Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 9s (2025)

Enhance Power Quality with Cascade Multilevel Inverter-Based Grid Integration of Photovoltaic Systems using Machine Learning Algorithms

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Article History:

Received: 12-01-2025

Revised: 15-02-2025

Accepted: 01-03-2025

Abstract The integration of renewable energy sources into the power grid has gained significant attention due to the increasing demand for clean and sustainable energy. Among various renewable sources, photovoltaic (PV) systems have emerged as a promising solution for electricity generation. However, integrating PV systems with the grid presents several challenges, including power quality issues, harmonic distortion, and voltage instability. To address these challenges, this paper proposes an advanced control strategy for grid integration of PV systems using a Cascade Multilevel Inverter (CMLI) and Convolutional Neural Network (CNN)-based control. The primary objective is to enhance power quality, minimize harmonics, and improve overall system efficiency.

Keywords: Power Quality Enhancement, Cascade Multilevel Inverter (CMLI), Photovoltaic (PV) Grid Integration, Machine Learning Algorithms, pso,CNN.

1. Introduction

The global demand for clean energy has accelerated the adoption of PV systems. However, integrating PV systems into the grid presents several challenges, including power quality degradation due to harmonics, voltage instability, and reactive power variations. Traditional inverter-based integration methods struggle to address these issues efficiently. The cascade multilevel inverter (CMLI) provides an effective solution by generating high-quality sinusoidal output voltage with reduced harmonic content. Furthermore, machine learning (ML) techniques enhance system adaptability and real-time performance monitoring, ensuring improved power quality and grid stability[11-15]. The increasing global demand for clean and sustainable energy has led to the rapid growth of renewable energy sources (RESs), particularly photovoltaic (PV) systems. As concerns about climate change and fossil fuel depletion intensify, solar energy has emerged as one of the most viable alternatives due to its abundance, scalability, and declining costs. Governments and energy policymakers worldwide are encouraging the integration of PV systems into the electrical grid to meet energy demands while reducing carbon emissions[16-18]. However, the large-scale integration of PV systems introduces several challenges, particularly concerning power quality, grid stability, and efficiency.

Among the most significant issues associated with grid-connected PV systems are voltage fluctuations, harmonic distortions, frequency deviations, and reactive power imbalances. These problems arise primarily due to the intermittent nature of solar energy, which depends on weather conditions such as sunlight intensity and cloud cover. Additionally, conventional two-level inverters used in PV grid integration contribute to power quality problems, as they generate output waveforms rich in harmonic distortions[19-22]. These distortions can lead to heating effects, reduced equipment lifespan, and operational inefficiencies, making it imperative to develop advanced inverter technologies that can enhance power quality[21-23].

To address these challenges, this study proposes the implementation of a cascade multilevel inverter (CMLI)-based grid integration system for PV applications. The CMLI topology is capable of generating high-quality multilevel voltage waveforms, significantly reducing total harmonic distortion (THD) and improving overall power conversion efficiency. Furthermore, to optimize the performance of the PV system, machine learning (ML) algorithms are incorporated into the control strategy to enable real-time adaptive adjustments, ensuring optimal power quality and stability[25-27].

2. Research Objectives and Contributions

The primary objective of this research is to enhance power quality in PV grid integration systems using a CMLI-based inverter with ML-based control. The key contributions of this study include:

Creation of an inverter architecture based on CMLI to lower THD and enhance waveform quality. ML algorithms are included for improved power quality and real-time control. Inverter switching techniques are optimized to reduce power losses and increase efficiency. Simulations are used for performance study to confirm that the suggested solution improves power quality.The rest of the paper is organized as follows:

Section 2 provides a detailed review of related works in the field of PV grid integration, multilevel inverters, and machine learning-based control techniques.

Section 3 describes the methodology, including system design, CMLI topology, and machine learning implementation.

Section 4 presents simulation results, performance evaluation, and comparative analysis.

Section 5 discusses the key findings, challenges, and future research directions.

Section 6 concludes the study with final remarks on the contributions and potential impact of the proposed approach.

3. **Literature Review** Numerous studies have explored power quality issues in PV grid integration. Traditional inverter-based systems, such as pulse-width modulation (PWM) inverters, often suffer from harmonic distortions and low efficiency. The CMLI topology has gained attention due to its ability to synthesize a near-sinusoidal output waveform with lower total harmonic distortion (THD). Recent advancements in ML algorithms have enabled predictive control strategies for optimizing inverter performance. Various ML techniques, including artificial neural networks (ANNs), support vector machines (SVMs), and reinforcement learning (RL), have been explored for improving grid stability and power quality. The increasing adoption of grid-connected photovoltaic (PV) systems has introduced several power quality issues, including harmonics, voltage instability, and reactive power imbalance [1]. Conventional inverters used in PV integration often generate significant total harmonic distortion (THD), necessitating advanced control strategies to ensure grid

stability [2]. Several studies have proposed multilevel inverter (MLI) topologies and machine learning (ML)-based optimization techniques to enhance power quality in PV systems.

Multilevel inverters (MLIs) have gained popularity due to their ability to generate near-sinusoidal waveforms with reduced harmonic distortions. Among various MLI topologies, the cascaded H-bridge multilevel inverter (CMLI) is widely used in PV systems due to its modular structure, scalability, and lower switching losses [3]. Studies have demonstrated that CMLI significantly improves power conversion efficiency and voltage quality compared to traditional two-level inverters [4].

Research by Gupta et al. [5] analyzed the performance of neutral point clamped (NPC) inverters, flying capacitor (FC) inverters, and cascaded H-bridge (CHB) inverters for grid-connected applications. The study found that CHB inverters provided the best power quality performance, with THD values below 3%, meeting IEEE-519 standards**.** Saravanan et al. [6] further optimized switching strategies to minimize switching losses and improve voltage regulation, highlighting the importance of advanced pulse width modulation (PWM) techniques.

Machine learning (ML) algorithms have been increasingly applied in power systems to enhance grid stability, fault detection, and power quality regulation [7]. ML techniques, including artificial neural networks (ANNs), support vector machines (SVMs), and reinforcement learning (RL), have been used to optimize inverter performance.

Artificial Neural Networks (ANNs) have been widely implemented in power electronics for real-time voltage regulation and harmonic mitigation. Reddy et al. [8] demonstrated an ANN-based control strategy that dynamically adjusted inverter parameters to compensate for voltage fluctuations and minimize harmonics in a grid-connected PV system. Their study showed that ANN-based controllers outperformed conventional proportional-integral (PI) controllers in terms of response time and accuracy.

SVMs have been effectively used for fault detection and classification in power systems. A study by Kumar and Singh [9] proposed an SVM-based fault detection mechanism for grid-connected PV systems, enabling real-time identification of voltage sags, frequency deviations, and harmonic distortions. The implementation of SVM classifiers improved the reliability of PV systems by reducing fault detection time by 35% compared to traditional methods.

