GRID INTEGRATION OF RENEWABLE ENERGY SYSTEM WITH ARTIFICIAL NEURAL NETWORK CONTROL

Abstract

This paper focuses on effective integration of solar photovoltaic system to the distribution grid. In this regard an artificial neural network (ANN) based maximum power point tracking (MPPT) is employed for the PV system. A DC –DC boost converter along with the single phase bridge inverter is developed for the PV system to grid integration. The training of ANN is performed using the historical data related to solar insolation. The analysis is concentrated on assessing voltage and current at the grid as well as at the load side subjected to variations in PV partial shading conditions. In this regard, the voltage current and power variations at the source, grid, and load side are analysed. Simulation analysis showcased that, under the PV partial shading conditions also the proposed ANN methodology able to locate the maximum power point (MPP) while integration to the grid.

Keywords: ANN controller, MPPT technique, DC-DC boosts converter, Partial shading, and Photo voltaic system.

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I. INTRODUCTION

The integration of renewable energy sources in to the existing power grid has become a pivotal focus in the quest for sustainable and resilient energy future [1]. As the world grapples with the challenges posed by climate change and the depletion of finite fossil fuels, harnessing the potential of renewable resources like solar, wind, and hydroelectric power has gained unprecedented importance [2]. However the intermittent and unpredictable nature of these energy sources poses significant technical and operational challenges to the stability and reliability of conventional power grids [17].

In this context, the utilization of advanced technologies, particularly Artificial Neural Networks (ANN), has emerged as promising solution to enhance the grid integration of renewable energy systems [3]. By applying ANN based control strategies it becomes possible to optimize the deployment, operation, and management of renewable energy sources within the power grid. This synergy between renewable energy systems and artificial neural network control opens a new realm of possibilities [16]. ANN can aid in forecasting renewable energy generation, enabling grid operators to anticipate fluctuations and adjust power distribution accordingly [1]. Grid-connected photovoltaic (PV) systems are the dominant choice worldwide, constituting approximately 99% of the total installed solar capacity [18]. These systems are directly linked to the electricity grid and offer numerous advantages over standalone setups that incorporate batteries.

This literature review explores the evolving landscape of using machine learning techniques to address challenges associated with the grid integration of renewable energy sources.

The foundation of this review rests on the works of Haykin (2009) and Zhang et al. (2017). Haykin's seminal book, "Neural Networks and Learning Machines," provides insights into the fundamentals of neural networks, a cornerstone for many machine learning applications [1]. Zhang et al.'s review paper comprehensively analyzes the "Application of Artificial Neural Networks in Renewable Energy Systems," highlighting the versatility of neural networks in addressing renewable energy challenges [2].

Acharya and Mahapatra (2019) build on this foundation by proposing a "Neural Network-Based Energy Management System" specifically tailored for the grid integration of renewable energy sources [3]. Yu and Zhu (2019) expand the scope by presenting a "Review of Machine Learning Algorithms for Renewable Energy Forecasting," showcasing the role of machine learning in predicting renewable energy outputs and optimizing integration [4].

Bhattacharya et al. (2016) delve into "Control Strategies for Renewable Energy and Smart Grid Integration," offering a comprehensive view of control methodologies that facilitate seamless energy flow between renewable sources and the grid [5]. Yang et al. (2017) focus on the specific domain of photovoltaic power forecasting, presenting "A Comprehensive Review on Artificial Neural Network for Photovoltaic Power Forecasting" and emphasizing the accuracy achieved through neural network models [6].

Machine learning techniques also shine in addressing challenges posed by real-world conditions. Bouselham et al. (2017) tackle partial shading conditions in photovoltaic systems with their "New MPPT-based ANN," which maximizes energy output even under shading scenarios [7]. Kesraoui et al. (2016) offer insights into modeling and simulation for grid-connected solar PV systems, bridging the gap between theory and real-world testing [8]. Mohammed et al. (2017) contribute to the discourse with their work on "Grid Connected Photovoltaic System," focusing on practical implementation and grid synchronization [9].

The integration of renewable sources into weak grids is addressed by Kumar et al. (references [10] to [15]). They introduce novel techniques such as the Normalized Laplacian Kernel Adaptive Kalman Filter and Multi-Objective Solar Power Conversion System to enhance stability and performance [10][11][13]. Naqvi et al. (references [3] and [12]) emphasize power quality improvement features under varying operating conditions [3][12]. Similarly, Debnath et al. (reference [15]) propose a Multi-Port Autonomous Reconfigurable Solar Power Plant for hybrid AC/DC systems, facilitating efficient renewable integration [15].

