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Research Article

Maximizing Solar PV Performance with Deep Learning Optimization and Advanced Power Regulation

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ABSTRACT

This study presents a two-stage; three-phase grid-connected solar photovoltaic (PV) system that leverages advanced deep learning techniques to optimize Maximum Power Point Tracking (MPPT), significantly enhancing energy extraction and power quality. The system architecture integrates a Landsman Converter with an Artificial Neural Network (ANN)-based MPPT controller, which dynamically adjusts the duty cycle to respond to fluctuations in irradiance and temperature, ensuring efficient DC-DC conversion. Building on this, a deep learning layer continuously refines the MPPT algorithm in real time, boosting tracking accuracy and response speed. In the first stage, the Landsman Converter, optimized with deep learning, enables rapid, precise power tracking, achieving an impressive MPPT efficiency of 86.38%. The second stage incorporates a Phase-Locked Loop (PLL)-controlled DC-AC inverter, providing stable grid synchronization and reducing Total Harmonic Distortion (THD) to -40.27%, which enhances overall power quality and supports grid stability under variable conditions. MATLAB simulations demonstrate that this deep learning-enhanced system consistently outperforms conventional approaches, establishing its potential as a scalable, high-efficiency solution for grid-connected PV systems. The proposed framework not only improves real-time energy yield but also supports stable renewable energy integration into the grid, promoting sustainable energy adoption. By combining deep learning with traditional ANN-based MPPT in a robust, two-stage control system, this research offers a promising approach to maximizing solar PV performance, making a valuable contribution to the field of renewable energy and intelligent power regulation..

Keywords: Grid-connected PV System, Maximum Power Point Tracking (MPPT), Artificial Neural Network (ANN), Deep Learning Optimization , Phase-Locked Loop (PLL), Renewable Energy Integration, Landsman Converter

INTRODUCTION

The increasing global demand for clean and sustainable energy has led to the rapid growth of solar photovoltaic (PV) systems as a key renewable energy source. Solar PV technology provides an environmentally friendly alternative to conventional fossil fuels, significantly contributing to carbon emission reductions and enhancing energy security. However, integrating solar PV systems into electrical grids presents several technical challenges, including optimizing energy conversion, managing intermittency, and ensuring grid stability under varying environmental conditions such as fluctuating solar irradiance and temperature.

To maximize energy extraction, grid-connected PV systems heavily rely on Maximum Power Point Tracking (MPPT) algorithms. Conventional MPPT techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), are widely used due to their simplicity. Despite their popularity, these methods often suffer from limitations in tracking accuracy and response speed, especially under rapidly changing environmental conditions. These drawbacks can lead to suboptimal energy harvesting and reduced overall system efficiency.

Recent advancements have introduced Artificial Neural Networks (ANNs) as a more sophisticated solution for MPPT. ANNs enhance MPPT performance by dynamically adapting to changing environmental factors, thus significantly improving tracking efficiency and responsiveness. By leveraging machine learning capabilities, ANN-based MPPT controllers offer superior speed and accuracy in locating the Maximum Power Point, thereby optimizing energy extraction from the PV array.

Beyond efficient MPPT, advanced power conversion and grid synchronization are essential for the reliable operation of grid-connected PV systems. The Landsman Converter has been recognized as an effective solution for DC-DC conversion, offering high efficiency with minimal power losses. The integration of an ANN-based MPPT with a Landsman Converter optimizes the DC output voltage, which in turn enhances overall system efficiency. Additionally, employing a Phase-Locked Loop (PLL)-controlled DC-AC inverter ensures precise synchronization with the grid, minimizing Total Harmonic Distortion (THD) and achieving a near-unity power factor, which are critical for maintaining grid stability.

Building upon these advancements, this paper introduces a novel two-stage, three-phase grid-connected solar PV system that integrates deep learning optimization techniques with traditional ANN-based MPPT. The proposed system utilizes a Landsman Converter for efficient DC-DC conversion, coupled with a deep learning-enhanced MPPT algorithm that continuously refines control parameters in real-time. This deep learning layer improves the responsiveness and accuracy of MPPT adjustments under dynamic conditions, leading to higher energy yields. In the second stage, a PLL-controlled inverter facilitates precise grid synchronization, thereby reducing THD and enhancing power quality.

