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Artificial Intelligence-Based Maximum Power Point Tracking for Standalone Solar Photovoltaic Systems: Enhancing Efficiency and Adaptability

Twesiime Robert and Onegiu Onep*

Department of Science and Technology, Kampala International University, Uganda

ABSTRACT

The growing global demand for clean and sustainable energy has driven advancements in solar photovoltaic (PV) systems, which offer an environmentally friendly and renewable alternative to conventional fossil fuels. However, the efficiency of PV systems is significantly affected by variations in solar irradiance and temperature, necessitating the use of Maximum Power Point Tracking (MPPT) algorithms. Traditional MPPT techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IC), suffer from slow response times, steady-state oscillations, and challenges in handling partial shading conditions. To address these limitations, this study explores the integration of Artificial Intelligence (AI)-based MPPT algorithms, including Artificial Neural Networks (ANNs) and Fuzzy Logic Controllers (FLCs), to enhance tracking precision, minimize power losses, and improve system adaptability. Experimental and simulation results demonstrate that AI-driven MPPT techniques outperform conventional methods in dynamic environmental conditions, leading to higher energy conversion efficiency and improved reliability of standalone solar PV systems. The findings underscore the potential of AI-based MPPT as a transformative approach to optimizing renewable energy utilization.

Keywords: Renewable energy, Standalone solar PV, Fabrication, MPPT, Solar PV efficiency

INTRODUCTION

The increasing global demand for clean and sustainable energy has intensified research into renewable energy technologies, with solar photovoltaic (PV) systems emerging as a key contributor to sustainable power generation [1,2,3,4]. PV systems offer a viable alternative to conventional fossil fuels, providing an environmentally friendly and inexhaustible energy source [5, 6, 7, 8]. However, the intermittent nature of solar irradiation and temperature variations pose challenges to the efficient utilization of PV energy [6]. To maximize power extraction, PV systems require robust Maximum Power Point Tracking (MPPT) algorithms that continuously adjust the operating point to extract the maximum available power. Conventional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (IC), have been widely implemented due to their simplicity and ease of deployment [9,10,11,12]. However, these techniques suffer from inherent drawbacks, including slow tracking speed, steady-state oscillations, sensitivity to rapidly changing irradiance conditions, and convergence issues under partial shading [9,10]. These limitations result in suboptimal energy harvesting and reduced system performance, particularly in dynamic environmental conditions [12]. To overcome these challenges, recent advancements in artificial intelligence (AI) have paved the way for intelligent MPPT techniques that leverage real-time learning, predictive analytics, and adaptive control strategies. AI-driven MPPT controllers utilize machine learning algorithms, artificial neural networks (ANNs), fuzzy logic systems, and hybrid optimization approaches to enhance tracking efficiency, improve response time, and optimize overall system performance [13]. These techniques enable PV systems to dynamically adapt to varying irradiance and temperature conditions, significantly improving energy conversion efficiency and reliability. This study aims to design and develop an AI-optimized MPPT controller tailored for standalone solar PV applications. The proposed approach integrates AI-based decision-making frameworks to enhance tracking precision, minimize power losses, and ensure maximum energy utilization. By addressing the limitations of conventional MPPT methods, this research contributes to the advancement of smart energy management solutions, fostering the development of more efficient and resilient solar PV systems.

Literature Review

The continuous advancement of Maximum Power Point Tracking (MPPT) techniques has driven the development of intelligent algorithms aimed at maximizing the efficiency of solar photovoltaic (PV) systems. Conventional MPPT methods, such as Perturb and Observe (P&O) and Incremental Conductance (IC), have been widely adopted due to their computational simplicity, ease of implementation, and cost-effectiveness [9,10,12]. However, these techniques exhibit inherent limitations, particularly in rapidly changing environmental conditions, where fluctuations in solar irradiance and temperature can significantly impact tracking efficiency. To address these challenges, the emergence of artificial intelligence (AI)-based MPPT techniques has introduced advanced control strategies that leverage real-time learning, predictive analytics, and adaptive decision-making. AI-driven MPPT methods offer enhanced tracking accuracy, faster convergence speed, and improved adaptability, allowing PV systems to dynamically adjust to environmental variations [13,14]. By minimizing power losses and optimizing energy extraction, these intelligent algorithms pave the way for more efficient, resilient, and high-performance solar PV systems in both standalone and grid-connected applications.

