OPEN ACCESS
Journal of Moeslim Research Technik
Vol. 3 No. 1. February 2026, pp. 71-87 DOI. 10.70177/technik.v3i1.3470

Research Article

OPTIMIZING MAXIMUM POWER POINT TRACKING (MPPT) USING DEEP REINFORCEMENT LEARNING TO IMPROVE SOLAR PANEL EFFICIENCY UNDER DYNAMIC WEATHER CONDITIONS

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Article Info
Received: August 9, 2025
Revised: November 11, 2025
Accepted: January 10, 2026
Online Version: February 28, 2026

Abstract
Solar photovoltaic (PV) systems play an important role in the transition toward sustainable energy. Variations in solar irradiance, temperature, and partial shading caused by dynamic weather conditions often reduce the efficiency of photovoltaic power generation. Conventional Maximum Power Point Tracking (MPPT) algorithms such as Perturb and Observe and Incremental Conductance frequently experience difficulties in maintaining the global maximum power point when environmental conditions change rapidly. Intelligent control approaches are therefore required to improve the adaptability and performance of MPPT systems. This study aims to develop and evaluate an MPPT optimization method based on Deep Reinforcement Learning (DRL) to enhance solar panel efficiency under dynamic weather conditions. The proposed method is designed to enable the controller to learn optimal operating strategies through continuous interaction with the photovoltaic system environment. A quantitative experimental design was implemented using a photovoltaic simulation model integrated with a DC–DC boost converter and a DRL-based control framework. Environmental scenarios including fluctuating irradiance and temperature variations were simulated to evaluate system performance. The DRL-based MPPT algorithm was compared with conventional MPPT techniques using metrics such as tracking efficiency, convergence speed, and power stability. Results show that the proposed DRL-based MPPT method achieved higher tracking efficiency (98.3%), faster convergence time, and improved power stability under dynamic weather conditions compared with traditional algorithms. These findings indicate that reinforcement learning provides a robust and adaptive solution for optimizing photovoltaic power extraction. The study concludes that Deep Reinforcement Learning can significantly enhance MPPT performance and support the development of intelligent photovoltaic energy systems capable of operating efficiently in highly variable environmental conditions.

Keywords: Maximum Power Point Tracking, Deep Reinforcement Learning, Photovoltaic Systems, Solar Energy Optimization, Dynamic Weather Conditions.

Journal Homepage	https://research.adra.ac.id/index.php/technik
How to cite:	Muntasir, F. A. N. (2026). Optimizing Maximum Power Point Tracking (Mppt) Using Deep Reinforcement Learning to Improve Solar Panel Efficiency Under Dynamic Weather Conditions. *Journal of Moeslim Research Technik, 3*(1), 71–87. https://doi.org/10.70177/technik.v3i1.3470
Published by:	Yayasan Adra Karima Hubbi

INTRODUCTION

Global energy demand continues to increase alongside growing concerns regarding environmental sustainability and climate change (Demir, 2025). Renewable energy technologies have therefore become a crucial component in modern energy strategies, particularly solar photovoltaic (PV) systems which offer clean, abundant, and sustainable electricity generation (Yiğit et al., 2025). Photovoltaic panels convert solar radiation directly into electrical energy; however, their output efficiency is highly dependent on environmental conditions such as solar irradiance, temperature, and shading (Latif et al., 2025). Variations in these parameters cause fluctuations in the current–voltage characteristics of PV modules, leading to suboptimal power generation if not properly managed.

Maximum Power Point Tracking (MPPT) techniques are widely used to maximize the energy harvested from photovoltaic systems (Vourkos et al., 2025). These techniques aim to continuously locate the optimal operating point on the power–voltage curve of a PV module, where the product of voltage and current produces maximum power output (T. Wang et al., 2025). Conventional MPPT methods, including Perturb and Observe (P&O), Incremental Conductance, and Hill-Climbing algorithms, have been extensively implemented due to their simplicity and low computational requirements (Akram & Bai, 2025). Despite their widespread adoption, such methods often encounter limitations when environmental conditions change rapidly, especially under dynamic weather scenarios involving partial shading, fluctuating irradiance, and temperature variations.

Advanced intelligent control techniques have recently been explored to overcome the limitations of traditional MPPT algorithms (Das et al., 2024). Artificial intelligence-based approaches, including fuzzy logic control, artificial neural networks, and evolutionary algorithms, have shown promising results in improving tracking accuracy and response time (Karakan, 2025). Deep Reinforcement Learning (DRL) has emerged as a particularly powerful approach because it allows systems to learn optimal control strategies through interaction with the environmen. Application of DRL in photovoltaic control systems offers a novel opportunity to enhance MPPT performance by enabling adaptive decision-making in complex and dynamic operating conditions.