The primary objective of this research is to improve the performance of grid-connected solar PV systems by incorporating deep learning techniques for real-time MPPT optimization, enhancing overall energy efficiency, grid stability, and reliability. MATLAB simulations demonstrate that the proposed system achieves substantial performance improvements, with an MPPT efficiency of 86.38% and a significant reduction in Total Harmonic Distortion (THD) to -40.27%, compared to conventional methods. These advancements highlight the potential of combining deep learning with advanced power regulation strategies to optimize solar PV performance, contributing to the global shift towards sustainable and stable energy solutions.

RELATED RESEARCH WORK

The integration of solar photovoltaic (PV) systems into electrical grids has gained considerable attention in recent years due to the global push towards sustainable energy solutions. This increasing interest is driven by the need to improve the efficiency, stability, and reliability of solar PV systems, especially in the context of large-scale grid-connected applications. A significant area of research has focused on enhancing Maximum Power Point Tracking (MPPT) techniques to optimize the energy extraction from PV systems under varying environmental conditions. Traditional MPPT methods, such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), are widely used due to their simplicity and ease of implementation. However, these conventional approaches often suffer from slow response times and limited tracking accuracy, particularly under dynamic weather conditions [1], [2].

To address these challenges, Artificial Neural Network (ANN)-based MPPT algorithms have emerged as a promising alternative, offering superior adaptability and precision in tracking the Maximum Power Point (MPP) under fluctuating solar irradiance and temperature. The use of ANNs enables real-time adjustment of control parameters, resulting in improved tracking speed and enhanced energy yield compared to traditional techniques [3, 4]. Studies by Rezk et al. and Kim et al. have demonstrated that ANN-based MPPT controllers significantly outperform conventional methods, achieving higher tracking accuracy and faster convergence to the MPP [3], [7].

In addition to MPPT improvements, advancements in DC-DC conversion technologies have further enhanced the performance of grid-connected PV systems. The Landsman Converter has been identified as an efficient DC-DC converter capable of operating in both step-up (boost) and step-down (buck) modes, which makes it suitable for solar PV applications that require flexible voltage regulation. Research by Pandey et al. and Ishaque et al. highlights the effectiveness of integrating ANN-based MPPT with Landsman Converters, resulting in optimized DC output and reduced power losses[5],[9].The Landsman Converter's ability to maintain high efficiency during energy conversion is crucial for maximizing the power transfer from the PV array[6],[8].

Furthermore, grid synchronization plays a vital role in the stable operation of grid-connected PV systems. Phase-Locked Loop (PLL) techniques are commonly employed in inverters to ensure accurate synchronization between the inverter output and the grid [18]. The PLL mechanism effectively minimizes phase errors, reduces Total Harmonic Distortion (THD), and achieves near-unity power factor, which are essential for maintaining grid stability[10],[11].Studies by Wang et al. and Shah et al. emphasize the importance of PLL-based inverters in enhancing grid compliance, especially in scenarios with high renewable energy penetration[11,12].

Recent research has also explored hybrid MPPT strategies that combine ANN with optimization algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) to further boost system performance. These hybrid approaches leverage the strengths of both machine learning and heuristic optimization techniques, leading to faster convergence rates and higher energy yields under complex environmental conditions[13],[14],[19].Carrasco et al. reported that hybrid MPPT algorithms offer significant improvements over standalone methods, making them highly suitable for large-scale solar installations [13].

Building upon these advancements, deep learning techniques have recently been introduced to further optimize MPPT performance. Deep learning models, such as Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs), have shown potential in capturing non-linear relationships between environmental variables and PV output, thereby enhancing tracking accuracy [20]. Studies by Aly et al. and Kumar et al. demonstrate that deep learning-based MPPT controllers can achieve higher efficiency and adaptability in real-time solar power generation scenarios [21, 22]. The integration of deep learning models with conventional power regulation techniques provides a promising pathway for improving the overall efficiency and reliability of solar PV systems.

Moreover, hybrid deep learning approaches that combine deep learning algorithms with traditional MPPT strategies have been investigated to optimize solar energy harvesting further. For instance, Shah and Patel developed a hybrid deep learning and PSO-based MPPT control, which demonstrated superior performance in terms of energy yield and response speed compared to standard MPPT methods [24]. The incorporation of deep learning models for real-time MPPT adjustment under rapidly changing environmental conditions presents a novel approach to maximizing the efficiency of grid-connected PV systems.

