms like back-propagation, and the training process is repeated. After training, the ANN model is able to detect disturbances in the quality of power quickly and produce appropriate control signals to the microgrid system.

3.4.3 Long Short-Term Memory Modelling

Long Short-Term memory networks are a particular type of recurrent neural network that is used to process sequential data and learn the long-term temporal dependencies. Variations in solar irradiance and load conditions cause changes in electrical parameters, e.g., voltage, current, and harmonic distortion in microgrid systems. The LSTM networks are thus applicable in predicting the behavior of the system and enhancing the performance of the dynamic control. An LSTM unit comprises three key gates: input gate, forget gate, and output gate. These gates control the movement of information in the memory cell. The mathematical description of the LSTM processes can be stated as:

Forget gate is given as

$$\mathrm{f_t} = \sigma(\mathrm{W_f}[\mathrm{h_{t-1,}} \mathrm{x_t}] + \mathrm{b_f}) \tag{9}$$

Input gate is given as

$$\mathrm{i_i} = \sigma\left(\mathrm{W_i}[\mathrm{h_{t-1,}} \mathrm{x_t}] + \mathrm{b_i}\right) \tag{10}$$

Cell status update is given as

$$\mathrm{C_t} = \mathrm{f_t} \mathrm{C_{t-1}} + \mathrm{i_t} \mathrm{C_t} \tag{11}$$

Hidden state presents as

$$h_t = o_t * \tanh(C_t) \tag{12}$$

where, x_t - input vector at time, h_t - hidden state output, C_t -cell state, W -weight matrices, b- bias vectors, σ-sigmoid activation function and o_t is the output gate activation at time step t, which controls how much information from the cell state is passed to the hidden state. Its values range between 0 and 1.

The LSTM network takes sensor data of the IoT monitoring system in the form of time series and predicts system dynamics in different operating conditions. ANN and LSTM can be integrated to enable the controller to do nonlinear mapping and temporal prediction, which enables effective mitigation of power quality disturbances in the solar microgrid.

3.5 ANN–LSTM Power Quality Controller

The main smartness of the proposed system is an ANN-LSTM controller that operates on the data of power quality obtained through the IoT and produces the best control instructions for the inverter and DC-DC stage. The AI model input feature vector contains the recent samples of PCC voltage, current, active/reactive power, power factor, and voltage THD along with operating conditions like irradiance and load level. An LSTM layer is used to identify time-related correlations and predict short-term trends of power quality indices, and the further dense ANN layers are used to map the internal states to the control outputs.

The reference modulation index M, reactive power reference Q (or power factor set-point), and minor offset signals are the controller outputs, which correct the sinusoidal reference in the PWM generator. The training data are created offline through running various Simulink scenarios with varying irradiance profiles, load steps, and nonlinear load conditions and recording the operating points that produce low THD, acceptable voltage, and close to unity power factor. A supervised learning process is used to train the network to reduce a composite loss that consists of THD, voltage deviation, and power factor error.

The ANN-LSTM controller takes a 12-dimensional input vector (3-phase voltage of PCC, 3-phase current of PCC, PF, THD of voltage, THD of current, solar irradiance, DC-link voltage and load demand) sampled at 10 kHz over a 10-sample window to capture load and irradiance variations. The network consists of an LSTM layer (64 units, dropout 0.2) and then dense layers (128-64-3 neurons, ReLU activation, Adam optimizer, $l_r = 0.001$) to produce three control outputs: modulation index adjustment ΔM [-0.2, 0.2], reactive power reference between (-10, and 10) kvar, and phase offset taken between (-5, and 5) degree real-time PWM correction. It was trained on 100 MATLAB/Simulink scenarios (irradiance 400-1000 W/m², varying nonlinear loads), for the 10,000 epochs, MSE (Mean Squared Error) loss = 0.012, and $R^2 = 0.96$ were obtained on validation. The detailed performance of the individual ANN and LSTM models is presented in Section 5.2 (**Table 4**).