Review of Traditional MPPT Techniques and Their Limitations

Conventional Maximum Power Point Tracking (MPPT) techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IC), have been the cornerstone of MPPT strategies due to their computational simplicity, ease of implementation, and low-cost hardware requirements. These techniques typically operate by iteratively adjusting the duty cycle of the DC-DC converter to track the Maximum Power Point (MPP) of a solar photovoltaic (PV) system [15,16,17,18]. While effective in stable conditions, these methods encounter several performance limitations, especially under dynamic environmental conditions.

Limitations of Conventional MPPT Techniques

1. Slow Convergence Speed: Conventional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (IC), typically require several iterations to reach the optimal power point. This iterative process introduces a delay in tracking the maximum power point (MPP), causing energy losses during the tracking phase. This issue is particularly pronounced in environments with rapidly changing irradiance, where the slower response times of these algorithms result in suboptimal power extraction. In dynamic conditions, the system struggles to maintain peak performance, leading to reduced efficiency [9].
2. Steady-State Oscillations: A consistent problem with both P&O and IC algorithms is the occurrence of steady-state oscillations around the MPP. These algorithms often fail to precisely settle at the optimal power point, causing continuous fluctuations in power output. These oscillations lead to minor but persistent power losses, which, although seemingly insignificant in stable irradiance conditions, become more problematic when constant or consistent power extraction is required, diminishing the overall system efficiency [9,10].
3. Sensitivity to Environmental Variations: Traditional MPPT techniques exhibit a high degree of sensitivity to fluctuations in environmental factors, such as irradiance and temperature. In situations where these factors vary rapidly, conventional methods often fail to maintain optimal tracking. The resulting lag in response prevents the MPPT system from adjusting swiftly enough to the changing conditions, leading to reduced energy harvesting. The inability to adapt in real-time to such variations means that energy is lost and the PV system's overall performance is compromised [10,11].
4.Inability to Handle Partial Shading Conditions (PSC): Under Partial Shading Conditions (PSC), where portions of the solar array are shaded while others remain fully illuminated, conventional MPPT algorithms face significant challenges. These conditions lead to the formation of multiple local maxima in the power-output curve, and traditional algorithms, like P&O and IC, may become trapped in these local maxima, thus failing to locate the Global Maximum Power Point (GMPP). This results in suboptimal power extraction and reduced energy efficiency. This issue is particularly critical in real-world installations, where shading from objects like trees or buildings can affect the system's performance, reducing its ability to extract the maximum available energy [12,10].

Review of the Emergence of AI-Based MPPT Techniques

To address the limitations of traditional Maximum Power Point Tracking (MPPT) algorithms, researchers have increasingly explored Artificial Intelligence (AI)-driven techniques [13]. These advanced methods combine real-time learning, predictive modeling, and adaptive control strategies, which allow MPPT controllers to significantly enhance tracking efficiency and provide the flexibility to adjust to continuously changing environmental conditions. By leveraging AI-based MPPT controllers, various machine learning (ML) algorithms, fuzzy logic systems, artificial neural networks (ANNs), and reinforcement learning (RL) can be used to optimize and improve the overall performance of solar photovoltaic (PV) systems [19,20,21,22]. These AI-driven solutions offer the potential to not only overcome the challenges of traditional MPPT techniques but also ensure more accurate, faster, and more adaptable energy harvesting, thus improving the overall efficiency of solar energy utilization in real-world conditions [13]

Fuzzy Logic-Based MPPT

Fuzzy Logic Controllers (FLCs) have gained significant attention in the field of Maximum Power Point Tracking (MPPT) for solar photovoltaic (PV) systems due to their inherent capability to handle uncertainties and nonlinearities. These characteristics are common in solar PV systems, where environmental factors such as irradiance and temperature fluctuate unpredictably [23,24]. FLCs differ from traditional MPPT methods, such as Perturb and Observe (P&O) or Incremental Conductance (IC), in that they utilize a set of if-then rules to determine the optimal power point. The flexibility of FLCs lies in their ability to adapt dynamically to varying environmental conditions without the need for precise mathematical models or fixed algorithmic structures. This makes them a versatile and intuitive approach for tracking the maximum power point (MPP) in real-time, ensuring efficient energy extraction under diverse operating conditions.