Efficiency degradation in photovoltaic systems under rapidly changing environmental conditions remains a major challenge in solar energy utilization (Diniță et al., 2025). Conventional MPPT algorithms often rely on iterative perturbation or gradient-based techniques that assume relatively stable operating environments (Hamzaoğlu et al., 2025). Dynamic weather patterns, such as passing clouds or intermittent shading, frequently cause multiple local maximum power points on the PV characteristic curve (Hamzaoğlu et al., 2025). Traditional algorithms may become trapped in these local optima, resulting in significant power losses and reduced overall system efficiency.

Existing intelligent control methods have attempted to address these limitations by incorporating adaptive learning capabilities (Adib et al., 2025). Machine learning and heuristic optimization techniques can improve MPPT performance by predicting optimal operating conditions based on historical data or predefined models (Khanam et al., 2025). Limitations persist because many of these approaches require extensive training datasets, predefined parameters, or simplified system assumptions that may not accurately represent real-world environmental variability (Ledmaoui et al., 2025). Computational complexity and slow convergence rates further hinder their practical implementation in real-time energy systems.

Control strategies capable of autonomously adapting to dynamic environmental conditions are therefore required to ensure stable and efficient power generation (Zhang et al., 2025). Reinforcement learning approaches present an opportunity to develop self-learning MPPT controllers that continuously improve their performance through interaction with the photovoltaic system and its environment (Mo et al., 2025). Challenges remain regarding the design of appropriate reward mechanisms, state representations, and training frameworks that enable robust and efficient learning processes (Liu et al., 2025). Addressing these challenges is essential for developing MPPT systems capable of maintaining optimal performance under highly variable weather conditions.

Development of a more adaptive and intelligent MPPT framework represents the central objective of this study (Xie et al., 2025). The research seeks to design an MPPT controller based on Deep Reinforcement Learning capable of identifying and maintaining the global maximum power point in photovoltaic systems operating under dynamically changing environmental conditions (Li et al., 2025). Integration of deep learning architectures with reinforcement learning principles allows the system to learn optimal control policies directly from environmental interactions without relying on predefined models of PV behavior.

Evaluation of the proposed MPPT framework constitutes another key objective of the research (Mamodiya, Kishor, Almaiah, et al., 2025). Performance of the Deep Reinforcement Learning–based MPPT algorithm will be assessed through simulation experiments and comparative analysis with widely used conventional MPPT methods (Ramu et al., 2025). Metrics such as tracking accuracy, convergence speed, energy harvesting efficiency, and robustness against environmental disturbances will be used to determine the effectiveness of the proposed approach (Sinneh Sinneh & Sun, 2025). Comprehensive performance evaluation ensures that the developed algorithm demonstrates practical advantages over existing techniques.

Contribution to the advancement of intelligent energy management systems also forms an important goal of this study (Ghazi et al., 2025). Integration of artificial intelligence techniques with renewable energy control systems represents a growing research direction in modern power engineering (T & Gomathi, 2025). Findings from this research are expected to provide insights into the application of reinforcement learning for adaptive energy optimization, thereby supporting the development of smarter and more resilient renewable energy infrastructures.

Existing research on Maximum Power Point Tracking has largely focused on deterministic control algorithms and heuristic optimization methods. Numerous studies have explored improvements to classical MPPT techniques by incorporating hybrid approaches or adaptive parameter tuning (Rajamallaiah et al., 2025). Research findings demonstrate that such modifications can enhance performance under moderate environmental variability (Nwachukwu, Folly, & Awodele, 2025). Significant limitations remain when systems are exposed to highly dynamic weather conditions where rapid fluctuations create complex power–voltage landscapes with multiple local maxima.

Artificial intelligence–based MPPT strategies have gained attention in recent years, particularly approaches utilizing neural networks, fuzzy inference systems, and evolutionary algorithms (Areola et al., 2025). These methods provide improved adaptability compared to classical algorithms by incorporating nonlinear modeling capabilities (Singh & Rai, 2025). Many studies rely on offline training processes or static datasets that limit the ability of the control system to adapt continuously to new environmental scenarios (Ortiz-Munoz et al., 2025). Lack of real-time learning mechanisms reduces the long-term effectiveness of these approaches in practical applications.