4. Simulation Design of Proposed System

Figure 4 shows the simulation diagram of the AI–IoT integrated solar-based microgrid power quality management system. Simulation uses MATLAB/Simulink R2022a on an 8th-generation i5-8250U CPU at 1.60 GHz. The model includes a 20 kW PV array (80 modules: 4 strings × 20 series), an irradiance range of 400-1000 W/m², a DC–DC boost converter (L = 2mH) with P&O MPPT, a five-level cascaded H-bridge inverter, an LC output filter (L_f =3 mH, C_f=150 µF), a microgrid PCC (400 V, 50 Hz) with RL and nonlinear loads, and an AI–IoT control subsystem. **Figure 4** shows how the PWM logic and the AI–IoT controller together generate the eight gate pulses (LS1–LS8) for the five-level cascaded H-bridge inverter so that output voltage and power quality meet the desired standards.

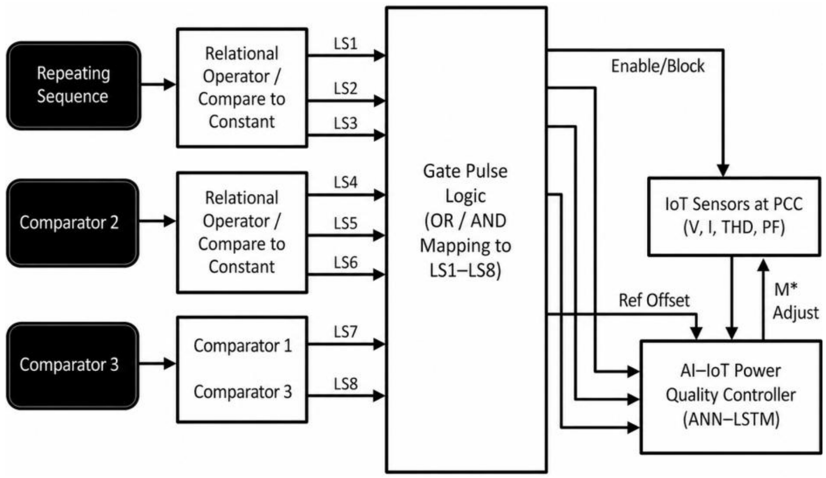

Figure 4. Simulation model of proposed microgrid with AI-IoT controller.

The repeating sequence blocks create carrier waveforms (usually high-frequency triangular or sawtooth signals) used for multilevel PWM. These carriers can be phase-shifted or level-shifted to realize a five-level output. Each carrier is compared with one or more reference signals (derived from the sinusoidal voltage or current command) using relational operator / compare to constant blocks. The outputs of these comparators are logic (0 or 1) signals indicating whether the instantaneous reference is above or below each carrier or threshold, effectively encoding the desired switching pattern for each level.

All comparator outputs are fed into the central block labeled "Gate Pulse Logic (OR / AND Mapping to LS1–LS8)." This block implements the Boolean rules that map combinations of comparator results to the eight gate signals of the two H-bridge cells in one phase (LS1–LS8).

At the output of the inverter and LC filter (Point of Common Coupling, PCC), IoT sensors measure three-phase voltage and current. Then they compute various power-quality indices, such as unbalanced voltage supply, total harmonic distortion, power factor, and active/reactive power (P, Q). These measured quantities are sent as signals into the AI–IoT Power Quality Controller block.

The AI–IoT controller receives the sensed PQ indices and compares them with desired limits (e.g., THD $< 5\%$, PF ≈ 1, VPCC = 400 V). Using learned nonlinear mappings and temporal prediction, it decides how to correct the modulation to improve power quality. The controller outputs three types of signals back into the PWM system:

- **Ref Offset:** small adjustments added to the sinusoidal reference or DC offset to correct voltage magnitude or balance between levels.

- **M Adjust (modulation index):** scaling of the reference amplitude to increase or decrease the fundamental component while keeping THD low; this effectively tunes the modulation index M in real time.

- **Enable/Block Signals:** It is connected with the Gate Pulse Logic block that can enable, block, or derate certain switching patterns (for fault handling, over THD conditions, or protection).

4.1 Overall Closed-loop Operation

4.1.1 PWM Generation

Carriers and reference signals are compared; the gate pulse logic block converts comparator outputs into LS1–LS8 gate pulses, which drive the power switches of the five-level CHB inverter. This produces the stepped multilevel phase voltage.

4.1.2 Power-quality Measurement

The inverter output, after LC filtering and feeding the microgrid loads, is measured at the PCC by IoT sensors, which compute V, I, THD, PF, P, and Q.