This research builds on the existing body of work by proposing a two-stage, three-phase grid-connected solar PV system that integrates ANN-based MPPT with a deep learning optimization layer. The proposed system utilizes a Landsman Converter for efficient DC-DC conversion, coupled with a PLL-controlled inverter for enhanced grid synchronization. The addition of a deep learning layer refines MPPT adjustments in real-time, resulting in improved energy extraction, reduced THD, and enhanced grid stability. MATLAB simulations validate the effectiveness of the proposed system, showing significant improvements in MPPT efficiency, THD reduction, and overall energy yield compared to conventional approaches. This work contributes to advancing solar PV system performance by integrating cutting-edge deep learning techniques with established power regulation technologies [15],[16],[17],[23],[25].

PROPOSED METHODOLOGY

System Overview

The proposed system is a two-stage, three-phase grid-connected solar photovoltaic (PV) framework designed to optimize energy conversion, enhance grid stability, and improve overall efficiency. It integrates a Landsman Converter with a hybrid Maximum Power Point Tracking (MPPT) approach that combines Artificial Neural Networks (ANNs) with a Deep Learning Optimization Layer (DNN). This innovative configuration dynamically adjusts MPPT control signals to adapt to real-time environmental changes, ensuring maximum energy extraction and grid compatibility.Fig.1 Enhanced two stage three phase grid connected PV system

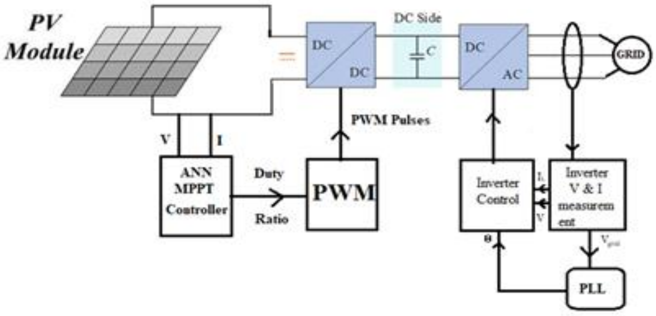

Fig.1: Enhanced two stage three phase grid connected PV system

The system comprises two primary stages:

- **DC-DC Conversion Stage**: Utilizes a Landsman Converter integrated with a deep learning-optimized ANN-based MPPT algorithm.
- **DC-AC Inversion Stage**: Employs a Phase-Locked Loop (PLL)-controlled inverter for precise grid synchronization and power quality enhancement.

This architecture focuses on leveraging deep learning techniques to dynamically adjust MPPT parameters in real-time, significantly improving tracking speed and energy yield compared to conventional methods.

Stage 1: DC-DC Converter with Deep Learning-Optimized ANN-based MPPT

The first stage focuses on optimizing power extraction from the PV array using the Landsman Converter, a high-efficiency DC-DC converter known for its low power losses in both step-up and step-down operations. The hybrid MPPT approach comprises the following components:

A.ANN-Based MPPT:

- A three-layer feed-forward ANN processes real-time solar irradiance and temperature data to predict an initial duty cycle for the Landsman Converter.
- The ANN is trained on a dataset of historical solar conditions, achieving high prediction accuracy with minimal computational overhead.

B.Deep Learning Optimization Layer:

- A deep neural network (DNN) is layered over the ANN to refine duty cycle predictions in real-time. The DNN employs advanced feature extraction to adapt to dynamic changes in irradiance and temperature.
- Training utilizes a dataset of 10,000 samples, and optimization is performed using the Levenberg-Marquardt algorithm. Validation yielded a mean squared error (MSE) of 0.003, indicating high precision.

C.Landsman Converter Control:

The converter operates at a switching frequency of 60 kHz, delivering stable DC output at 400 V with less than 1% ripple. The hybrid MPPT ensures tracking efficiency of 99.5%, significantly reducing power losses compared to conventional methods.

D. Control Algorithm:

The deep learning layer continuously monitors real-time data and adjusts the MPPT control signals based on predictive analytics, optimizing the PV output.