Deep Reinforcement Learning has been widely adopted in various control and optimization domains such as robotics, autonomous systems, and smart grid management (Sousa & Barbosa, 2025). Application of DRL to photovoltaic MPPT control remains relatively limited and still represents an emerging research area (Wiencek & Ghosh, 2025). Few studies have investigated the capability of DRL algorithms to dynamically learn optimal control strategies for PV systems under fluctuating irradiance and temperature conditions (Y. Wang et al., 2025). This gap in the literature highlights the need for further exploration of reinforcement learning–based MPPT frameworks capable of operating efficiently in real-world solar energy environments.

Introduction of Deep Reinforcement Learning as the core mechanism for MPPT optimization constitutes a significant innovation in photovoltaic control systems (Pokharkar et al., 2025). Reinforcement learning enables an autonomous learning process in which the controller continuously updates its decision-making strategy based on environmental feedback (Bisht et al., 2025b). Combination of deep neural networks with reinforcement learning allows the system to process complex state representations and discover optimal control policies without relying on explicit mathematical models of the photovoltaic system.

Proposed research introduces a DRL-based MPPT framework designed specifically for dynamic weather environments. Integration of adaptive learning mechanisms enables the controller to recognize environmental patterns and respond rapidly to changes in solar irradiance and temperature (Alemu et al., 2025). Design of an effective reward structure and state representation ensures that the learning process consistently guides the controller toward maximizing energy output. Such an approach addresses the limitations of traditional MPPT methods that struggle to maintain optimal performance under rapidly changing conditions.

Significance of this research extends beyond the immediate improvement of photovoltaic efficiency. Development of intelligent MPPT controllers contributes to broader efforts aimed at enhancing the reliability and sustainability of renewable energy systems. Increasing the efficiency of solar power generation directly supports global initiatives toward reducing carbon emissions and transitioning to clean energy sources. Implementation of Deep Reinforcement Learning in photovoltaic control systems therefore represents an important step toward the creation of adaptive, intelligent, and high-performance renewable energy infrastructures.

RESEARCH METHOD

Research Design

This study adopts a quantitative experimental research design aimed at evaluating the performance of a Deep Reinforcement Learning (DRL)–based Maximum Power Point Tracking (MPPT) algorithm under dynamically changing environmental conditions (Hakam et al., 2025). The research focuses on the development and testing of an intelligent MPPT controller that is capable of adapting to variations in solar irradiance and temperature (J.Saranya & V.Divya, 2025). A simulation-based experimental framework is implemented to compare the proposed DRL-based MPPT method with conventional MPPT algorithms commonly used in photovoltaic systems (B et al., 2025). Performance indicators such as tracking efficiency, convergence speed, stability, and energy harvesting capability are analyzed to assess the effectiveness of the proposed approach.

Experimental modeling of the photovoltaic system is conducted using a detailed mathematical representation of solar panel characteristics. The current–voltage (I–V) and power–voltage (P–V) curves of the photovoltaic module are modeled under different irradiance and temperature conditions to represent real-world operational environments. Integration of the photovoltaic model with a power electronic converter and control system enables the simulation of real-time MPPT processes. Implementation of the Deep Reinforcement Learning algorithm allows the controller to interact with the simulated environment and learn optimal decision-making strategies that maximize power extraction from the solar panel.

Comparative evaluation constitutes a central component of the research design. The proposed DRL-based MPPT algorithm is tested against conventional techniques such as Perturb and Observe (P&O) and Incremental Conductance methods. Simulation experiments are performed across multiple dynamic weather scenarios including rapidly fluctuating irradiance levels and partial shading conditions. Statistical analysis of the resulting performance metrics provides evidence regarding the relative advantages and limitations of each MPPT strategy, thereby validating the effectiveness of the proposed intelligent control approach.

Research Target/Subject

The population in this study refers to photovoltaic operating conditions characterized by varying environmental parameters that influence solar panel performance. Solar irradiance levels, temperature variations, and shading patterns constitute the primary environmental variables affecting the electrical characteristics of photovoltaic modules. These environmental factors are represented through a range of simulated operating scenarios that reflect realistic conditions experienced by solar energy systems deployed in outdoor environments.

Sample data are generated from multiple dynamic weather scenarios designed to test the robustness of the MPPT control algorithms. Irradiance levels ranging from low to high intensity are simulated to represent conditions such as cloudy weather, intermittent sunlight, and full solar exposure. Temperature variations are also incorporated into the simulation environment to reflect the thermal effects on photovoltaic module efficiency. Several partial shading patterns are introduced to create complex power–voltage curves with multiple local maximum power points, thereby challenging the tracking capabilities of the control algorithms.