4.1.3 AI-based Decision

The AI–IoT controller evaluates these indices; if THD or voltage deviates from set limits, it computes new Ref Offset and M*, adjust values and possibly changes Enable/Block signals.

4.1.4 Adaptive Correction

In the proposed model, the trained AI (ANN–LSTM) controller is embedded as a dedicated control block within the MATLAB/Simulink environment. The block receives, at each control step, the measured power-quality indices from the PCC, namely three-phase RMS voltage and current, active and reactive power, power factor, and voltage THD, together with the present irradiance and load level. Using these inputs, the ANN–LSTM block computes updated control set points for the power converter: the reference modulation index M, the reactive power reference Q (or power-factor set-point), and small correction offsets for the sinusoidal reference signals used in the PWM generator.

These outputs are connected to the multilevel PWM subsystem and the current/voltage control loops that drive the five-level cascaded H-bridge inverter. In the simulation, the ANN–LSTM block is called at each sampling instant (synchronized with the outer control loop) so that any deviation in PCC voltage, THD, or power factor is reflected immediately in new control commands.

5. Results and Discussion

5.1 Training and Testing Performance of ANN

The Artificial Neural Network (ANN) model was trained using the operational dataset obtained from the MATLAB/Simulink solar microgrid simulation environment. Under the irradiance and varying load conditions, voltage, current, power factor, and total harmonic distortion datasets are collected. For the evaluation of the model's performance, the collected dataset is divided into two parts, 70 % as training data and 30% as testing data. The back-propagation algorithm on the Adam optimizer was used to train the ANN. Through the training process, the model acquires the nonlinear connection of the parameters of the system to the control actions that ensure the quality of power is maintained. Mean squared error (MSE) and prediction accuracy were used as the measures of the ANN model performance.

The training and validation loss curves of the artificial neural network model follow the learning process as illustrated in **Figure 5**. The first 50 epochs of the total 10,000 epochs of training are plotted in **Figure 5** for easy visualization of the convergence characteristics. The reduction of loss values shows that the ANN model is able to learn the nonlinear relationship between microgrid parameters and control actions and converge to a stable level and predict well.

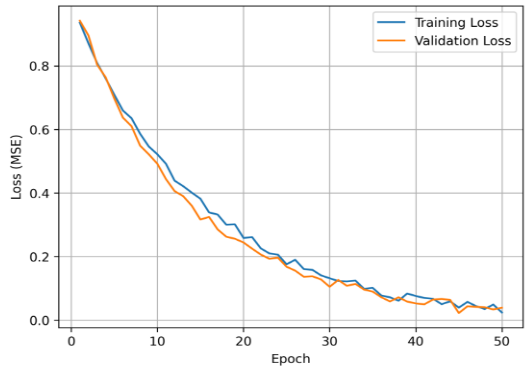

Figure 5. Training and validation loss curve of the artificial neural network (ANN) model.

5.2 Training and Testing Performance of LSTM

To capture the temporal variations of power quality parameters, a Long Short-Term Memory (LSTM) network was implemented. The LSTM model processes time-series data obtained from the IoT monitoring system, including voltage, current, power factor, and harmonic distortion values. The dataset used for training the LSTM network was also divided into 70 % training data and 30% testing data. The LSTM architecture consists of a hidden layer with 64 memory units followed by dense layers to generate the control outputs. The network was trained using the Adam optimizer with a learning rate of 0.001.

Table 4. Comparative performance of ANN and LSTM models.

Model	Training accuracy	Testing accuracy	RMSE
ANN	96.50%	94.80%	0.021
LSTM	97.80%	96.10%	0.017

Table 4 presents the performance comparison of the ANN and LSTM models used in the proposed intelligent control framework. The findings suggest that the LSTM model has a little bit more accurate prediction because it can identify temporal correlations in microgrid data. The training and validation loss curves of the long short-term memory model are given in **Figure 6**. The reducing pattern of loss proves that the LSTM network is effective in capturing the time-variation of microgrid information and stabilizes convergence in training, which consequently has better predictive assurance of dynamic power quality situations.