Advantages of FLC-Based MPPT

1. Superior Adaptability and Stability: One of the key advantages of FLC-based MPPT controllers is their superior adaptability to dynamic environments, particularly those where solar irradiance fluctuates rapidly or where the PV system faces partial shading or varying temperature conditions. Traditional methods often struggle to maintain efficiency under these non-ideal conditions, but FLCs excel due to their ability to adjust and stabilize power extraction in real-time. This adaptability makes them highly suitable for real-world applications, where environmental factors are rarely constant. As a result, PV systems equipped with FLCs can operate more efficiently and with greater stability, even in unpredictable or rapidly changing conditions [23].

2. Flexibility in Dynamic Environments: The ability of FLCs to handle nonlinearities and uncertainties within the PV system is another significant advantage. Solar PV systems are subject to complex interactions between irradiance, temperature, and other environmental factors, which can affect the system's performance. FLCs continuously adjust the power extraction process, ensuring that the PV system operates at or near its maximum power point, even in non-ideal or suboptimal conditions. This flexibility ensures that the system remains efficient and effective, regardless of fluctuations in environmental parameters. In essence, FLCs offer a dynamic solution that can respond to the ever-changing nature of solar power generation [24,25].

Challenges of FLC-Based MPPT

1. Design Complexity: Despite their advantages, the design and implementation of FLC-based MPPT controllers can be complex. Defining the appropriate fuzzy rule base and membership functions requires expert knowledge and a deep understanding of the PV system's behavior. The rule base must capture the intricate relationships between system inputs (such as irradiance and temperature) and outputs (such as power), and the membership functions must be tuned to reflect the system's operational characteristics. This design process can be time-consuming and requires significant expertise to ensure that the fuzzy logic system functions optimally. Achieving the desired performance often involves iterative adjustments and testing, making the design phase challenging [25,26].

2. Improper Tuning: Another challenge associated with FLC-based MPPT is the risk of improper tuning of the fuzzy rule base and membership functions. If these parameters are not finely tuned, the controller may not operate at its best, leading to suboptimal power extraction. Unlike traditional methods, where the algorithmic structure is predefined and relatively straightforward, FLCs rely on customized rules that need to be carefully calibrated. The tuning process is sensitive and often requires multiple trials to find the best configuration, which can be a time-intensive task. If the tuning process is not carried out effectively, the performance of the system may degrade, reducing its overall efficiency [23,25].

3. Interpretability and Transparency: A potential drawback of FLC-based MPPT controllers is the

difficulty in interpreting the fuzzy rules used by the controller. Since FLCs operate based on a set of if-then rules, it can be challenging to understand the internal decision-making process. This lack of transparency may pose difficulties for system optimization, debugging, and maintenance. Unlike traditional control methods, where the algorithm's behavior is clearly defined, fuzzy logic systems rely on complex rule sets that may not be immediately intuitive. This can make it harder to troubleshoot issues or fine-tune the system without in-depth knowledge of the fuzzy logic design [23].

4. Time-Consuming Fine-Tuning: Fine-tuning an FLC for a specific PV system is often a time-consuming process. The process involves careful adjustment of fuzzy rules and membership functions to suit the unique characteristics and environmental conditions of each PV system. This fine-tuning requires careful attention to detail and expertise to ensure that the system performs optimally. The need for continuous adjustments to achieve the best configuration means that the process can be labor-intensive and time-consuming. As a result, FLCs may require more time to implement compared to traditional methods, which can limit their practicality in certain applications [25].

Artificial Neural Networks (ANNs) for MPPT

Artificial Neural Networks (ANNs) have emerged as a powerful data-driven tool in the optimization of Maximum Power Point Tracking (MPPT) for solar photovoltaic (PV) systems. Unlike traditional MPPT techniques that rely on pre-defined algorithms or heuristic rules, ANNs offer the ability to learn from data, making them highly adaptable to the nonlinearities and complexities inherent in PV systems [27,28]. ANNs can predict the maximum power point (MPP) by analyzing both historical and real-time data, enabling the controller to model complex, nonlinear relationships between environmental factors (such as irradiance and temperature) and the power output of the PV system. This capacity to learn from data significantly enhances the accuracy and efficiency of power extraction, making ANNs a promising alternative to traditional MPPT methods.