The application of machine learning techniques, particularly neural networks, has revolutionized the integration of renewable energy systems into the grid. These studies collectively demonstrate the versatility of machine learning in addressing various aspects of renewable energy integration, including energy management, forecasting, control, and adaptation to challenging conditions.

1. **System under Consideration:** The simulation in this study focuses on a standard grid-connected photovoltaic (PV) system, aiming to investigate the ramifications associated with the integration of PV into the existing grid infrastructure. By selecting a representative PV system for simulation, the research seeks to gain a comprehensive understanding of the various effects and consequences that arise when PV units are interconnected with the conventional power grid.

   The configuration encompasses a photovoltaic (PV) array capable of producing a maximum output of 2 KW per day. Facilitating power optimization, a DC-DC converter is integrated with control features, including an artificial neural network (ANN)-based maximum power point tracking (MPPT) system. The amalgamation of the PV system with the grid is achieved through the deployment of a DC-AC inverter [7].

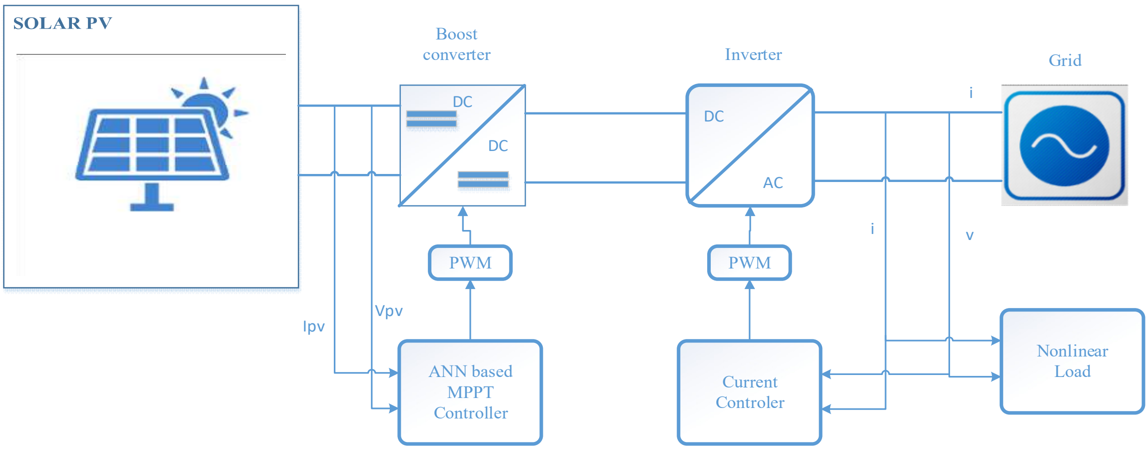

Figure 1: Single Phase Two Stage Grid Connected PV System

Many parts work together in a typical photovoltaic (PV) system to produce electrical energy from sunshine. A PV system's primary parts are:

- **Pv Modules:** These are the essential element of a PV system. Several solar cells make up these devices, which use sunlight to create direct current (DC) electricity. PV modules are available in a variety of shapes and sizes, and their output power is measured in watts.

- **DC-DC Converter (optional):** A DC-DC converter is used to increase or decrease the voltage of the DC electricity generated by the PV modules. This is crucial since the PV modules' voltage varies depending on the amount of sunshine and may not meet the inverter's requirements.

- **Inverter:** In order for the DC electricity generated by the PV modules to be compatible with the electrical grid, the DC electricity must be transformed to alternating current (AC). The DC electricity is changed into AC electricity using an inverter.

Together, these elements enable the creation of solar-powered electricity that can be used immediately by integrating to grid. The PV system's specific requirements and the application it is intended for will determine the size and arrangement of each component. The photovoltaic (PV) array is composed of individual modules. In order to achieve a power output of 2 kilowatts (KW), the array configuration involves connecting the modules in both series and parallel combinations, specifically utilizing 6 modules in series and 1 module in parallel. The comprehensive data employed for simulating the PV array is elaborated in Table I.