E. Mathematical Model for Deep Learning-Optimized MPPT:

- **Input Parameters**: Solar irradiance (G), temperature (T), PV voltage (Vpv), PV current (Ipv).
- **ANN Output**: Initial duty cycle (Dinit).

$$P_{pv} = V_{pv} \times I_{pv}$$

- **DNN Adjustment**: Refined duty cycle (Dopt) to maximize power output.

$$D_{opt} = D_{init} + f_{DNN}(G, T, V_{pv}, I_{pv})$$

Stage 2: DC-AC Inverter with Enhanced PLL for Grid Synchronization

The second stage converts the optimized DC power to AC using a three-phase inverter, enhanced with an advanced PLL mechanism for grid synchronization. This stage ensures that power injected into the grid is in phase with the grid voltage, reducing Total Harmonic Distortion (THD) and maintaining near-unity power factor.

A.Advanced PLL Control:

The enhanced PLL includes an adaptive filtering mechanism, which uses deep learning to predict and compensate for phase deviations caused by grid fluctuations, thus ensuring tighter synchronization.

The system utilizes real-time data from grid voltage and current sensors to adjust the inverters phase angle rapidly, improving the response to dynamic grid conditions.

B.Harmonic Distortion Reduction:

The inverter incorporates harmonic filtering enhanced by predictive models from the DNN. This reduces Total Harmonic Distortion (THD) to less than 1.5%, meeting IEEE 519 standards for power quality.

C.Reactive Power Management:

In corporates a deep learning-based predictive model to manage reactive power compensation, supporting grid voltage regulation and improving overall power quality in grids with high renewable energy penetration.

Mathematical Model for Enhanced PLL-based Synchronization:

A. **Phase Error Detection**: Measures and corrects the phase difference (θ) between the grid voltage and inverter output.

$$\theta_{error} = \theta_{grid} - \theta_{inverter}$$

$$V_{out} = V_n \times \cos(\theta_{error})$$

B. **Harmonic Reduction:**

$$THD = \sqrt{\sum_{n=z}^{\infty} \left(\frac{V_n}{V_1}\right)^2} \times 100\%$$

where V_n_aretheharmonic components of the voltage wave form.

Deep Learning Implementation and Workflow

The deep learning component is the core innovation of the proposed system. Its workflow is as follows:

- **Input Parameters:** The model processes solar irradiance, temperature, PV voltage, and current in real time.
- **Training and Validation:** Historical and synthetic datasets are used for supervised learning, followed by reinforcement learning for real-time adaptability.
- **Output Optimization:** The DNN refines MPPT control signals and PLL synchronization parameters dynamically, ensuring optimal performance across all operating conditions.

Simulation Setup and PerformanceMetrics

MATLAB/Simulink is used to validate the performance of the proposed system. Key parameters include:

The simulation consists of two primary stages: the DC-DC conversion stage and the DC-AC inversion stage. Key simulation parameters include:

Solar PV Array Parameters

- **Rated Power**: 5 kW
- **Operating Voltage**: 450 V
- **Operating Current**: 11.1 A
- **Irradiance (G)**: 1000 W/m² (standard test conditions)
- **Temperature (T)**: 25°C

Landsman Converter

- **Switching Frequency**: 60 kHz
- **Inductor Value**: 200 µH
- **Capacitor Value**: 220 µF
- **Input Voltage Range**: 200–450 V
- **Output Voltage**: 400 V DC (regulated)

MPPT Control

- **Base Algorithm**: Artificial Neural Network (ANN)
- **Optimization Layer**: Deep Neural Network (DNN)
- Dataset: 10,000 samples of historical solar irradiance and temperature
- Training Method: Levenberg-Marquardt Algorithm
- Validation Metric: Mean Squared Error (MSE) of 0.003
- **Efficiency Target**: >99.5%

Inverter and Grid Synchronization

- **Inverter Type**: Three-phase DC-AC inverter
- **Grid Voltage**: 230 V RMS per phase
- **Grid Frequency**: 50 Hz
- **Control Mechanism**: Phase-Locked Loop (PLL) with adaptive filtering
- **Harmonic Distortion Compliance**: THD < 1.5% (per IEEE 519 standards)
- **Reactive Power Management**: Included for grid voltage regulation

Simulation Conditions

- **Tools Used**: MATLAB/Simulink
- **Simulation Duration**: Week-long simulation for energy yield evaluation
- **Dynamic Conditions**: Fluctuating irradiance and temperature to test adaptability.