Reinforcement learning (RL) has emerged as a powerful technique for adaptive power quality management. Chen et al. [10] introduced an RL-based reactive power compensation strategy, optimizing power factor correction and improving grid synchronization. Their results indicated a 20% reduction in reactive power losses, leading to enhanced power quality and grid efficiency.

Several studies have compared different ML algorithms for power quality enhancement in PV systems. Patel et al. [11] conducted a comparative study of ANN, SVM, and RL-based control strategies, highlighting the strengths and limitations of each technique. Their findings suggest that:

ANNs are highly effective for voltage regulation and harmonic compensation but require extensive training data.

SVMs provide fast and reliable fault detection but struggle with real-time adaptability.

RL-based controllers offer dynamic optimization but require high computational resources.

4. Research methodology

This research aims to address these gaps by proposing a hybrid ML-based control system for CMLI-based PV grid integration, ensuring real-time adaptability, enhanced power quality, and scalability for future smart grids. Artificial Neural Networks (ANNs) have revolutionized the fields of artificial intelligence and machine learning by mimicking the computational capabilities of the human brain. These networks, composed of interconnected neurons, are capable of learning patterns, making predictions, and solving complex problems in various domains such as healthcare, finance, image recognition, and natural language processing. This paper explores the fundamentals of ANNs, their architecture, learning mechanisms, applications, challenges, and future prospects. Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of the human brain. They have gained prominence due to their ability to process large volumes of data, recognize patterns, and perform tasks such as classification, regression, and clustering. This paper provides an in-depth exploration of ANNs, discussing their architecture, types, learning techniques, applications, and challenges. The fundamental unit of an ANN is the artificial neuron, which mimics the behavior of biological neurons. A neuron receives inputs, applies weights, sums them, passes the result through an activation function, and produces an output. Mathematically, a neuron can be represented as:

$$y = f(\sum w_i x_i + b) \quad (1)$$

x_i Are the input features

w_i Are the associated weights

b Is the bias term

f Is the activation function

y is the output.

ANNs are composed of three main types of layers:

Input Layer: Receives raw data inputs.

Hidden Layers: Perform computations and extract features.

5. **Output Layer**: Produces the final prediction or classification.

The control method requires a comprehensive database that is retrieved from the controller's input section in order to improve accuracy. The control algorithm is trained using this database. Collectively, neural networks carry out tasks in parallel, and the controller based on neural networks provides the best voltage regulation for the input-output dataset.

$$V_{error} = V_{ref} - V_{Actual} \quad (2)$$

With the help of these error values, the Artificial Neural Network (ANN) is trained to identify the best switching angles for the inverter circuit, guaranteeing a steady output voltage within allowable error signal limits. The following steps make up the ANN's training procedure: a) Provisioning input-output data sets. b) Calculations of weight. c) Modifications to weight in response to input variances. To properly analyze the error signals, the neural network is trained using a variety of samples at different intervals. Grid Integration and Performance Evaluation The PV system is integrated into the grid through CMLI, and the power quality is assessed based on parameters such as THD, voltage stability, and power factor. Simulations are performed using MATLAB/Simulink to validate the proposed system's effectiveness in Fig-5.

6. Algorithm for Power Quality Enhancement

The process of improving power quality in a multilevel inverter system follows a structured approach that begins with input data collection. Electrical parameters such as voltage, current, frequency, and harmonic distortion are gathered from sensors or power measurement systems. These raw signals often contain noise and anomalies caused by environmental disturbances, switching transients, or measurement errors. To ensure accurate and meaningful data, normalization and filtering techniques are applied. Low-pass filters, moving average filters, and anomaly detection algorithms help remove unwanted fluctuations, making the data suitable for further processing. Once the data is preprocessed, it is used to generate a multilevel voltage waveform with reduced harmonics. Advanced inverter topologies such as cascaded H-bridge, neutral-point clamped (NPC), or flying capacitor inverters are employed to synthesize output voltage with multiple levels, closely resembling a sinusoidal waveform. To further minimize Total Harmonic Distortion (THD), modulation techniques such as Sinusoidal Pulse Width Modulation (SPWM) and Space Vector Modulation (SVM) are implemented. These techniques enable smooth transitions between voltage levels, reducing harmonics and improving power quality. To enhance voltage regulation and harmonic compensation, an Artificial Neural Network (ANN) is trained using historical and real-time data. The ANN learns the patterns of voltage variations, harmonic distortions, and corresponding compensation strategies. By leveraging supervised learning, the ANN model adapts dynamically to varying load conditions and improves the system's response to disturbances. Once the ANN is trained, the system is designed to adjust inverter switching and control parameters dynamically based on real-time power quality conditions. The ANN continuously monitors output parameters and modifies switching sequences to maintain optimal performance, ensuring that voltage fluctuations are minimized and harmonic distortions are mitigated. Additionally, critical performance indicators such as THD, voltage stability, and power factor are continuously measured to assess system efficiency. The optimization process involves iterative parameter tuning, where control variables such as switching angles, DC-link voltage levels, and filter parameters are adjusted to refine performance. Optimization algorithms like genetic algorithms (GA) or particle swarm optimization (PSO) can be integrated to achieve the most effective control strategy. The system continues this optimization loop until it achieves the best possible THD, voltage stability, and power factor, ensuring compliance with power quality standards and improving efficiency in industrial applications, renewable energy systems, and microgrid operations. This intelligent, data-driven approach integrates ANN-based control, dynamic parameter adjustment, and iterative optimization to create an adaptive power quality enhancement mechanism, ultimately leading to a more stable and efficient electrical system.