Table I. Necessary Data for PV Array Simulation

Number of cells per module	80
Number of series modules	6
Number of parallel modules	1
Open circuit voltage	51.5
Short circuit current	9.4
Maximum power	349.59
Voltage at MPP	43
Current at MPP	8.13
Temperature coefficient of voc	-0.36
Temperature coefficient of Isc	0.09
Diode ideality factor	1.045
Reference solar intensity	1000

In a standard scenario where the entire photovoltaic (PV) string is exposed to consistent sunlight intensity, the characteristic current-voltage (I-V) and power-voltage (P-V) curve exhibit a phenomenon known as the Maximum Power Point (MPP) under varying solar irradiance levels. This is graphically depicted in Figure 2, illustrating how the MPP shifts in response to changes in solar irradiance across the PV system.

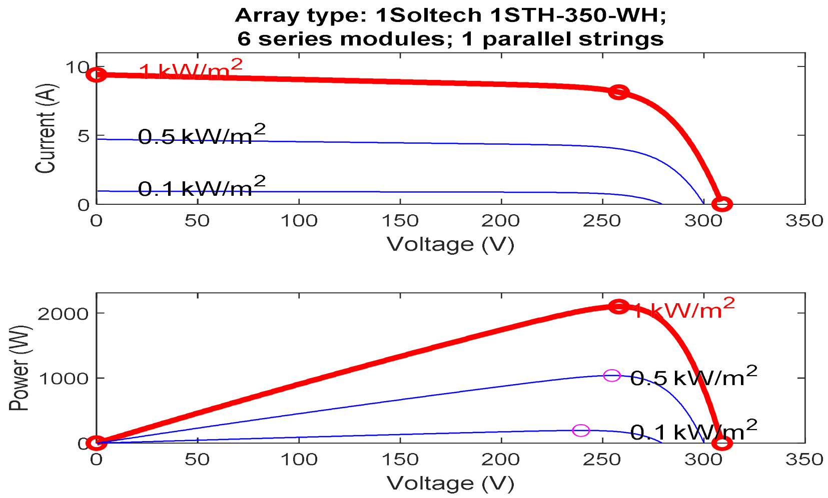

Figure 2: I-V and P-V Curves of Solar Array

2. **Proposed ANN Based MPPT Controller:** The ANN is a mathematical representation of biological neural networks that is used to tackle challenging issues. Its goal is to forecast a target output based on the inputs and training employed in the network. A multilayer network is required for difficult tasks. The following offers three layers (input, hidden and output layers).

$$H = O + 0.75 * L \text{ and } H < 2 * L$$

Where H is the Hidden neurons count, L is the count of input neurons, and O is the count of output neurons.

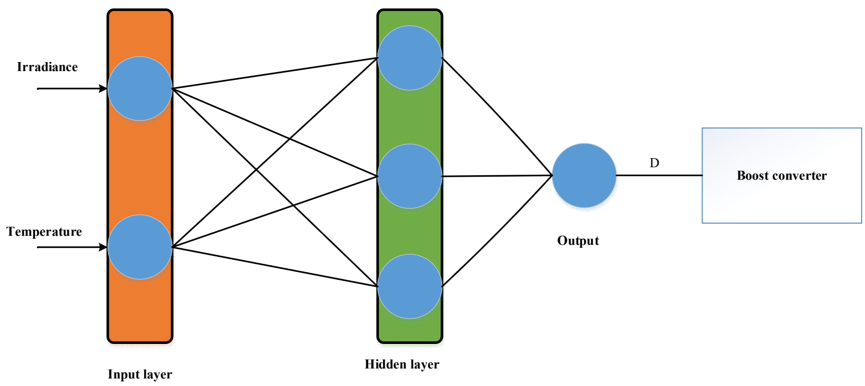

Figure 3: ANN Model

In this study, the regulation of the boost converter is managed by the duty cycle. This duty cycle is effectively generated by an Artificial Neural Network (ANN). The architecture of this ANN comprises three sequential layers, as illustrated in Figure 3. The initial layer, serving as the input, is composed of two neurons that take in external factors: irradiance and temperature. The subsequent layer, referred to as the hidden layer, utilizes a sigmoid activation function. Finally, the output layer encompasses a single neuron that provides the duty cycle, employing a linear activation function.

3. **Simulation Results:** The simulation of a grid-connected solar PV system took place within the MATLAB/SIMULINK environment. These simulations encompassed a range of weather conditions, each yielding distinct outcomes. The scenarios explored were:

- **Constant and Uniform Irradiation:** This condition involved consistent and even distribution of sunlight throughout the simulation.

- **Partially Shaded or Non-Uniform Irradiation:** In this scenario, the solar irradiation was irregular, with patches of shading affecting the PV system.

The goal was to observe how the PV system's performance and behavior varied under these different weather conditions.