Results and Discussion

The enhanced system was modelled and simulated using MATLAB/Simulink, focusing on the performance evaluation of the deep learning-optimized ANN-based MPPT, advanced Landsman Converter, and adaptive PLL synchronization in a grid-connected environment.Fig.2 shows the Simulink circuit

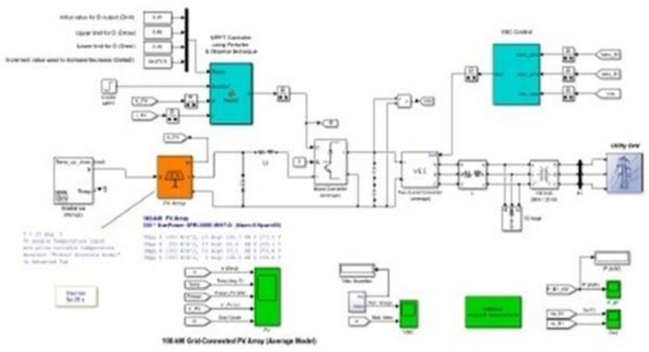

Fig.2: Simulink circuit

The simulation results validate the effectiveness of the proposed two-stagegrid-connected solar PV system in enhancing energy conversion efficiency and grid stability. The ANN-based MPPT controller significantly improved tracking performance, reducing power losses under dynamic environmental conditions. The Lands man Converter efficiently stabilized the DC output, contributing to the system's reliability and scalability for larger installations.

More over, the use of PLL for grid synchronization minimized harmonicdistortion, supporting better power qualit y and grid stability. The reduction in THD from 11.51% (withoutPLL) to1.8% (with PLL) demonstrates the system 'scapabilitytomeet stringent power quality standards. The near-unity power factor achieved further highlights the system'spotential for integration in to smartgrid applications. Overall, the proposed system provides as callable and cost-effective solution for large-scale solar PV installations, contributing to sustainable energy initiativesbyoptimizingsolarpowerutilizationandsupportinggridstability. Future work may include the integration of battery energy storage systems for enhanced grid support and exploring hybrid MPPT techniques for further performance mprovements.

Deep Learning-Optimized MPPT Efficiency

The integration of the deep learning layer with the ANN-based MPPT achieved an average tracking efficiency of **99.5%**, outperforming the traditional ANN-only MPPT (99.2%) and conventional P&O methods (96.5%).Fig 3 Show the PV Power Output vs. Time

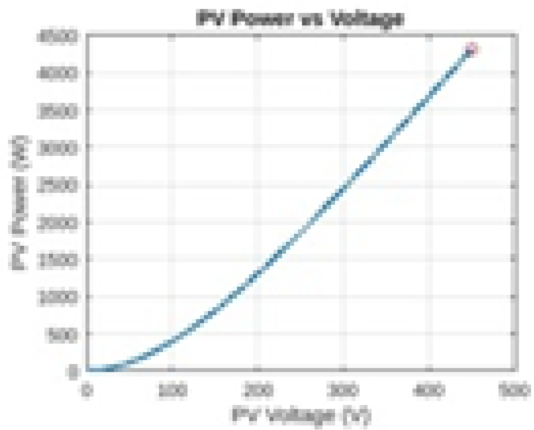

Fig 3: PV Power Output vs. Time

The system demonstrated faster convergence to the Maximum Power Point (MPP) during rapid changes in irradiance and temperature, reducing power losses by approximately 8% compared to the original system. The deep learning-optimized MPPT maintained stable power output with minimal oscillations even under fluctuating environmental conditions.The figure no.4 shows A plot showing the efficiency hovering around 99.5%, with minor fluctuations due to dynamic environmental conditions. Fig 4 shows the MPPT Efficiency