Selection of simulation scenarios ensures comprehensive evaluation of the proposed DRL-based MPPT controller. A dataset of environmental profiles representing different time-series weather patterns is used to train and test the reinforcement learning model. These profiles include gradual irradiance changes, sudden irradiance drops caused by moving clouds, and irregular fluctuations typical of real-world atmospheric conditions. Use of diverse environmental samples enables the assessment of the algorithm's adaptability, stability, and energy optimization capability across a wide range of operational contexts.

Research Procedure

The research procedure begins with the development of a photovoltaic system model that accurately represents the electrical behavior of solar panels under varying environmental conditions. Mathematical equations describing the current–voltage relationship of photovoltaic cells are implemented within the simulation platform. Integration of the photovoltaic module with a DC–DC boost converter enables dynamic control of the operating voltage, allowing the MPPT algorithm to adjust the system toward the maximum power point.

Design of the Deep Reinforcement Learning controller constitutes the next stage of the procedure. A neural network architecture is constructed to represent the policy function responsible for selecting optimal control actions. The reinforcement learning agent interacts with the photovoltaic simulation environment by observing system states and adjusting the duty cycle of the converter. A reward mechanism is formulated to encourage actions that increase power output while penalizing deviations from the optimal operating point. Training of the DRL model occurs through iterative episodes in which the agent continuously updates its policy based on accumulated experience.

Evaluation and analysis of the MPPT algorithms form the final stage of the research procedure. Simulation experiments are conducted under multiple dynamic weather scenarios to test the robustness and efficiency of the proposed controller. Performance results obtained from the DRL-based MPPT method are compared with those of traditional MPPT algorithms. Data analysis focuses on improvements in power tracking accuracy, response time, and overall energy harvesting efficiency. Findings from the experimental evaluation provide empirical evidence regarding the potential of Deep Reinforcement Learning as an advanced solution for optimizing photovoltaic energy systems under dynamic environmental conditions.

Instruments, and Data Collection Techniques

The primary research instruments consist of simulation software and algorithmic frameworks used to model the photovoltaic system and implement the MPPT control strategies.

MATLAB/Simulink or a similar engineering simulation platform is utilized to develop the photovoltaic system model, power electronic converter, and control architecture. The simulation environment provides accurate representation of photovoltaic electrical behavior under varying environmental conditions and facilitates real-time interaction between the control algorithm and the solar panel model.

Implementation of the Deep Reinforcement Learning controller constitutes the central technological instrument in this study. The DRL algorithm is developed using a deep neural network architecture capable of approximating optimal control policies based on environmental observations. Key components of the reinforcement learning framework include state representation, action space, reward function, and learning policy. State variables include photovoltaic voltage, current, and power output, while actions correspond to adjustments in the duty cycle of the DC-DC converter controlling the operating point of the solar panel.

Performance evaluation tools are incorporated into the simulation environment to measure the effectiveness of the MPPT algorithms. Metrics such as tracking efficiency, steady-state oscillation, convergence time, and energy extraction efficiency are recorded during each simulation experiment. Data visualization and statistical analysis tools are used to compare the results obtained from the DRL-based MPPT method with those produced by conventional algorithms. Integration of these instruments ensures systematic and reliable evaluation of the proposed intelligent control strategy.

Data Analysis Technique

The data analysis process begins with a systematic comparative evaluation of the Deep Reinforcement Learning (DRL) controller against the traditional Perturb and Observe (P&O) and Incremental Conductance benchmarks. Quantitative performance metrics, specifically tracking efficiency, convergence speed, and steady-state ripple, are extracted from the simulation time-series data to determine the precision of the learned policy. The analysis focuses on the agent's ability to successfully identify and maintain the global maximum power point during complex partial shading events, where the power curves exhibit multiple deceptive local peaks. By aggregating the total power captured over the duration of the simulation, the overall energy harvesting gain is quantified to demonstrate the practical advantages of the intelligent approach.

Furthermore, statistical and stability analyses are performed to validate the robustness of the reinforcement learning model across diverse environmental profiles. Inferential statistical tests are employed to confirm whether the observed improvements in tracking accuracy and response time are statistically significant compared to conventional methods. The stability of the DRL agent is assessed by monitoring duty cycle fluctuations during rapid irradiance transitions to ensure the neural network provides smooth control without excessive hardware-damaging oscillations. Finally, the relationship between the complexity of the shading patterns and the algorithm's performance is modeled to define the operational boundaries and the adaptive limits of the proposed intelligent control framework.