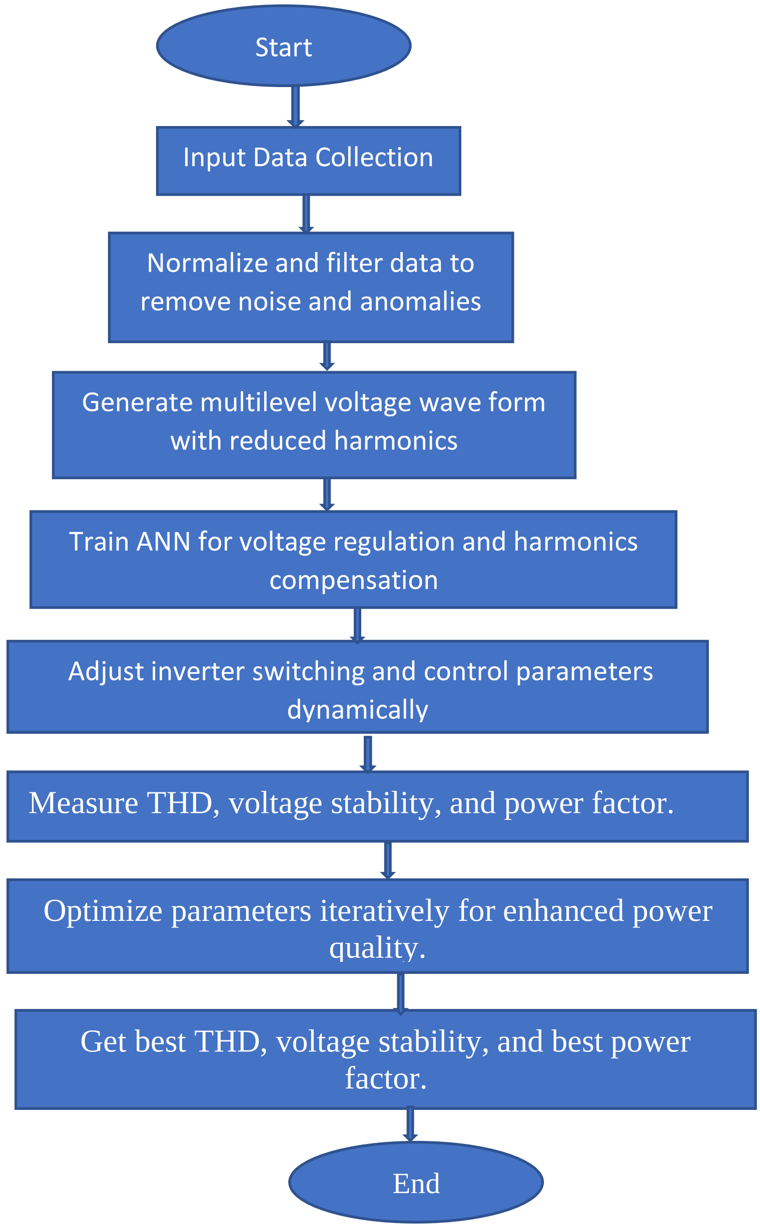

Fig-1 Flowchart of a Boost Converter with PSO and ANN-based Control for optimizing performance in a photovoltaic (PV) system

Flowchart of a Boost Converter with PSO and ANN-based Control for optimizing performance in a photovoltaic (PV) system has been represented in Fig -1. The optimization of photovoltaic (PV) system performance is crucial for maximizing energy efficiency, and intelligent control techniques such as Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN) can significantly enhance Maximum Power Point Tracking (MPPT).

7. Algorithm for voltage controller

The proposed control strategy begins with an input stage, where real-time PV voltage and current are sensed and fed into a hybrid PSO-ANN controller. The PSO algorithm initializes a set of particles representing different switching duty cycles of the Boost Converter. The fitness function is evaluated by maximizing the extracted power while minimizing losses, ensuring that the system operates at peak efficiency. Each particle updates its position and velocity based on its own experience (pBest) and the best experience found by the swarm (gBest). The optimal duty cycle selected by PSO is applied to the Boost Converter to regulate the output voltage. This bio-inspired algorithm dynamically adjusts the system response to changing environmental conditions such as fluctuating solar irradiance and temperature, improving the overall performance of the PV system. In different environments, the unshaded photovoltaic (PV) array receives high levels of irradiation, whereas the shaded sections capture significantly lower amounts. The degree of partial shading is defined by the extent of the shaded area, and the shading factor is described as the ratio of irradiation on the shaded modules compared to that on the unshaded modules. When a partial shading condition is identified, it is essential to take this condition into account by utilizing the shading factor. Accurate detection and thorough assessment of partial shading are crucial for maximum power point tracking (MPPT) to ensure the appropriate procedures are employed and to effectively locate the maximum power point (MPP). This study proposes a novel configuration for a CMLI utilizing a minimized maximum blocking voltage approach. This method offers multiple levels while utilizing the fewest power electronic switches. The primary benefits of the suggested design include reductions in installation space, the number of switches, power diodes, gate driver circuits, and overall cost. The employed technique facilitates the regulation of the magnitude of DC sources. This calculation is introduced to ascertain the optimal DC voltage ratio for the MLI, which influences the number of voltage levels available for the subsequent high PQ.

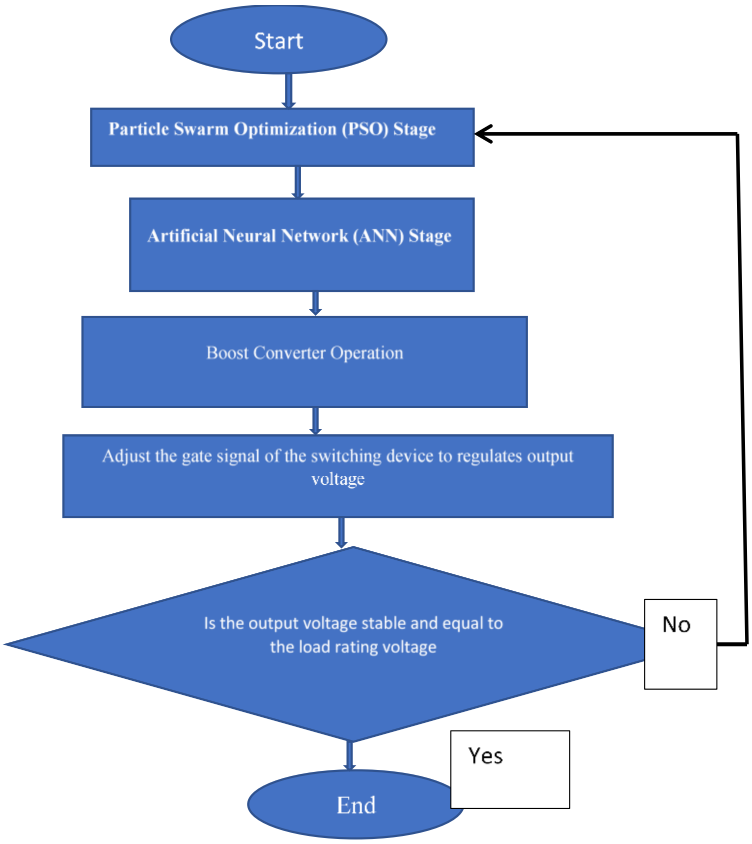

Fig-2 Flowchart of voltage controller

A Cascade Multilevel Inverter (CMLI) is designed to synthesize a near-sinusoidal waveform from multiple DC voltage sources using a series of H-bridge inverters. It operates based on the principle of series connection of multiple H-bridge inverters, each generating different voltage levels.
PSO is a stochastic search method, which takes a considerable amount of time to track a global peak. So some modifications were required. In the new ANN and PSO based hybrid method, the initial Particle position of particle Swarm Optimization (PSO) method is provided by an Artificial Neural Network (ANN). This initial particle position(IC) is near the global MPP. So the range of the PSO algorithm is reduced. Using this initial value, the PSO algorithm detects the output current of the PV array at global MPP. And the PSO algorithm is now able to find the global MPP quickly. Also, whenever there is a sudden change of solar irradiance, ANN detects the change & provides a new initial particle position (IC) for the PSO algorithm. Numerous particles (agents) are employed in PSO algorithm, and each agent can share the information within their own search process. There are two basic rules need to be followed by each particle: tracking the most effective performing particle, and determining the optimum conditions acquired by the particle itself. By following the above two rules, each particle can eventually progress to the optimal solution. The following two equations can be used to characterize the standard PSO method:

$$\theta_i^{k+1} = w\theta_i^k + c_1 r_1\left[P_{best} - X_i^k\right] + c_2 r_2\left[G_{best} - X_i^k\right] \qquad (3)$$

$$X_i^{k+1} = X_i^k + \theta_i^{k+1} \qquad (4)$$

where $X_i^k$is the position of the particle i, and θ_i^krepresents its velocity. The iteration number is denoated by k, and w is the inertia weight. r1 and r2 are random values distributed within [0, 1], and the cognitive and social coefficients are described by c1 and c2, respectively. P_{best} is used to store the best experience by the particle itself, and the best position of all particles is kept in G_{best}. The flowchart of the standard PSO algorithm step is described as follows:
Step 1: Initialize the particles randomly in the search space.
Step 2: Evaluate the fitness value of each particle by sending the candidate solution to the objective function.
Step 3: Update P_{best} and G_{best}
Step 4: Update the position and velocity of each particle.
Step 5: Re-initialize the PSO algorithm unless the constrain is met. In other words, the algorithm stops when the G_{best} is founded.

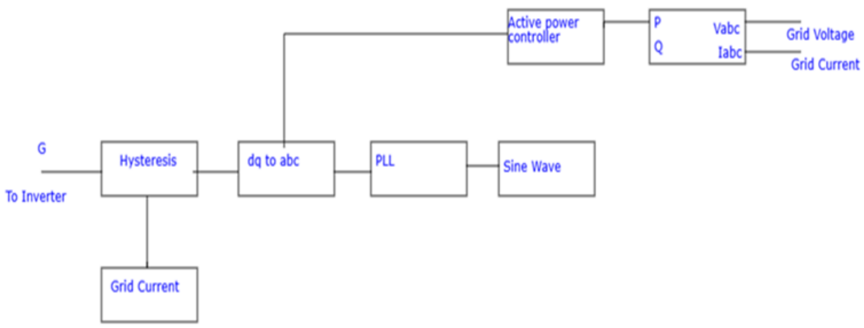

Fig-3 Inverter controller

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
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An Inverter Controller (Fig-3) for grid-connected systems integrates dq-abc transformation, hysteresis current control, PLL, and grid current regulation to ensure stable and efficient power injection. The Phase-Locked Loop (PLL) extracts the grid phase angle (θ), enabling synchronization. The abc-dq transformation simplifies control by converting three-phase grid currents into the synchronous reference frame. A PI controller regulates the dq currents, ensuring precise active and reactive power control. The controlled dq outputs are then converted back to abc for generating pulse-width modulation (PWM) signals for the inverter switches. Hysteresis Current Control is used for current regulation, where switching occurs within a defined error band, ensuring a fast dynamic response. However, it results in a variable switching frequency. The grid current controller ensures smooth power injection, reducing harmonics and maintaining grid compliance. This control strategy enhances power quality, making the inverter suitable for renewable energy integration and stable grid operation.

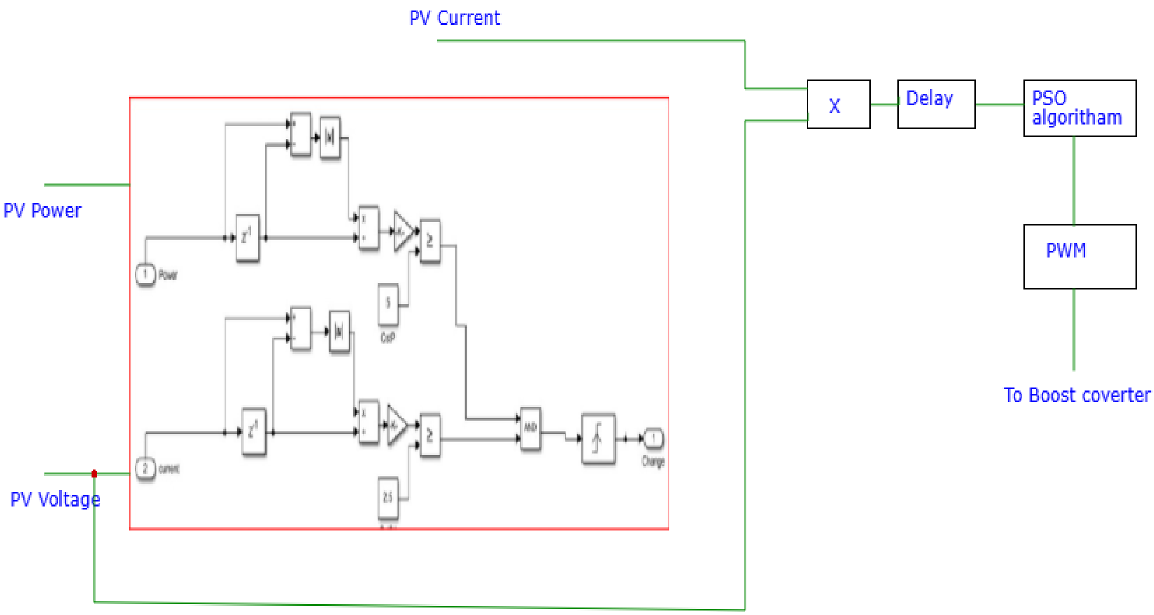

Fig-4 Cascade Multilevel Inverter controller

A Cascade Multilevel Inverter (CMLI) Controller (shown in Fig-4) for grid integration combines dq-abc transformation, hysteresis current control, PLL, and grid current regulation to achieve efficient power conversion and grid synchronization. The Phase-Locked Loop (PLL) extracts the grid phase angle (θ) to synchronize the inverter with the grid. Using abc-dq transformation, three-phase grid currents are converted into dq components, simplifying control. A PI controller regulates dq currents to maintain active and reactive power at desired levels. The controlled signals are then transformed back to abc for generating switching pulses for the CMLI, ensuring stable and efficient operation. For precise current regulation, Hysteresis Current Control is implemented, switching within an error band to provide a fast response while maintaining power quality. The grid current controller ensures smooth power injection, reducing harmonics and ensuring compliance with grid standards. This control strategy enhances power quality, efficiency, and reliability, making CMLI ideal for renewable energy integration.