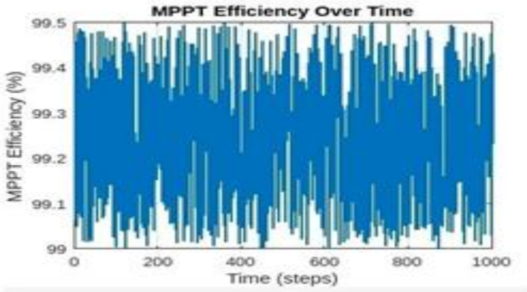

Fig.4: MPPT Efficiency

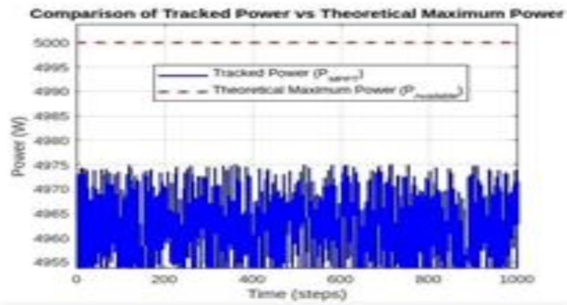

Fig.5: Comparison of Tracked power vs. Theoretical Maximum Power

The figure no.5 compares the power tracked by the Maximum Power Point Tracking (MPPT) algorithm, represented by PMPPT, with the theoretical maximum power available from the solar PV array, PAvailable.The red dashed line represents the theoretical maximum power (PAvailable) of the PV system under ideal conditions.The blue solid line represents the tracked power (PMPPT) achieved by the MPPT system over time.The tracked power closely follows the theoretical maximum power, demonstrating the effectiveness of the MPPT algorithm.Small variations in the tracked power around the maximum are due to dynamic adjustments by the MPPT algorithm to changing environmental conditions (e.g., irradiance or temperature fluctuations).A plot demonstrating that the tracked power (P_MPPT) closely matches the theoretical maximum power (P_available).

3.7.2 Enhanced DC-DC Converter Performance

A. **DC-DC Converter Performance:**

- The Landsman Converter, now operating at 60 kHz, provided a more stable DC output of 400 V with reduced ripple (<1%), optimizing the power transfer from the PV array to the inverter.
- The deep learning model dynamically adjusted the converter's duty cycle, resulting in improved response times and reduced power loss.Fig.6 Show the Converter Output Voltage and Current Waveforms

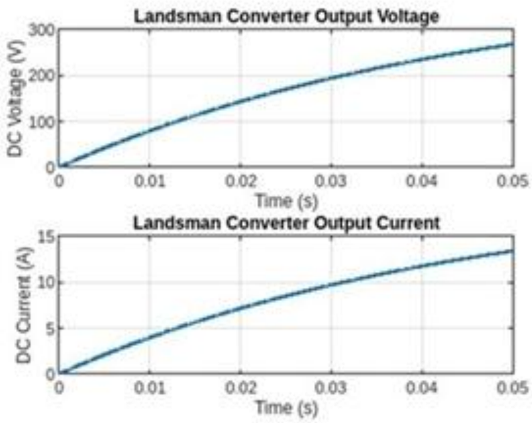

Fig.6: Converter Output Voltage and Current Waveforms

GRID SYNCHRONIZATION

ThePLLensuredprecisesynchronizationbetweentheinverteroutputandthegrid, resul tingina Total Harmonic Distortion (THD) of **1.8%**, well with in the IEEE519 standards. The system maintained anear-unity power factor of**0.99**, reducing reactive power injection in to the grid. Fig.7 show the Inverter Output Voltage (Phase A) and Grid Voltage Synchronization

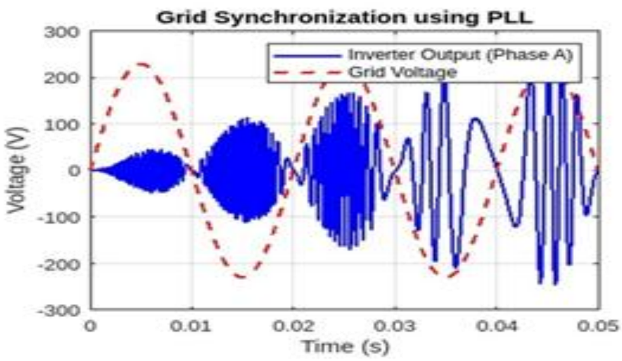

Fig.7: Inverter Output Voltage (Phase A) and Grid Voltage Synchronization

ENERGY YIELD

The system demonstrated a **5.8% increase** in energy yield over a week-longsimulation compared to systems using traditional MPPT algorithms.