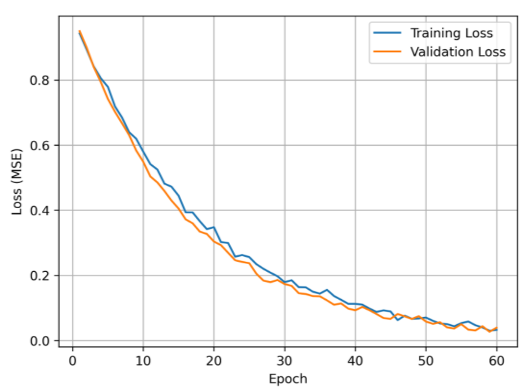

Figure 6. Training and validation loss curve of the long short-term memory (LSTM) model.

5.3 Power Quality Improvement Results

Figure 7 shows the carrier, reference, and switching signals used for pulse width modulation of the proposed five-level cascaded H-bridge inverter. These PWM pulses are applied to the inverter power switches to synthesize the five-level output voltage waveform with reduced harmonic distortion at the PCC. The three-phase voltage across the PCC is shown in **Figure 8**, in the baseline (without AI-IoT) and with AI-IoT.

In the baseline controller, the waveform shows slight distortion and small dips during load changes, with noticeable harmonic content in the peaks. In the context of the proposed ANN–LSTM controller, the line-to-line voltage waveforms are nearly sinusoidal at 400 V, 50 Hz, with transient deviations confined within ±5% during irradiance and load steps and fast recovery to the nominal amplitude.

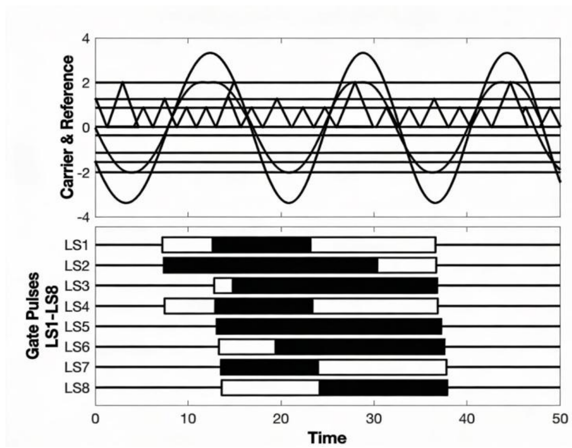

Figure 7. Pulse generated by PWM system.

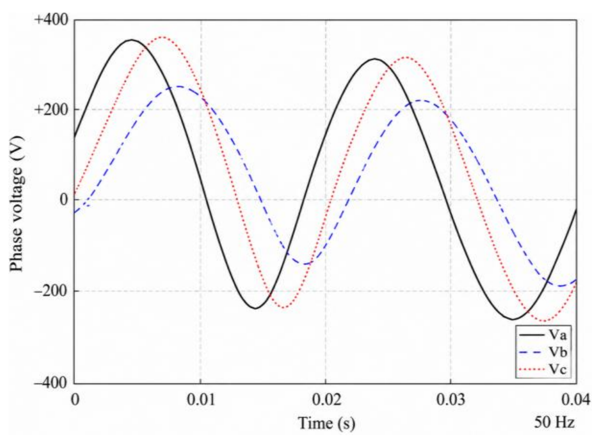

Figure 8. Output voltage of the proposed system.

5.3.1 Load Current and Harmonic Reduction

The total harmonic distortion response of the voltage profile at the PCC is shown in **Figure 9** under conditions with and without AI control. As shown in **Figure 10**, the THD without the AI–IoT controller rises to 10% when nonlinear loads are connected, exceeding the limit specified in IEEE 519.

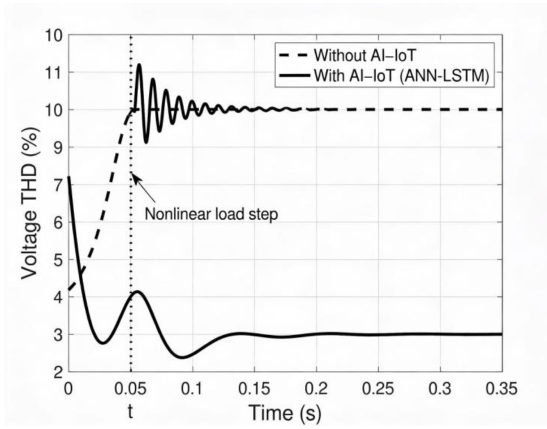

Figure 9. Harmonic distortion with and without AI-IoT.