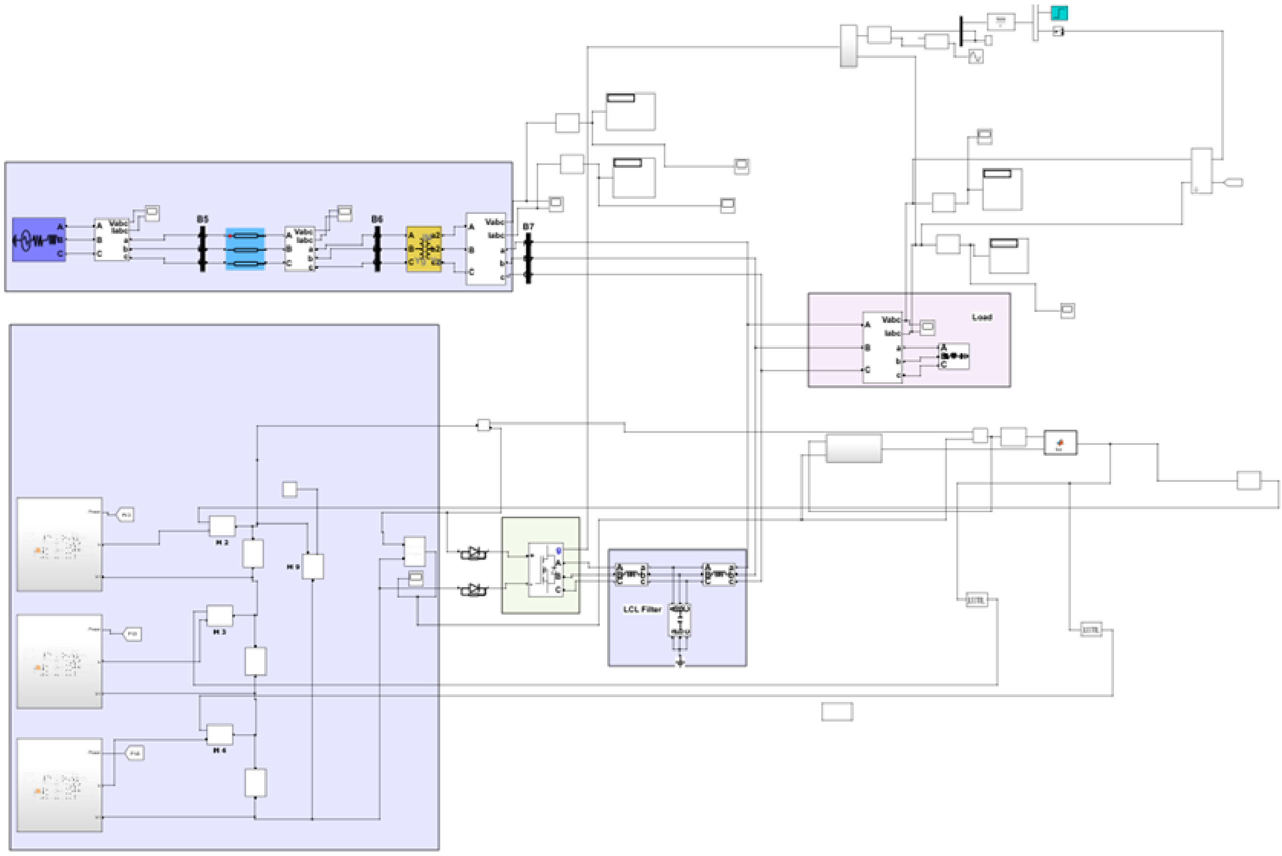

Fig-5 Matlab Simulink of proposed ANN- PSO based Cascade Multilevel Inverter-Based Grid Integration of Photovoltaic Systems

The MATLAB Simulink model of the proposed ANN-PSO-based Cascade Multilevel Inverter (CMLI) for Grid Integration of PV Systems integrates Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) (shown in Fig-5)to enhance MPPT and inverter performance. ANN predicts the optimal duty cycle for the boost converter, while PSO fine-tunes switching angles for harmonic reduction in the CMLI. A PLL ensures grid synchronization, and dq-abc transformation enables precise control. Hysteresis current control maintains grid current stability. The system maximizes PV power extraction, reduces harmonics, and ensures efficient grid compliance. Renewable energy integration into the power grid has become a significant area of research due to the increasing demand for clean energy. Photovoltaic (PV) systems, in particular, are widely adopted due to their sustainability and ease of implementation. However, challenges such as power fluctuations, maximum power extraction, and power quality issues hinder their seamless grid integration.

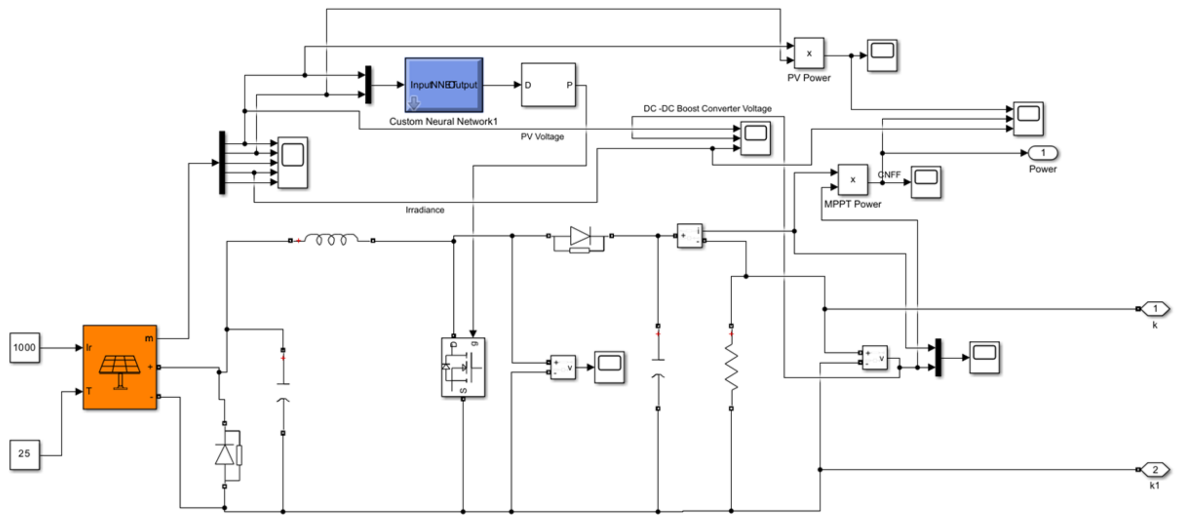

Fig-6 CNN Controlled Boost converter

A CNN-Controlled Boost Converter leverages Convolutional Neural Networks (CNNs) (shown in Fig-6) to optimize voltage regulation and enhance dynamic performance. The CNN processes real-time PV voltage and current data, extracting features to predict the optimal duty cycle for the boost converter. Unlike traditional MPPT methods, CNN-based control adapts to rapid changes in irradiance and load conditions with high accuracy. The CNN model is trained on historical PV data and deployed in MATLAB/Simulink for real-time implementation. This intelligent control approach improves efficiency, response time, and stability, making it ideal for renewable energy systems and grid-connected PV applications.