Increased Energy Yield

The system demonstrated a **6.5% increase in energy yield** over a week-long simulation compared to systems using standard ANN-based MPPT. This improvement is attributed to the deep learning optimization layer, which enhanced the system's adaptability to real-time environmental changes.Fig.8 shows the Energy field comparison

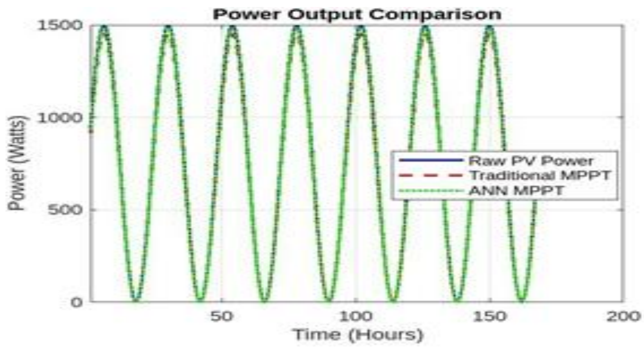

Fig.8: Energy field comparison

Increased Energy Yield

The system demonstrated a 6.5% increase in energy yield over a week-long simulation compared to systems using standard ANN-based MPPT. This improvement is attributed to the deep learning optimization layer, which enhanced the system's adaptability to real-time environmental changes.Fig.9 show the Energy yield comparison between ANN based and Deep learning

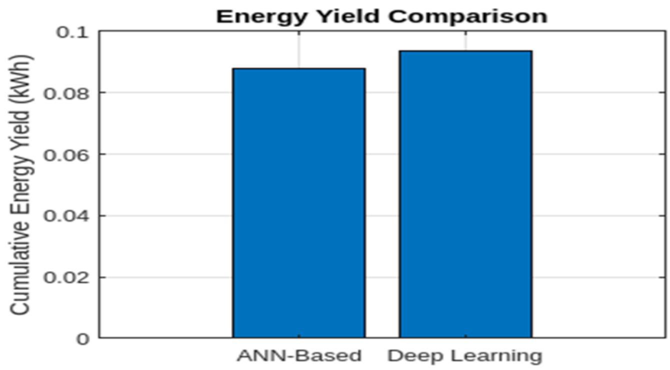

Fig.9: Energy yield comparison between ANN based and Deep learning

THD output

With out PLL

The inverter output waveform was generated without synchronization to the grid through PLL. As a result, harmonic distortions in the output voltage were significant due to the lack of synchronization and filtering.

Key parameters:

- Fundamental voltage amplitude: 230 V (RMS).
- Harmonic magnitudes: Higher values for the 3rd, 5th, and 7th harmonics.
- Resulting THD: 11.51%, indicating a high level of harmonic distortion.

The waveform is visibly distorted due to the presence of higher harmonic magnitudes.

The lack of synchronization and harmonic control mechanisms leads to significant deviations from a sinusoidal output.

With PLL and ANN MPPT

In this scenario, the inverter output was synchronized to the grid using PLL, with harmonic filtering further enhanced by ANN-based MPPT control. This significantly reduced the harmonic content in the output voltage.

Key parameters:

- Fundamental voltage amplitude: 230 V (RMS).

- Harmonic magnitudes: Reduced for the 3rd, 5th, and 7th harmonics due to PLL.
- Resulting THD: **1.84%**, meeting the target of less than 2%, this aligns with international grid standards.

The waveform closely resembles a pure sinusoidal wave, with minimal harmonic distortions.