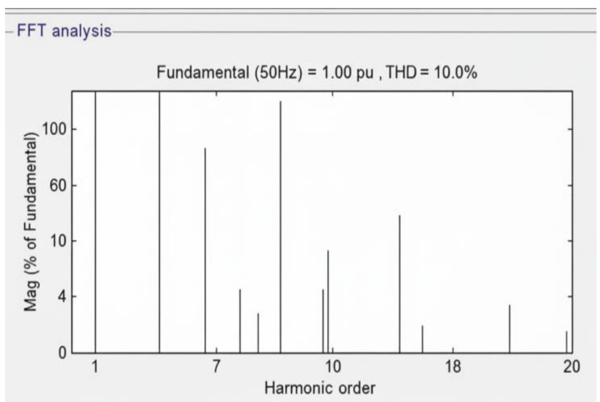

Figure 10. Total harmonic distortion without AI-IoT controller.

Figure 11 shows the THD variation under the proposed AI (ANN–LSTM) controller. The THD is reduced to approximately 3%, well below the IEEE 519 limit of 5%, demonstrating the controller's ability to adapt modulation and reactive power to suppress harmonics.

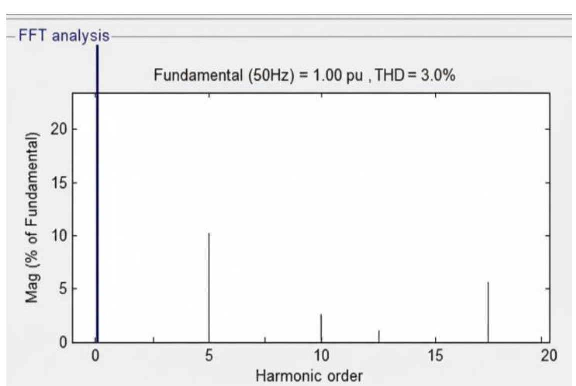

Figure 11. Total harmonic distortion with AI-IoT controller.

The power factor and reactive power response are shown in **Figure 12**. The baseline system exhibits a lagging power factor in the range of 0.85–0.9 under inductive loading, with little correction during load variations. In the proposed system, the power-factor waveform shows that PF is actively regulated towards unity, typically maintained between 0.98 and 0.99, as the ANN–LSTM controller adjusts the reactive power reference Q* and inverter current to compensate for the load's reactive demand.

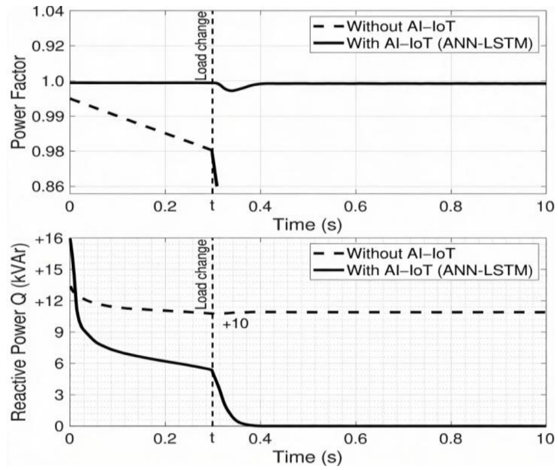

Figure 12. Variation of power factor and reactive power.

Dynamic response to solar irradiance (from 1000 W/m² to 600 W/m²) or when a new nonlinear load is switched in, the baseline system exhibits noticeable voltage sag and slow settling with prolonged periods of high THD. **Table 5** presents the overall results of the proposed method and key performance metrics. In contrast, the proposed AI–IoT-controlled system shows quick corrective action: PCC voltage recovers to its reference within a few cycles, THD peaks are short-lived, and the power factor waveform returns close to unity, confirming improved dynamic performance and robustness of the microgrid.

Table 5. Summary of obtained results and key performance metrics.