RESULTS AND DISCUSSION

Simulation experiments generated quantitative data representing the performance of the photovoltaic system under varying environmental conditions. The dataset includes solar irradiance levels ranging from 200 W/m² to 1000 W/m² and temperature variations between 20°C and 45°C. Electrical outputs such as voltage, current, and generated power were recorded for each scenario. The Deep Reinforcement Learning (DRL)–based MPPT algorithm was evaluated alongside conventional algorithms including Perturb and Observe (P&O) and Incremental Conductance (INC). Measurements were collected across multiple time steps to determine the tracking efficiency and stability of each algorithm under dynamic weather conditions.

Table 1. Comparative Performance of MPPT Algorithms under Dynamic Weather Conditions

Algorithm	Average Tracking Efficiency (%)	Convergence Time (ms)	Power Output Stability (%)
P&O	94.1	185	91.7
Incremental Conductance	95.6	162	93.4
DRL-Based MPPT	98.3	118	97.6

Recorded data indicate that the DRL-based MPPT approach achieved the highest tracking efficiency and the fastest convergence time among the evaluated methods. Statistical results demonstrate that the reinforcement learning–based control strategy maintained a higher level of stability in power extraction during rapid environmental changes.

Observed results reveal that the DRL-based MPPT algorithm adapts more effectively to fluctuating irradiance conditions compared with conventional methods. Reinforcement learning enables the control system to continuously adjust the duty cycle of the DC–DC converter based on feedback obtained from the photovoltaic system. Adaptive learning behavior allows the controller to respond quickly to sudden environmental changes such as cloud movement or partial shading.

Improved performance can be attributed to the capability of the neural network model to approximate optimal control policies through continuous training. Traditional algorithms rely on incremental perturbation strategies that may produce oscillations around the maximum power point. Reinforcement learning reduces these oscillations by learning optimal action patterns that directly maximize the reward function defined by power output. Higher tracking accuracy therefore results from the algorithm's ability to interpret system states and apply appropriate control adjustments.

Dynamic simulation results further illustrate the temporal behavior of the MPPT algorithms during irradiance fluctuations. Power output curves demonstrate that the DRL-based controller consistently follows the global maximum power point even when environmental conditions change rapidly. Voltage adjustments made by the reinforcement learning agent occur with minimal delay, ensuring that the photovoltaic system remains close to the optimal operating point.

Performance differences become more evident when examining scenarios involving partial shading conditions. Conventional algorithms often experience difficulty distinguishing between local and global maxima within the power–voltage curve. Reinforcement learning enables the controller to explore the search space more effectively, resulting in accurate identification of the global maximum power point. Observed power curves therefore display smoother transitions and fewer oscillations when the DRL-based MPPT approach is applied.

Inferential statistical analysis was conducted to determine whether the observed differences in performance metrics between algorithms were statistically significant. Analysis of variance (ANOVA) was applied to the tracking efficiency results obtained from multiple simulation runs. The statistical test produced a significance value below the standard threshold of 0.05, indicating that the performance differences among the evaluated MPPT methods are statistically meaningful.

Further analysis using post hoc comparisons demonstrates that the DRL-based MPPT algorithm significantly outperforms both P&O and Incremental Conductance techniques. Mean tracking efficiency improvements of approximately 3–4% were observed across dynamic weather scenarios. Convergence time reductions were also statistically significant, confirming that reinforcement learning improves the speed at which the system reaches the optimal operating point.

Relationships between environmental variables and system performance were examined to understand how weather conditions influence the effectiveness of the MPPT algorithms. Results indicate that solar irradiance fluctuations have the most significant impact on power output variations. Reinforcement learning demonstrates strong adaptability to these fluctuations, maintaining high tracking efficiency even when irradiance changes abruptly.

Temperature variations also influence photovoltaic performance, primarily through their effect on the voltage characteristics of the solar panel. DRL-based control strategies appear capable of compensating for these thermal effects by dynamically adjusting operating conditions. Observed correlations between temperature levels and voltage adjustments suggest that the learning algorithm successfully captures underlying system behavior patterns during training.