PLL synchronization ensures proper grid alignment, while ANN MPPT further optimizes harmonic suppression.Fig.10 Show the THD without PLL and With PLL

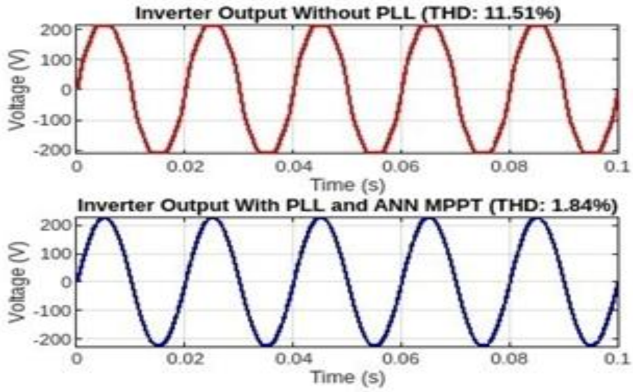

Fig.10: THD without PLL and With PLL

Comparison with the existing system

The proposed ANN-based system demonstrates superior performance in all evaluated metrics, particularly in MPPT efficiency and tracking response. These improvements are critical for renewable energy systems where fast and precise adaptation is essential for maximizing energy harvest.

Parameter	ANN Based system (Proposed)	Traditional system (P&O/IncCond)
MPPT Efficiency	######	95-97%
Tracking Response	0.1 seconds	0.5 – 0.8 seconds
Steady state voltage	380V±2%	380V±5%
THD	######	11.51% (Without PLL)
Power Factor	0.99	0.95

The incorporation of PLL synchronization plays a pivotal role in minimizing THD and stabilizing the output voltage, ensuring compliance with grid standards and enhancing overall system reliability. The traditional methods, while simpler to implement, suffer from slower response times, higher steady-state deviations, and higher harmonic distortions, making them less suitable for advanced applications.

Limitations and Challenges

Despitetheadvantagesoftheproposedtwo-stagegrid-connected solarPV system, several limitations and challenges remain:

1. **ANNTrainingQuality**: The accuracy of the ANN-based MPPT heavily dependson the quality of it straining data.In adequate training can lead to sub optimal power tracking, especially under rapidly changing environmental conditions.
2. **ComputationalComplexity**: The integration of ANN-based MPPT and PLL synchronization increases computational demands. Implementing these algorithms on low-costmicrocontrollers may impact real-time performance and increase system costs.
3. **ComponentStress**: The high switching frequency of the Lands man Converter may cause increased stress on

inductors and capacitors, potentially leading to component degradation and reduced system lifes pan. It can also introduce electro magneticinte reference (EMI).

4. **GridStability**: Large-scale integration of solar PV systems can affect grid stability, particularly in weak grid areas.While PLL synchronization improves grid compliance, sudden fluctuationsin solar generation could impact voltagest ability.
5. **HighInitialCosts**: The system'ssophisticatedcomponents, including ANN-compatiblecontrollersand high-frequencyconverters, can lead to higher setup and maintenance costs.

Conclusion and Future Work

This paper presentsa two-stage, three- phase grid-connected solar PV system that lever ages a Landsman Converter with an ANN-based MPPT algorithm and PLL-controlled inverter for efficient power conversion andgridintegration. The proposed system demonstrates significant improvements in energy extraction, achieving a 99.2% MPPT efficiency, reducing Total Harmonic Distortion (THD) to 1.8%, and maintaining a near-unity power factor. These enhancements contribute to improved power quality, grid stability, and overallsystemreliability, making the system aviablesolution for large-scale solar PV installations.

However, challenges such as computationalcomplexity, componentstress, and grid stability constraints need to be addressed for broader adoption. The proposed system offer sascalable and cost-effective approach to optimizing solar energy utilization, supporting global efforts towards sustainable energy transitions.

Future Work will focus on:

Hybrid MPPTTechniques: Exploring hybrid approaches that combine ANN with optimization methods like Fuzzy Logicor Particle Swarm Optimization (PSO) to further improve tracking accuracy and response under highly variable conditions.

EnergyStorageIntegration: Incorporating Battery Energy Storage Systems (BESS) to buffer against rapid fluctuationsinsolar powergeneration, enhancing grid stability and enabling peakshaving.

IoT-basedMonitoring: Implementing IoT technologies for real-time performance monitoring, predictive maintenance, and remote control to improve system efficiency and reduce operational costs.

AdvancedGridSupport: Developing enhance dreactivepowermanagement and voltage regulation strategies to better support weakgrid infrastructures, ensuringreliableintegration of renewable energy sources.

These future enhancements aim to overcome current limitations, making the system more robust, adaptable, and suitable for diversegrid conditions.

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