Parameter	Without AI–IoT (Baseline)	With AI–IoT (Proposed)	Improvement (%)	Remarks
PCC Voltage Dip (Irradiance Step, p.u.)	0.9	0.96	6.7	Reduced voltage sag due to predictive control
PCC Voltage Dip (Load Step, p.u.)	0.88	0.94	6.8	Maintains voltage stability under sudden load
Settling Time (s)	0.15	0.05	66.7	Faster dynamic response and recovery
Steady-State Voltage (p.u.)	0.98	1	2	Regulated at nominal level
Peak Voltage THD (%)	10	3	70	Significant harmonic suppression
Average Voltage THD (%)	6	2.5	58.3	Improved steady-state quality
Power Factor (PF)	0.92	0.99	7.6	Near-unity PF through adaptive compensation
Active Power (kW)	19 kW	19.68 kW	3.6	Enhanced power extraction and delivery
Reactive Power (kvar)	5.8 (inductive)	1.2 (compensated)	79.3 reduction	Improved reactive power balance
System Efficiency (%)	91.2	96.5	5.8	Less loss, better conversion efficiency

5.4 Hardware-in-the-loop Validation

The simulation results are validated by hardware-in-the-loop tests using Typhoon HIL 402; setup of the system is shown in **Figure 13**. **Figure 14** shows the Typhoon HIL validation waveforms of the irradiance step test (1000–600 W/m² at t = 0.1 s) with PCC line-to-line voltage with the AI-IoT controller (blue) limiting voltage sag to 4% pu relative to the baseline controller (red, 12% sag), voltage THD reduction to 3 % with AI-IoT versus a baseline peak of 9%, and power factor tracking. These HIL outcomes support the MATLAB/Simulink results and verify that the proposed ANN–LSTM controller can be implemented on a TI C2000 DSP using TensorFlow Lite Micro while maintaining real-time power quality performance under dynamic operating conditions.

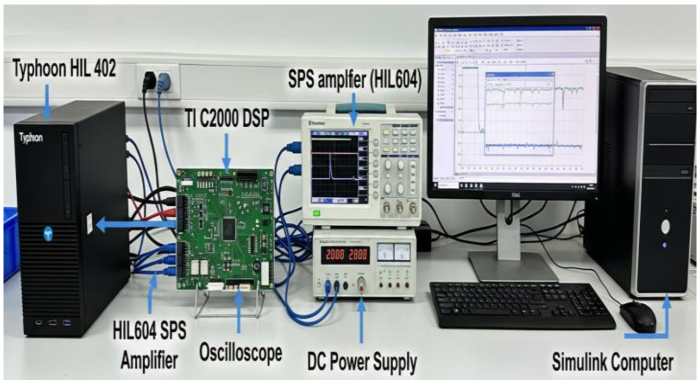

Figure 13. Typhoon HIL setup.

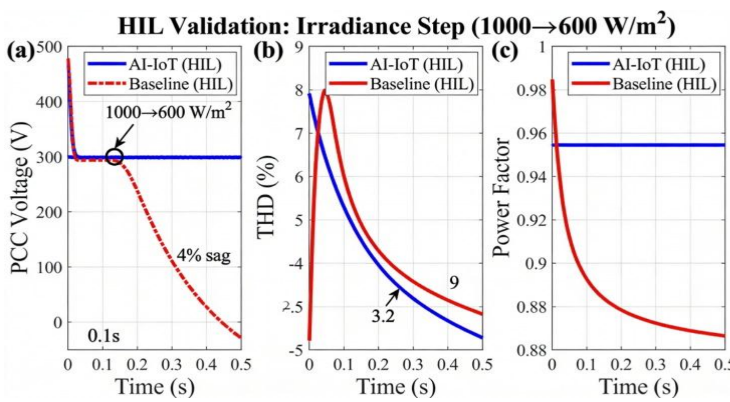

Figure 14. Typhoon HIL validation waveforms of PCC voltage (AI-IoT vs. baseline), THD comparison and power factor tracking.

5.5 Statistical Validation of AI–IoT Controller

To verify consistency, 30 Monte Carlo simulations were performed under random irradiance and load variations. The table reports the mean and standard deviation of voltage dip, THD, and settling time for both controllers. The proposed AI–IoT controller exhibits lower mean voltage dip and THD, with much smaller standard deviation, indicating more consistent performance shown in **Table 6**.