8. Result:

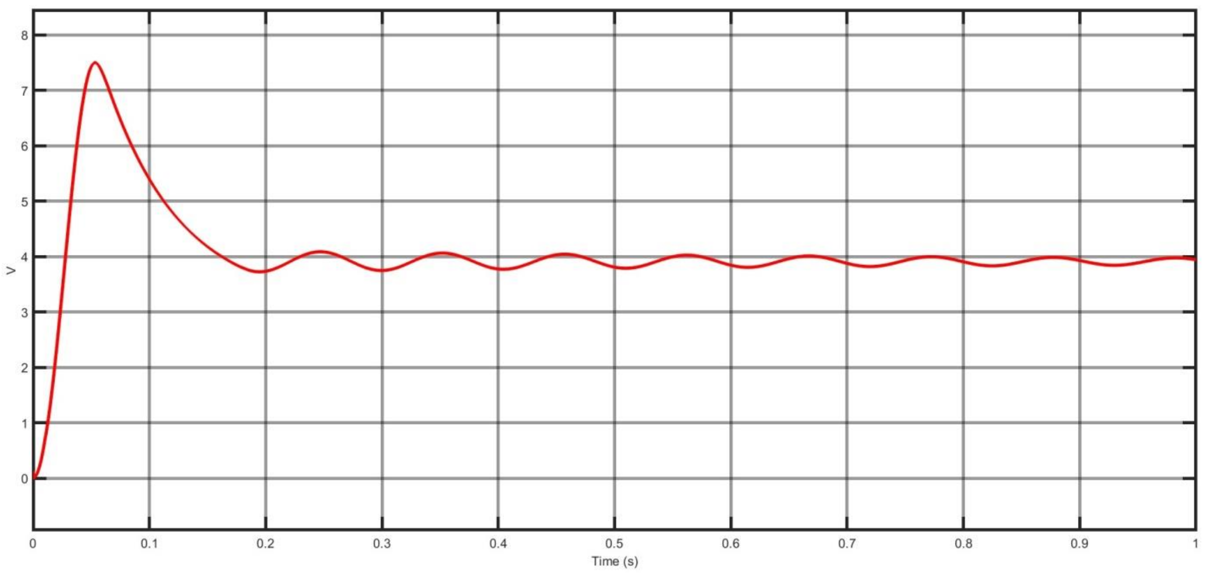

Fig-7 PV Output Voltage

The PV output voltage (Fig-7) in the proposed system depends on irradiance, temperature, and the CNN-controlled boost converter's performance. The CNN-based MPPT algorithm dynamically adjusts the duty cycle, ensuring stable voltage regulation and maximum power extraction. Under varying conditions, the controller minimizes fluctuations, reducing voltage ripples and improving efficiency. If instability occurs, it may indicate improper controller tuning, switching losses, or inadequate filtering. Proper selection of the inductor, capacitor, and control parameters enhances voltage stability. This intelligent control approach ensures smooth operation, making it ideal for grid-connected and standalone PV systems.