- **Constant and Uniform Irradiation:** In this instance, the photovoltaic (PV) system underwent simulation with a uniform distribution of irradiation across all solar cells. Throughout the simulation, a consistent irradiation level of 1000 W/m² and a temperature of 25°C were sustained, ensuring uniform conditions on the PV panels.

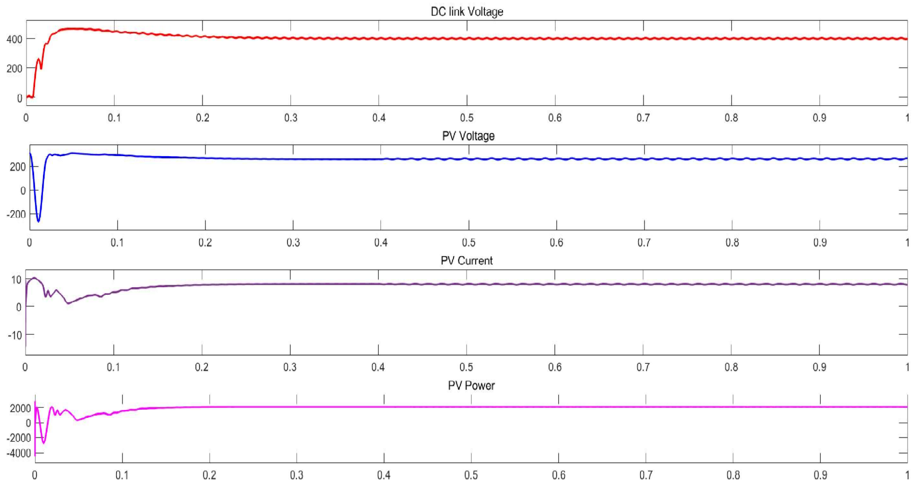

Figure 5: Source Side Parameters with Constant Uniform Irradance

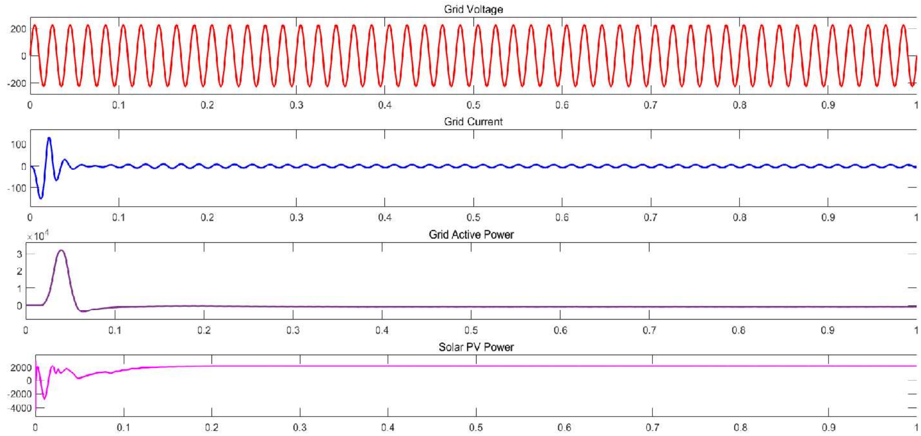

Figure 6: Grid Parameters with Constant Uniform Irradance

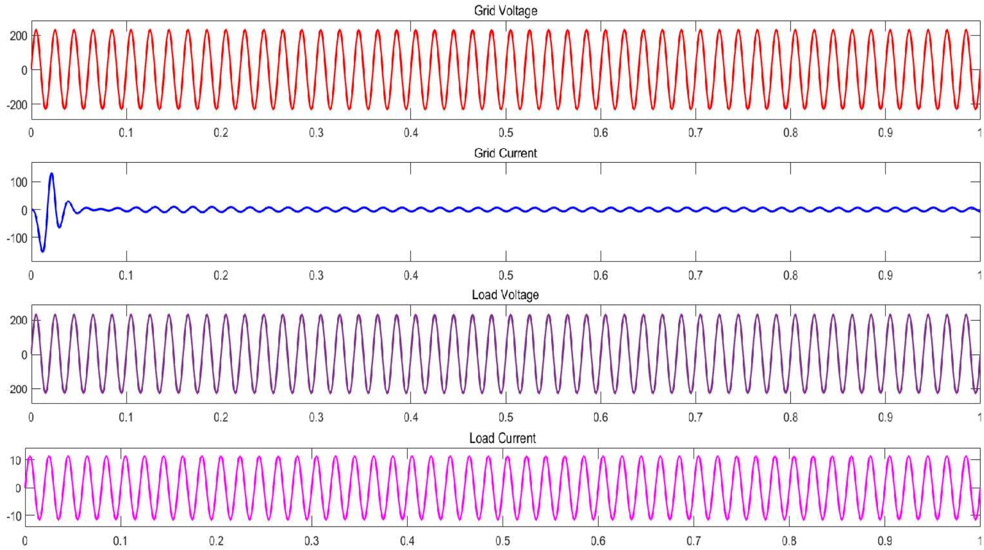

Figure 7: Load Parameters with Constant Uniform Irradance

4. **Partially Shaded or Non-Uniform Irradiation:** When assessing the effectiveness of the suggested Maximum Power Point Tracking (MPPT) controller under varying irradiance conditions. Initially, the solar irradiance was set at 1000 w/m^2 and then abruptly dropped to 400 w/m^2 subsequently, it was raised to 800 w/m^2.

During this transition, a notable pattern emerged. Between 0.3 seconds and 0.6 seconds, a decline in photovoltaic (PV) power output was observed as the solar irradiance decreased. However, as the irradiance levels were restored to 800 w/m^2, the PV power output began to rise again. In essence, the performance of the proposed MPPT controller showcased fluctuations in PV power in response to the non-uniform changes in solar irradiance, with a clear relationship between irradiance levels and power output.