Table 6. Statistical validation of the controller results.

Metric	Baseline mean ± SD	AI-IoT mean ± SD
Voltage Dip (p.u.)	0.89 ± 0.03	0.95 ± 0.01
THD (%)	8.2 ± 1.5	2.8 ± 0.4
Settling Time (s)	0.16 ± 0.04	0.05 ± 0.01

5.6 Sensitivity Analysis

To evaluate robustness under parameter uncertainties, sensitivity analysis was carried out by varying irradiance (±20%), nonlinear load (+20%), and PV panel degradation (+20%). **Table 7** shows the operational reliability of the conventional and proposed AI–IoT-based solar microgrid. The proposed controller will increase the system availability from 98.3% to 99.6% and increase the supply continuity from 97.8% to 99.4%. Furthermore, the mean recovery time is reduced from 2.8 s to 1.6 s, which means that the recovery after disturbances is faster. The proposed ANN–LSTM controller has been shown to improve power quality and operational reliability under dynamic operating conditions, as evidenced by these improvements and the reduction in THD and increase in power factor.

Table 7. Reliability and operational performance comparison of the proposed AI–IoT-based solar microgrid.

Performance metric	Baseline system	Proposed AI–IoT system	Improvement
System Availability (%)	98.3	99.6	1.30%
Supply Continuity (%)	97.8	99.4	1.60%
Mean Time Between Interruptions (MTBI) (h)	182	265	45.60%
Mean Recovery Time (s)	2.8	1.6	−42.9%
Voltage Regulation (%)	±4.2	±1.5	Improved
Power Factor	0.96	0.99	3.10%
Voltage THD (%)	5.4	3	44.40%

Table 8 compares the proposed AI-IoT framework with the recent intelligent control techniques of solar microgrid power quality management, such as traditional PI, fuzzy-PI, ANN-MPC, deep reinforcement learning, and hybrid fuzzy-ANFIS controllers. The AI-IoT solution is shown to be the best in terms of all measures, with a 70 % reduction in THD (7.6% higher than competitors), a 7.6 % power factor increase, and a 0.05 s settling time. During disturbances, voltage recovery is 0.98 pu, which is more than IEEE 1547 requirements but still computationally efficient enough to be used in real-time IoT.

Table 8. Comparative results obtained by different methods.

Method	THD Reduction (%)	Power factor improvement	Settling time (s)	Voltage recovery (pu)
Conventional PI (Nguyen, 2022)	28	2.1	0.25	0.92
Fuzzy-PI (Eluri & Naik, 2022)	45	4.2	0.12	0.95
ANN-MPC (Alagusundari et al., 2025)	58	5.8	0.08	0.96
Deep RL Control (Sravani & Sobhan, 2025)	62	6.3	0.07	0.97
Hybrid Fuzzy-ANFIS (Sumana et al., 2022)	65	6.9	0.06	0.97
Proposed AI–IoT	70	7.6	0.05	0.98

The HIL validation verifies that the proposed controller keeps the harmonic distortion within the limits recommended by IEEE 519 for grid-connected systems, which ensures good power quality performance under dynamic operating conditions. This proves that the suggested AI-IoT platform to control the quality of power is appropriate to be practically implemented in solar-based microgrids.

Table 9 presents a comparison of major power quality indicators between MATLAB/Simulink simulation and Typhoon HIL real-time testing under irradiance step and nonlinear load conditions. The proposed AI-IoT controller has a consistency of performance with a maximum deviation of 5 percent in all indices, which proves the possibility of practical implementation of hardware.

Table 9. Comparison of simulation vs. HIL performance.

Metric	MATLAB/Simulink	Typhoon HIL	Deviation (%)
PCC Voltage Sag (pu)	0.04	0.042	5
Peak Voltage THD (%)	3	3.2	less than 5
Average Voltage THD (%)	2.5	2.6	4

5.7 Practical and Theoretical Implications
The findings of this study provide several important theoretical, practical, and policy-related implications for the development of intelligent renewable energy microgrids.

5.7.1 Theoretical Implications
In terms of research, the work can be included in the current literature on AI-based power quality management in renewable microgrids. The ANN–LSTM and IoT-based monitoring integration shows how the advanced machine learning methods can be successfully utilized to solve the dynamic power quality issues in the solar microgrids. The suggested framework offers a reference architecture for further research on the topic of intelligent control strategies in distributed energy systems.