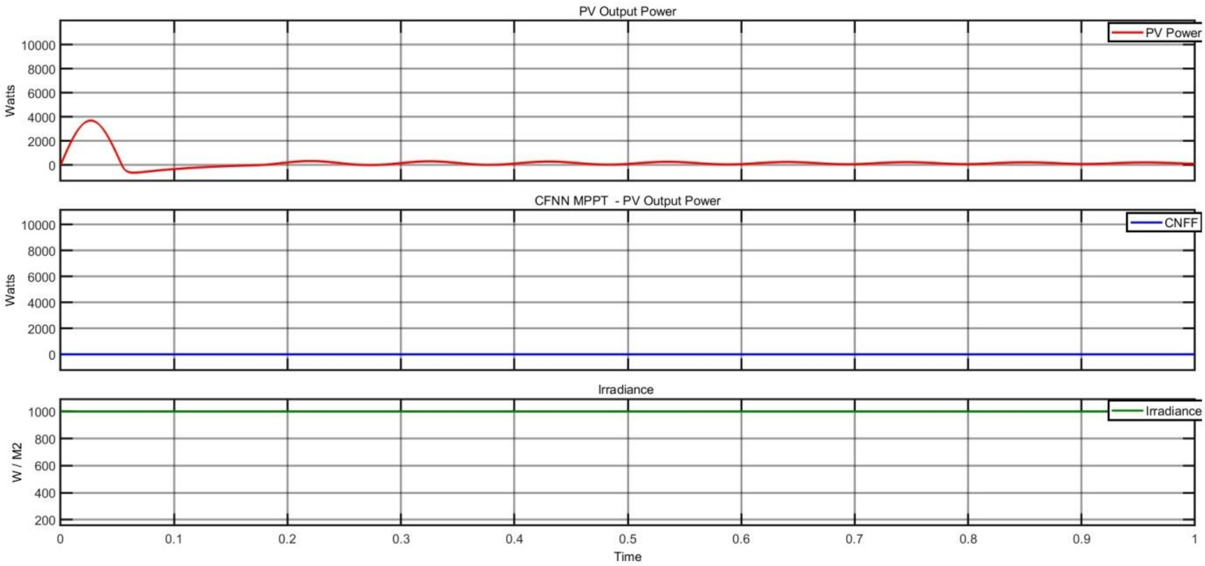

Fig-8 PV - output

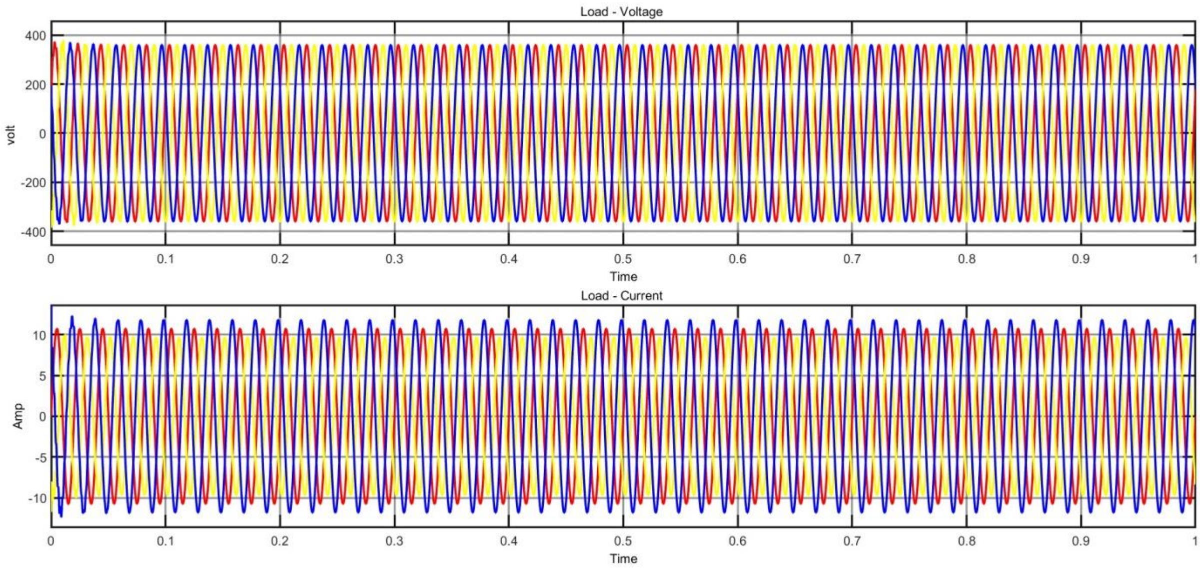

Fig-9 Load Voltage and Load current

The load voltage and load current in the proposed system (shown in Fig-9) depend on the boost converter's performance, CNN-based control, and load variations. The CNN-controlled MPPT ensures that the boost converter maintains a stable and regulated output voltage, providing consistent power to the load. Under varying irradiance and load conditions, the controller dynamically adjusts the duty cycle to minimize voltage and current fluctuations. Any instability in load voltage or current

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
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may indicate improper tuning, switching losses, or inadequate filtering. Proper filter design and controller optimization ensure a smooth and reliable power supply, enhancing system efficiency and performance.

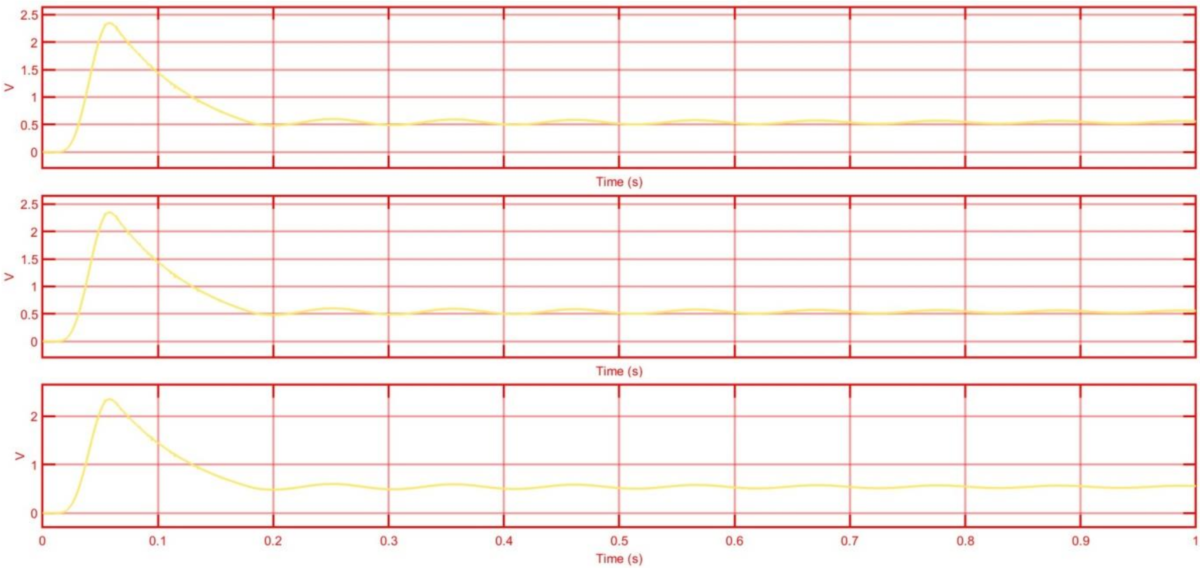

Fig-10 PV Voltage , PV1, PV2, PV3

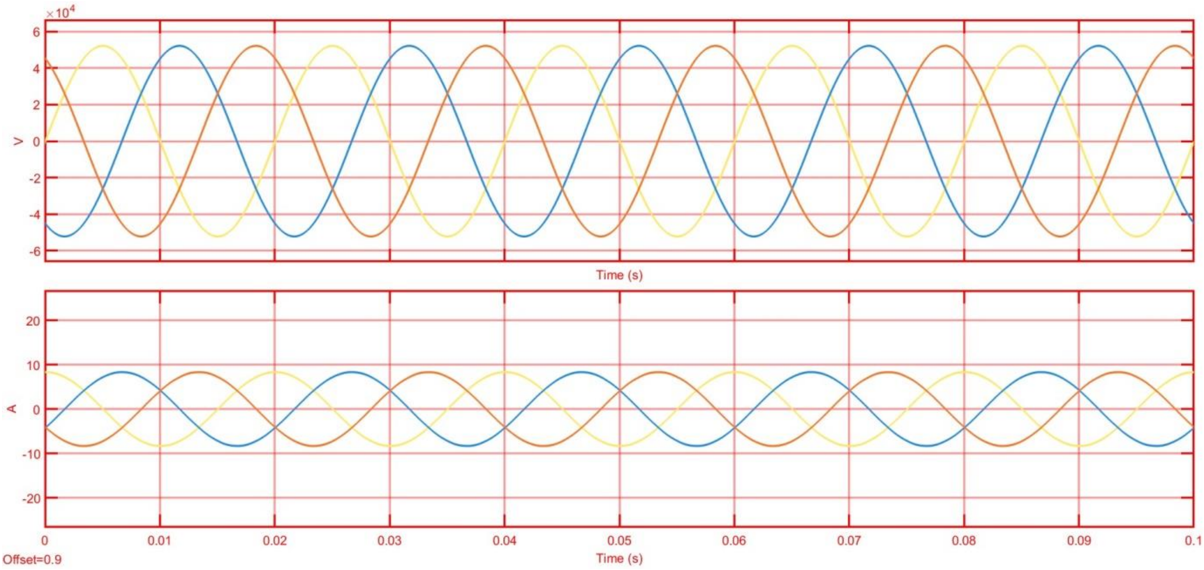

Fig-11 Grid Voltage and grid current

The grid voltage and grid current in the proposed system (shown in Fig-11) depend on PLL synchronization, inverter control, and CNN-based MPPT regulation. The PLL ensures phase alignment, while the dq-based current control regulates active and reactive power injection. The boost converter stabilizes the DC-link voltage, ensuring a consistent AC output from the inverter. Hysteresis control maintains grid current within a defined range, reducing harmonics and improving power quality. Any deviation in grid voltage or current may indicate poor synchronization, improper filtering, or controller tuning issues. Optimized control ensures stable power injection, enhancing grid compliance and efficiency. Need