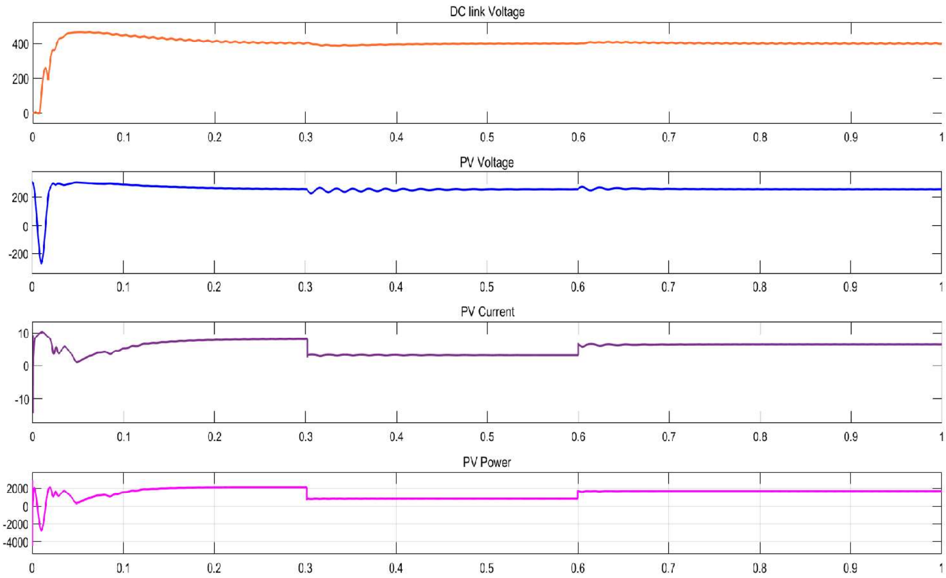

Figure 8: Source Side Parameters with Non-Uniform Irradance

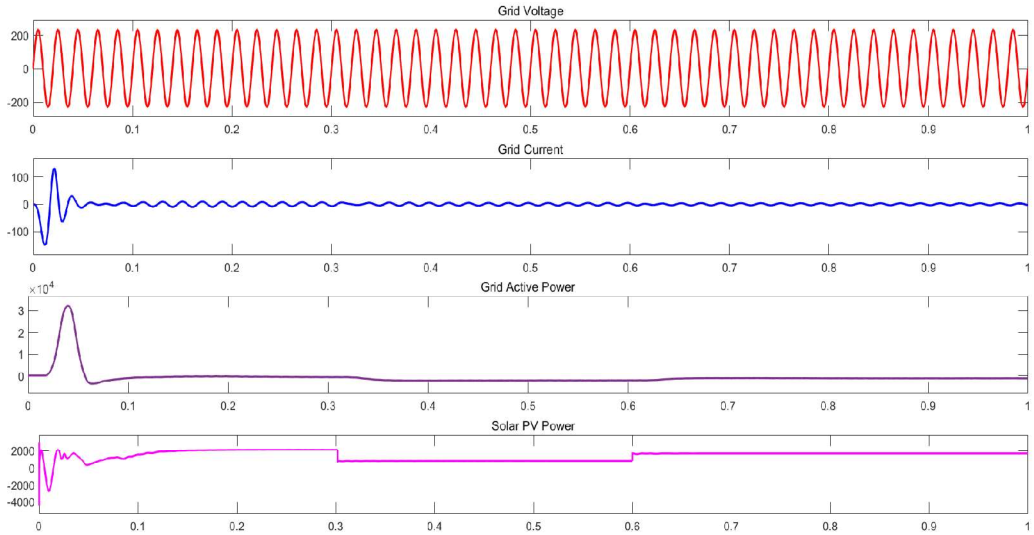

Figure 9: Grid parameters with Non-Uniform Irradance

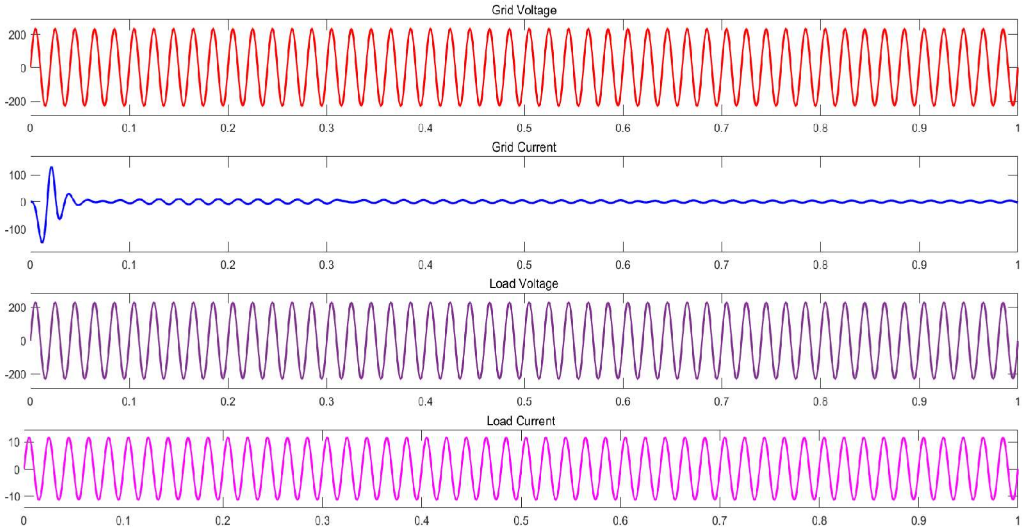

Figure 10: Load Side Parameters with Non-Uniform Irradance

The simulation results revealed an interesting behavior: under consistent solar irradiation, the electrical load was solely sustained by the solar photovoltaic (PV) system, with no external power drawn from the grid. However, a significant finding emerged when partial shading occurred between 0.3 seconds and 0.6 seconds.

During this interval, the solar PV system encountered a limitation in meeting the entire load demand on its own due to the partial shading effects. Consequently, in order to fulfill the required power demand during this shading episode, supplementary power was drawn from the grid. This observation underscores the system's adaptive behavior in tapping into grid resources when the solar PV output alone is insufficient to meet the load requirements during periods of partial shading.

II. CONCLUSION

This paper delves into a comprehensive exploration of the seamless integration of solar photovoltaic systems into distribution grids. By harnessing the power of artificial neural networks (ANNs) for maximum power point tracking (MPPT), the study demonstrates an innovative approach to optimizing PV system performance. The development of a DC-DC boost converter in tandem with a single-phase bridge inverter further exemplifies the commitment to efficient PV-to-grid integration. The utilization of historical solar insolation data for ANN training underscores the practicality of the proposed methodology.

The core emphasis of the analysis lies in the thorough evaluation of voltage and current parameters at both the grid and load sides, particularly under the challenging circumstances of PV partial shading. This investigation provides valuable insights into the system's resilience and adaptability to fluctuating conditions. As the world continues to prioritize sustainable energy solutions, the findings presented in this paper contribute to the growing body of knowledge surrounding the effective integration of renewable energy sources into existing power infrastructures.

Ultimately, the research underscores the significance of advanced control strategies and innovative hardware design in ensuring the optimal functioning of solar photovoltaic systems within distribution grids. The outcomes of this study not only enhance our understanding of the technical intricacies involved but also offer practical guidance for practitioners and researchers engaged in shaping the future of clean and efficient energy distribution. Further, the ANN training with novel and effective learning methods, hybridized ANN models, edge and quantum computing type networks are having the potential application in enhancing the grid stability and resilience as future perspectives.

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