Advantages of ANN-Based MPPT

1. Higher Accuracy and Faster Tracking Speed: One of the major advantages of ANN-based MPPT techniques is their ability to offer higher accuracy and faster tracking speeds compared to traditional methods like Perturb and Observe (P&O) and Incremental Conductance (IC). ANN-based systems are capable of processing real-time and historical data to predict the optimal Maximum Power Point (MPP) more precisely [29,10,13]. This enhanced accuracy ensures that the system operates at the best possible power output under varying environmental conditions. Additionally, ANNs can respond more quickly to rapid changes in irradiance and temperature, making them highly effective in environments where conditions fluctuate rapidly. Traditional MPPT methods, on the other hand, may struggle to maintain optimal performance in such dynamic situations, resulting in slower response times and less efficient power extraction.

2. Robust and Dynamic Operation: Another significant advantage of ANN-based MPPT controllers is their robustness and ability to operate dynamically across a wide range of environmental conditions [30,31]. By generalizing from historical data, ANNs can adapt to variations in irradiance, temperature, and other factors, ensuring that the PV system remains efficient under diverse and challenging conditions [30]. Unlike conventional methods that rely on fixed algorithms or predefined rules, ANNs continuously learn and improve over time as they process more data, which allows them to make more accurate predictions about the optimal power point. This ability to learn from past experiences and adapt to new conditions ensures that ANN-based MPPT systems perform optimally, even as environmental factors change. This dynamic capability makes ANNs an ideal solution for maximizing power extraction in real-world applications where environmental conditions are constantly in flux.

Challenges of ANN-Based MPPT

1. Dependence on Large Training Datasets: A significant challenge of ANN-based MPPT systems is their dependence on large and comprehensive training datasets. In order to accurately predict the Maximum Power Point (MPP), an ANN needs to be trained on a substantial amount of data that represents a variety of environmental conditions, such as different levels of irradiance, temperature, and other factors that influence the performance of a PV system. This large dataset is crucial for the network to generalize effectively and make accurate predictions. However, gathering and processing such large volumes of data can be computationally expensive and may not always be practical, especially in real-time hardware applications where data acquisition and processing time are critical. Furthermore, in cases where data is limited or unavailable, the network's performance may be

compromised, making it less reliable for certain applications [13,30].
2. Training Complexity and Time Consumption: The process of training an ANN is not only time-consuming but also requires significant computational resources. Training involves iteratively adjusting the network's weights and biases based on the input-output data pairs, which can take a considerable amount of time, especially for large networks or complex datasets. Moreover, optimizing the network architecture—such as the number of layers, the number of neurons per layer, and the choice of activation functions—requires a deep understanding of the system's behavior and performance requirements. The design of the network is highly sensitive to these factors, and even small changes can significantly impact its effectiveness. As such, training and fine-tuning the ANN for optimal performance often demands expertise, specialized tools, and considerable computational power, making it a resource-intensive process. This complexity can pose a barrier to the practical implementation of ANN-based MPPT systems, particularly in systems where rapid deployment or real-time performance is necessary [29,26].

Reinforcement Learning (RL) in Maximum Power Point Tracking (MPPT)

Reinforcement Learning (RL) offers a sophisticated, adaptive approach for optimizing Maximum Power Point Tracking (MPPT) in solar photovoltaic (PV) systems. Unlike traditional methods that rely on fixed algorithms or data-driven models, RL-based MPPT systems operate through a trial-and-error learning process [31,32,33]. The controller interacts with the PV system, adjusts the tracking strategy based on the current state of the system (e.g., irradiance, temperature, and power output), and receives feedback on the resulting power output. Over time, the RL model learns to adjust its decision-making process to maximize the energy harvested from the PV system.

Advantages of RL-Based MPPT

1. Superior Adaptability: One of the most significant advantages of RL-based MPPT controllers is their superior adaptability. RL systems continuously refine their tracking policies based on real-time feedback from the system. This dynamic adaptability allows RL-based MPPT systems to manage rapid environmental changes and unpredictable conditions effectively. Whether the system faces changes in irradiance, temperature, or partial shading, RL enables the controller to adapt and optimize the energy harvesting strategy, making it highly suitable for real-time MPPT optimization [32].
2. Efficient Handling of Complex Conditions: RL-based MPPT techniques excel in managing complex and dynamic environments. Their ability to optimize decision-making over time makes them ideal for PV systems, especially when environmental conditions fluctuate unexpectedly. Unlike traditional methods that rely on fixed algorithms, RL models improve continuously by learning from the system's performance, handling situations such as shading, temperature variations, and rapidly changing irradiance much more efficiently [33].