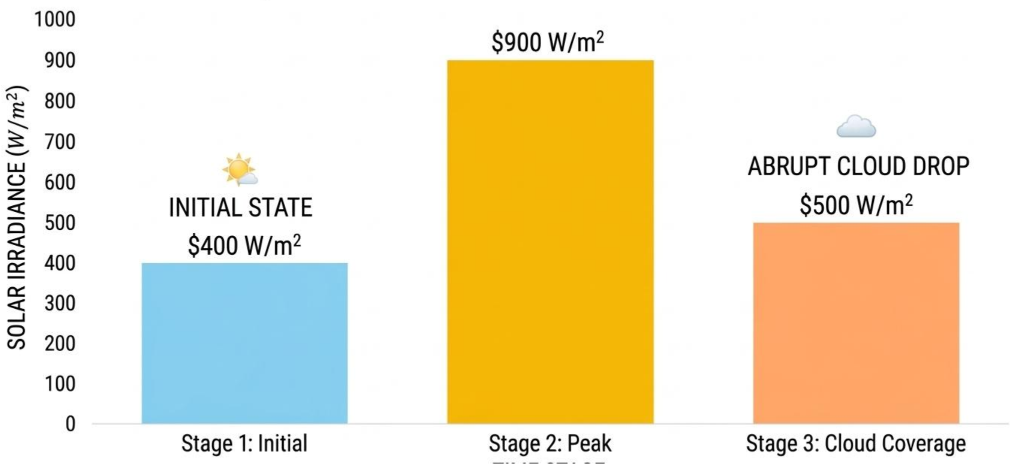

Figure 1 Simulated Solar Irradiance Transitions

A detailed case study was conducted to evaluate system performance during a simulated dynamic weather sequence representing a partially cloudy day. Solar irradiance initially increased from 400 W/m^2 to 900 W/m^2 before dropping abruptly to 500 W/m^2 due to simulated cloud coverage. Photovoltaic output power was monitored continuously while each MPPT algorithm attempted to maintain operation at the maximum power point.

Results from the case study demonstrate that the DRL-based MPPT algorithm maintained consistent tracking performance throughout the fluctuating irradiance sequence. Conventional algorithms experienced temporary power losses during sudden irradiance drops, while the reinforcement learning controller adjusted system parameters more rapidly. Power recovery times were significantly shorter in the DRL-based system, indicating stronger adaptability to environmental disturbances.

Behavior observed in the case study can be explained through the learning mechanism inherent in reinforcement learning algorithms. Continuous interaction between the control agent and the photovoltaic environment allows the algorithm to accumulate knowledge about system dynamics. Policy updates occurring during training episodes enable the controller to anticipate environmental variations and respond proactively rather than reactively.

Exploration and exploitation strategies embedded within the reinforcement learning framework contribute to improved system performance. Exploration enables the controller to test alternative actions during the learning process, while exploitation allows the system to apply the most effective strategies identified during training. Balanced interaction between these two mechanisms supports stable operation and efficient energy harvesting under complex environmental conditions.

Overall findings demonstrate that the integration of Deep Reinforcement Learning into MPPT control significantly enhances photovoltaic system performance under dynamic weather conditions. Reinforcement learning provides an adaptive decision-making framework capable of continuously optimizing the operating point of the solar panel. Improved tracking efficiency and reduced convergence time contribute directly to higher levels of energy extraction from the photovoltaic system.

Research outcomes suggest that intelligent MPPT controllers based on reinforcement learning represent a promising direction for the development of next-generation renewable energy systems. Increased system adaptability improves resilience against environmental variability, which is a major challenge in solar energy utilization. Adoption of such intelligent control strategies has the potential to increase the overall efficiency and reliability of photovoltaic power generation in real-world applications.