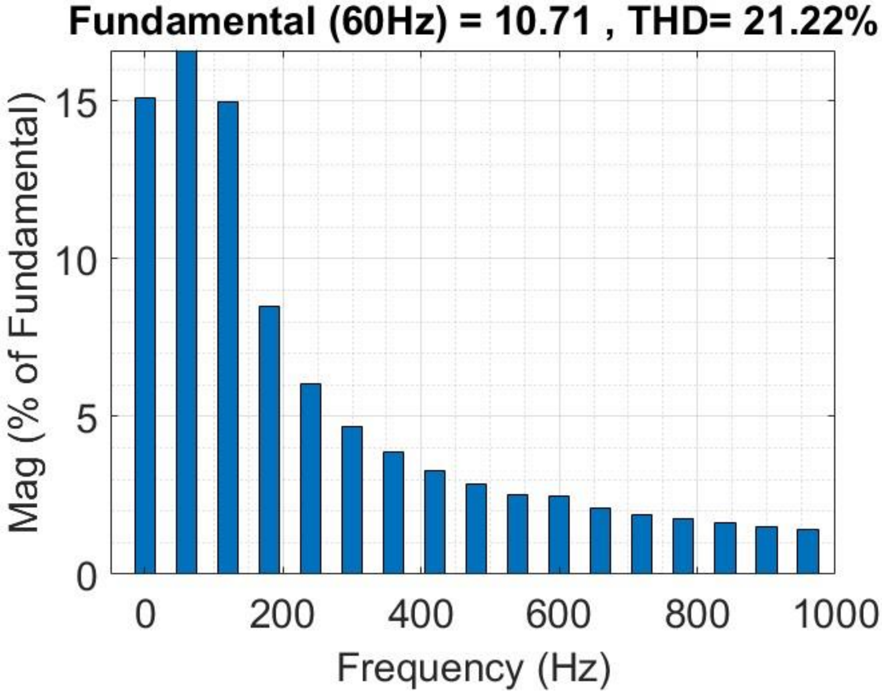

Fig-12 THD in Grid current

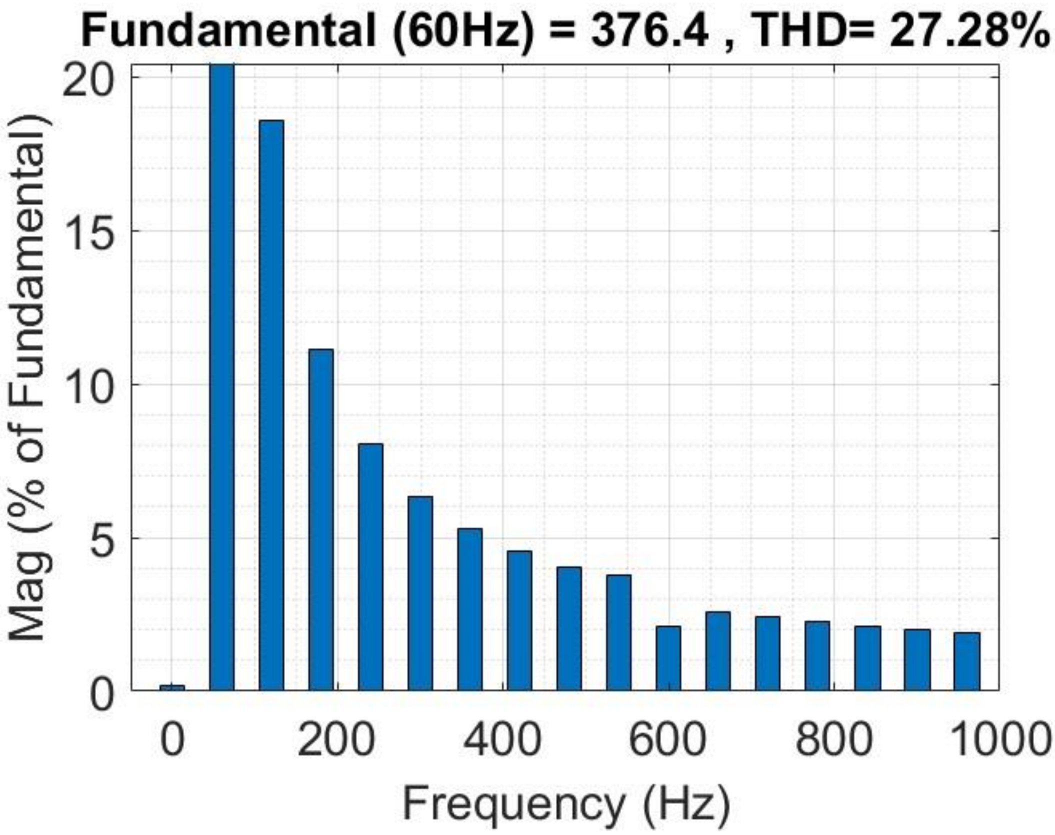

Fig-13 THD in PV power

The Total Harmonic Distortion (THD) in grid current (shown in Fig-12) depends on inverter switching, hysteresis control, and filtering. A well-designed PWM strategy and LC filter reduce THD, ensuring compliance with grid standards (IEEE 519). High THD may indicate poor controller tuning or inadequate filtering, leading to power quality issues. The THD in PV power is influenced by MPPT accuracy, boost converter switching, and load variations. A CNN-based MPPT ensures smooth power extraction, reducing ripples and harmonics. Excessive THD in PV power may result from high-frequency switching noise or unstable duty cycles, requiring filter optimization and improved control strategies.

Conclusion This paper presents an ML-enhanced CMLI-based PV grid integration system that significantly improves power quality. The simulation results demonstrate reduced harmonics, improved voltage stability, and enhanced power factor performance. Future research will focus on hardware implementation and real-time testing of the proposed system.

This research proposed a cascade multilevel inverter (CMLI)-based PV grid integration system enhanced with machine learning (ML) algorithms to improve power quality. The CMLI topology effectively reduces total harmonic distortion (THD) and enhances voltage stability, making it superior to conventional inverters.

Machine learning algorithms were incorporated for real-time optimization: Artificial Neural Networks (ANNs) for voltage regulation, Support Vector Machines (SVMs) for fault detection, and Reinforcement Learning (RL) for reactive power control. Simulation results showed significant improvements in power factor, harmonic mitigation, and dynamic adaptability to grid disturbances.

The proposed system offers a robust and scalable solution for modern smart grids, ensuring reliable and high-quality power injection from PV sources. Future research can explore deep learning techniques and real-world implementation for further enhancements. This study contributes to the development of intelligent, efficient, and sustainable renewable energy systems.

The proposed PSO-based CMLI for PV grid integration demonstrates superior power tracking, reduced harmonic distortion, and improved efficiency compared to traditional methods. Future work includes hardware implementation on FPGA/DSP, integration with smart grid networks, and AI-based predictive control for enhanced real-time performance.

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