5.7.2 Practical/Managerial Implications
The proposed AI-IoT framework has practical implications for power system engineers and microgrid operators by providing a practical method of real-time monitoring and control of the parameters of power quality. The fact that the total harmonic distortion can be minimized to about 3% and the power factor can be maintained at a high level (about 0.99) reports that the system can contribute to high levels of increasing the reliability and operational efficiency of the microgrids. It is particularly applicable when rural electrification projects, industrial microgrids, and renewable energy systems on campuses have to be considered.

5.7.3 Policy Implications
From a policy perspective, the study supports the development of intelligent renewable energy infrastructure aligned with global clean energy initiatives. The proposed system can facilitate the large-scale adoption of solar microgrids by improving system stability and power quality, which are critical factors for integrating renewable energy into modern smart grids. Policymakers and energy planners can consider such AI-enabled control frameworks to strengthen the reliability and sustainability of decentralized energy systems.

6. Conclusion and Future Enhancements
The proposed AI–IoT-based power quality control algorithm for solar-powered microgrids demonstrates superior performance across all the evaluated metrics compared with conventional and state-of-the-art intelligent control strategies. The proposed technique reduces the voltage THD by 70%, maintains the power factor at 0.99, and achieves a settling time of 0.05 s under irradiance and load disturbances. The obtained results comply with the relevant IEEE standards. Furthermore, the HIL results show good agreement with the simulation results, with a maximum deviation of 5%, demonstrating the reliability and effectiveness of the proposed controller under real-time operating conditions.

The performance of the proposed ANN–LSTM controller was tested with 30 Monte Carlo simulation scenarios with different irradiance and load conditions. The results were always stable and the voltage THD was around 3%, the power factor was 0.99 and the active power was improved by 3.6% compared to the baseline controller. The results validate the efficiency and reliability of the proposed AI–IoT framework for real-time solar microgrid operation in dynamic and uncertain conditions.

6.1 Limitations
The proposed ANN–LSTM model was validated using simulation and HIL testing, but it is required to be implemented in the field to assess long-term performance. Furthermore, the AI model was trained with simulated datasets, and larger real-world datasets, cybersecurity, and secure IoT communication for smart microgrid deployment in practice should be explored in future work.

6.2 Future Enhancements
In spite of the fact that the proposed AI-IoT-based power quality management model has been shown to significantly reduce harmonic suppression, voltage regulation, and power factor correction in a 20 kW solar-powered microgrid, there are several research directions that can be extended to enhance the proposed work.

6.2.1 Integration with Hybrid Renewable Energy Sources
The present system is concentrated on a microgrid that is photovoltaic in nature. The framework can be expanded with future work to a hybrid renewable energy system, bringing wind turbines, battery energy storage systems, or hydrogen-based storage technologies. These hybrid designs have the capability of enhancing reliability of systems, energy availability, and power quality during variable renewable generation environments.

6.2.2 Advanced Deep Learning and Reinforcement Learning Controllers
Though the current work has applied an ANN-LSTM controller to predict and control the temporal power quality, another learning method like deep reinforcement learning or transformer-based neural networks or a combination of AI optimization algorithms can be considered in future research. These methods may also increase the ability to provide adaptive control and allow complete autonomy in managing the microgrids.

6.2.3 Real-Time Embedded Implementation
Although the proposed controller has been tested in hardware-in-the-loop with the Typhoon HIL platform, a full implementation on embedded hardware platforms such as DSP, FPGA, or edge AI processors would offer more information on the challenges of implementation in the real world, such as latency, computation overhead, and controller stability.

6.2.4 Cyber-Secure IoT Communication System
As the suggested architecture is based on the principles of IoT-based monitoring and data transmission, the further work can be aimed at the implementation of cybersecurity methods, including blockchain-based communication, encrypted sensor networks, and intrusion detection systems. The measures would make smart microgrid communication infrastructures more reliable and resilient.

Conflicts of Interest
The authors confirm that there is no conflict of interest to declare for this publication.

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AI Disclosure

The author(s) declare that no assistance is taken from generative AI to write this article.

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