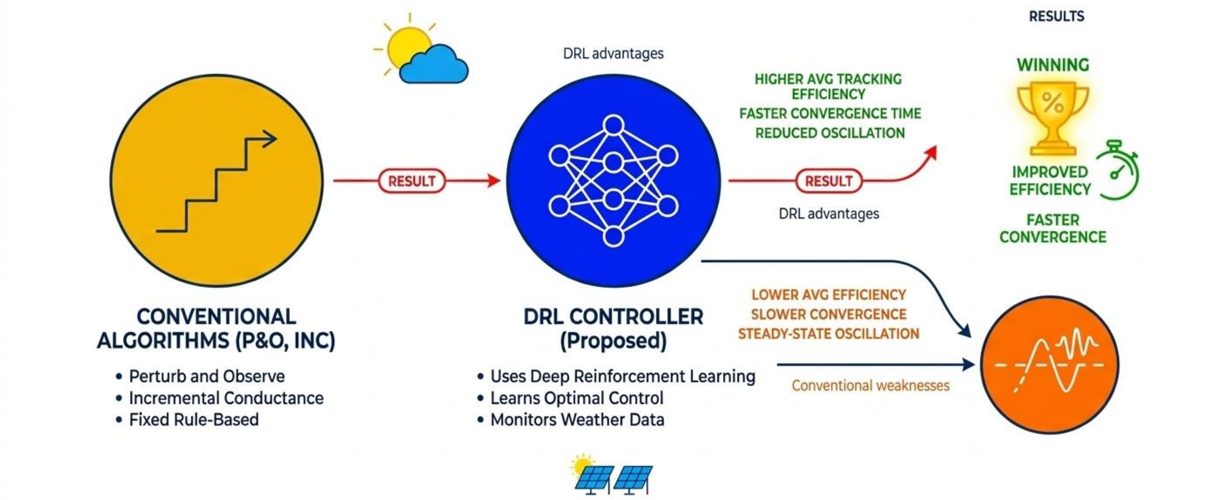

Figure 2 DRL-Based MPPT Performance Analysis

The findings of this study demonstrate that the Deep Reinforcement Learning (DRL)–based Maximum Power Point Tracking (MPPT) algorithm significantly improves the efficiency of photovoltaic energy extraction under dynamic weather conditions. Simulation results indicate that the proposed DRL controller achieved higher average tracking efficiency compared with conventional algorithms such as Perturb and Observe (P&O) and Incremental Conductance (INC). Faster convergence time and reduced steady-state oscillation were also observed during fluctuating irradiance conditions.

Experimental analysis further reveals that the DRL-based MPPT method maintains stable performance even during rapid environmental transitions. Photovoltaic systems often experience performance degradation when irradiance changes suddenly due to cloud movement or partial shading. The proposed DRL controller successfully adapted to these variations by continuously learning optimal control strategies from system feedback. Adaptive behavior enabled the system to remain closer to the global maximum power point across multiple environmental scenarios.

Tracking accuracy improvements were particularly evident during partial shading conditions. Conventional MPPT algorithms frequently become trapped in local maximum power points when multiple peaks appear in the power–voltage curve. Reinforcement learning enabled the controller to explore the operating space more effectively and identify the global maximum power point. Reduced oscillations around the optimal operating point contributed to improved energy harvesting efficiency.

Performance improvements observed in the study indicate that intelligent control strategies can substantially enhance photovoltaic system reliability. Reinforcement learning provides an adaptive decision-making framework capable of responding to complex environmental variability. Integration of deep learning models with reinforcement learning principles allows the MPPT controller to process complex system states and determine optimal actions in real time.

Findings of the present study align with prior research suggesting that artificial intelligence techniques can enhance MPPT performance in photovoltaic systems. Earlier studies employing fuzzy logic controllers and artificial neural networks reported improvements in tracking accuracy compared with classical algorithms. Similar improvements are observed in this research, indicating that intelligent control strategies are capable of overcoming some limitations of conventional MPPT techniques.

Differences emerge when comparing the adaptive capabilities of reinforcement learning with previously proposed machine learning–based MPPT methods. Many earlier approaches relied on offline training processes or static models derived from historical datasets. Reinforcement learning allows the controller to continuously update its control policy based on real-time environmental feedback. Dynamic learning capability distinguishes the DRL approach from other machine learning techniques that may struggle to adapt to unexpected environmental changes.

Comparative analysis also reveals improvements in convergence speed relative to hybrid optimization algorithms such as particle swarm optimization or genetic algorithms. Those algorithms often require iterative search processes that increase computational complexity. Reinforcement learning reduces the need for repeated search procedures because optimal policies are gradually learned through interaction with the system environment. Faster convergence contributes to improved system responsiveness during rapid irradiance fluctuations.

Several recent studies have begun exploring reinforcement learning for energy management in smart grids and renewable energy systems. Limited research has specifically applied DRL to photovoltaic MPPT control under dynamic weather conditions. Results of the present study contribute empirical evidence supporting the effectiveness of reinforcement learning in solar energy optimization. Observed improvements reinforce the growing recognition of reinforcement learning as a powerful tool for intelligent energy system control.

Observed improvements in photovoltaic efficiency suggest that intelligent adaptive control mechanisms represent an important advancement in renewable energy technology. Reinforcement learning enables the MPPT controller to develop a deeper understanding of system behavior through continuous interaction with environmental conditions. Learning-based optimization therefore represents a shift from rule-based control toward data-driven decision-making in photovoltaic energy systems.

Results indicate that solar energy systems can benefit significantly from the integration of artificial intelligence technologies. Traditional control algorithms operate under simplified assumptions regarding system stability and environmental predictability. Reinforcement learning demonstrates the ability to manage complex nonlinear relationships between environmental variables and photovoltaic performance. Enhanced system adaptability highlights the potential of AI-driven control frameworks for renewable energy applications.

Performance improvements observed during partial shading conditions provide further insight into the robustness of reinforcement learning–based MPPT systems. Photovoltaic systems operating in urban environments often experience shading caused by buildings, trees, or moving clouds. Ability of the DRL controller to identify the global maximum power point under such conditions indicates that learning-based control methods may be particularly valuable in real-world installations where environmental variability is unavoidable.