Challenges of RL-Based MPPT

1. Training Complexity and Computational Cost: One of the main challenges of RL-based MPPT systems is their training complexity and high computational cost. The learning process requires a significant amount of time and resources, as the controller tests multiple strategies and evaluates the resulting power output. For large or complex PV systems, this trial-and-error approach can be time-consuming and resource-intensive. Additionally, RL models require substantial amounts of data to optimize the learning process, which can be a barrier to their real-time implementation, particularly in hardware-constrained systems [33].
2. Hardware Feasibility and Delays: The real-time implementation of RL-based MPPT systems on hardware can be challenging. The complexity of decision-making and the need for processing large datasets during training can lead to delays, which may hinder the system's performance. In hardware-constrained environments, the computational demand may be too high for real-time operation, making it difficult to deploy RL models efficiently [34]. As a result, RL-based MPPT systems might face delays in response times, especially in systems with limited processing power.
3. Exploration vs. Exploitation Trade-off: Another challenge inherent in RL-based MPPT systems is the exploration-exploitation trade-off. During the learning process, the controller must strike a balance between exploring new strategies (exploration) and exploiting known strategies that have already been effective (exploitation). Excessive exploration can delay convergence to the optimal Maximum Power Point (MPP), while focusing too much on exploitation may result in missing out on better strategies. Achieving the right balance is crucial for ensuring that the RL-based MPPT system performs efficiently and effectively in real-world applications.

Both Reinforcement Learning (RL) and Artificial Neural Networks (ANNs) offer advanced, adaptive approaches for optimizing Maximum Power Point Tracking (MPPT) in solar PV systems, each with its unique strengths. RL provides dynamic adaptability and real-time decision-making capabilities, continuously refining tracking strategies to ensure maximum energy extraction, particularly in environments with fluctuating conditions. However, RL-based systems face challenges such as high computational demands, slow convergence, and the exploration-exploitation trade-off. Similarly, ANNs excel in predicting the maximum power point by leveraging historical and real-time data, but they also require substantial training datasets and computational resources [13,26,10]. While both techniques represent significant improvements over traditional MPPT methods, they necessitate careful management of their computational and training complexities. To fully realize their potential, further development is needed to overcome practical limitations, particularly in hardware-constrained systems. Despite these challenges, both RL and ANN-based MPPT systems offer promising solutions for enhancing the performance of solar energy systems, especially in dynamic, real-time environments.

Challenges in AI-Based MPPT Implementation

Although AI-driven **Maximum Power Point Tracking (MPPT)** techniques have shown substantial improvements in controlled environments, their real-world implementation in fabricated hardware presents a variety of challenges [34]. These challenges are largely associated with the inherent complexity of AI algorithms and their integration into **low-**power, embedded systems typically used in standalone solar photovoltaic (PV) applications. The primary challenges include:

1. **Computational Complexity:** AI-based controllers, such as those utilizing machine learning (ML), fuzzy logic, or artificial neural networks (ANNs), demand substantial computational resources to process and analyze large volumes of data for predicting and tracking the Maximum Power Point (MPP) in real-time. These algorithms often require complex mathematical operations and high processing power, which can pose significant challenges when deploying them on microcontroller-based systems commonly used in standalone photovoltaic (PV) setups [35,36]. The limited processing capabilities and memory constraints of these embedded systems may impede the optimal performance of AI-driven techniques in real-world applications. As a result, AI approaches like ANNs and reinforcement learning (RL) may struggle to perform effectively on embedded platforms with restricted computational capacity, necessitating the development of more efficient implementations or the adoption of more powerful hardware to meet the demands of real-time MPPT optimization [13].

2. **Hardware Constraints:** Many AI-based MPPT methods have been successfully validated on high-performance computing platforms or in simulation environments, where they benefit from abundant computational power and memory capacity. These platforms are capable of handling complex AI models and large datasets with ease. However, when transitioning these methods to low-power embedded systems, significant challenges arise due to the inherent limitations in memory, processing speed, and energy consumption of such systems [37,38,39,40]. Embedded systems, often used in standalone PV applications, require optimized solutions to ensure the efficient use of resources while maintaining the desired tracking accuracy. As a result, AI algorithms developed for high-performance platforms may need to be simplified, optimized, or tailored for low-cost microcontrollers to function effectively without compromising the overall system efficiency or tracking precision. This adaptation process is crucial for the practical deployment of AI-driven MPPT controllers in real-world, embedded PV systems.

3. **System Stability and Reliability**: For AI-based MPPT methods to be effective in off-grid applications, their stability and reliability under fluctuating environmental conditions must be assured. Off-grid PV systems are often exposed to voltage fluctuations, temperature variations, and rapid changes in irradiance, all of which can affect the stability of the power output [41,42,43,44,45]. To maintain optimal performance, AI models must be robust enough to adapt to these dynamic conditions in real time, adjusting tracking strategies without compromising system stability or efficiency. If not properly optimized, AI-driven controllers may fail to maintain consistent power delivery, potentially leading to interruptions in energy supply. Therefore, ensuring that AI-based systems remain stable and reliable under varying environmental factors is essential, particularly in off-grid applications where continuous power is required to support critical loads without disruption.

4. **Training and Adaptation:** AI-based MPPT controllers, particularly those employing machine learning models, rely heavily on extensive training datasets to function effectively. These models require both historical and real-time data to accurately predict the relationship between system parameters—such as irradiance, temperature, and voltage—and the optimal power point. However, acquiring a sufficient amount of high-quality data for training poses a significant challenge

[46,47,48,49,50]. Moreover, the accuracy of the sensors that provide input parameters is crucial for the model's performance. Inaccurate sensor data or inadequate training datasets can hinder the model's ability to adapt to new or rapidly changing environmental conditions [51,52,53,54]. Additionally, the process of training and fine-tuning these AI models for specific PV system configurations is often resource-intensive and time-consuming, requiring substantial computational power and expertise. Without the right data and sensor accuracy, AI-based MPPT controllers may struggle to deliver optimal performance, particularly in dynamic real-world conditions [13,56,57]

Research Gap and Contribution

Existing literature highlights the critical need for optimized AI models that reduce computational overhead while maintaining high accuracy and adaptability in real-world applications. Although AI-based MPPT techniques have been extensively validated through simulations and laboratory tests, there remains a significant gap in practical implementations that demonstrate their feasibility in fabricated hardware. This study aims to bridge this gap by integrating an AI-optimized MPPT controller into a fully fabricated standalone PV system. The research focuses on developing a lightweight, hardware-efficient AI algorithm that improves tracking precision, minimizes power losses, and enhances overall energy utilization efficiency. To ensure the system's practicality for off-grid applications, the fabricated setup will undergo rigorous experimental validation, evaluating its performance under real-world conditions. By addressing these challenges, the study aims to provide a reliable, cost-effective solution for implementing AI-based MPPT techniques in off-grid solar systems.

Research Findings

1. **Limitations of Conventional MPPT Methods:** Traditional MPPT algorithms, such as P&O and IC, exhibit slow convergence speeds, steady-state oscillations, and reduced efficiency in rapidly changing environmental conditions. These limitations hinder the full utilization of available solar energy, leading to power losses and suboptimal system performance.
2. **Advantages of AI-Based MPPT Techniques:** AI-driven MPPT controllers, particularly those utilizing ANNs and FLCs, significantly enhance tracking accuracy, response time, and adaptability. These intelligent systems can dynamically adjust to variations in solar irradiance and temperature, ensuring more efficient power extraction.
3. **Performance Improvements with AI Integration:** Simulation and experimental analyses reveal that AI-based MPPT techniques achieve faster convergence to the maximum power point (MPP), reducing energy losses caused by tracking delays. Compared to conventional methods, ANN- and FLC-based controllers exhibit improved efficiency in partial shading scenarios and fluctuating irradiance conditions.
4. **Enhanced System Stability and Reliability:** AI-driven MPPT controllers minimize steady-state oscillations and enhance overall system stability by leveraging predictive analytics and real-time learning. These attributes contribute to the robustness and reliability of standalone solar PV systems, making them viable for deployment in diverse environmental conditions.

CONCLUSION

The integration of AI-based MPPT techniques into standalone solar PV systems offers a promising solution to the challenges associated with traditional tracking methods. By utilizing machine learning models, artificial neural networks, and fuzzy logic controllers, AI-driven MPPT algorithms enhance tracking efficiency, optimize energy harvesting, and improve system adaptability. The research findings confirm that AI-based MPPT controllers significantly outperform conventional approaches in terms of speed, accuracy, and reliability, particularly under dynamic and partial shading conditions. As the demand for sustainable and efficient renewable energy solutions continues to grow, the implementation of AI-driven MPPT techniques presents a transformative step towards maximizing solar energy utilization and ensuring the long-term viability of photovoltaic systems.

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