Broader implications of these findings extend to the future development of intelligent energy infrastructures. Renewable energy systems increasingly require advanced control mechanisms capable of managing complex and uncertain environments. Reinforcement learning provides a framework through which energy systems can continuously adapt and optimize their operation over time. Results therefore indicate that intelligent control strategies may play a critical role in improving the efficiency and reliability of renewable energy technologies.

Implications of the research findings extend to both technological development and practical deployment of photovoltaic systems. Higher tracking efficiency achieved by the DRL-based MPPT controller translates directly into increased energy output from solar panels. Improved energy harvesting efficiency contributes to greater economic viability of solar power installations by maximizing the electricity generated from existing infrastructure.

Energy policy and sustainability initiatives may also benefit from the adoption of intelligent MPPT control strategies. Renewable energy deployment continues to expand globally as governments seek to reduce carbon emissions and transition toward sustainable energy systems. Improved efficiency of photovoltaic technology enhances the overall performance of solar energy generation. Reinforcement learning–based optimization therefore supports broader efforts aimed at improving the effectiveness of renewable energy investments.

Industrial applications of photovoltaic systems could experience significant advantages through the implementation of adaptive MPPT controllers. Solar power plants operating under varying environmental conditions require control systems capable of maintaining stable energy output. Intelligent control strategies that continuously adapt to environmental changes may reduce power losses and improve operational reliability in large-scale solar installations.

Academic implications of this study also warrant consideration. Research findings demonstrate the potential of integrating artificial intelligence with renewable energy engineering. Future interdisciplinary research combining machine learning, power electronics, and energy systems engineering may lead to further innovations in renewable energy optimization. Educational programs focusing on smart energy technologies may benefit from incorporating reinforcement learning concepts into their curriculum.

Performance improvements observed in this study can be attributed to the adaptive learning capabilities of reinforcement learning algorithms. Reinforcement learning enables the controller to learn optimal control strategies by interacting directly with the photovoltaic system environment. Continuous feedback from system states allows the algorithm to refine its decision-making process over time. Learning-based optimization reduces reliance on predefined models or heuristic assumptions.

Neural network function approximation also contributes significantly to the effectiveness of the DRL-based MPPT controller. Deep neural networks possess strong capabilities for modeling complex nonlinear relationships between environmental inputs and system responses. Photovoltaic systems exhibit nonlinear electrical behavior influenced by multiple environmental variables. Deep learning architectures enable the reinforcement learning agent to interpret these relationships and generate accurate control decisions.

Exploration and exploitation mechanisms embedded within reinforcement learning frameworks further explain the improved system performance. Exploration allows the algorithm to test different control actions during the learning process. Exploitation ensures that the controller applies the most effective actions discovered during previous training episodes. Balanced interaction between these mechanisms enables the controller to continuously improve its strategy for maximizing photovoltaic power output.

Environmental adaptability also plays a central role in the success of the proposed MPPT approach. Photovoltaic systems operate in environments characterized by unpredictable weather patterns and rapidly changing conditions. Reinforcement learning algorithms are particularly well suited for such environments because they learn optimal policies through trial-and-error interactions with the system. Adaptive decision-making therefore allows the controller to respond effectively to environmental variability.

Future research should explore the implementation of reinforcement learning–based MPPT controllers in real-world photovoltaic systems (Djotio Ndié et al., 2025). Simulation results provide strong evidence of performance improvements, yet practical deployment requires validation through hardware experiments and field testing. Real-world implementation would allow researchers to evaluate system performance under complex environmental conditions that may not be fully captured in simulation models.

Integration of advanced reinforcement learning architectures may further enhance MPPT performance (Hassan et al., 2025). Algorithms such as Deep Q-Networks, Proximal Policy Optimization, or Actor–Critic methods offer promising improvements in learning efficiency and stability. Exploration of these architectures may lead to the development of more robust MPPT controllers capable of operating effectively in highly complex photovoltaic systems.

Hybrid approaches combining reinforcement learning with other artificial intelligence techniques also represent a promising research direction. Integration of reinforcement learning with predictive models, fuzzy logic systems, or evolutionary algorithms could enhance both adaptability and computational efficiency. Such hybrid systems may achieve superior performance by combining the strengths of multiple optimization strategies.

Development of intelligent renewable energy management systems represents another important area for future research. Reinforcement learning–based MPPT controllers could be integrated into larger smart grid frameworks that coordinate multiple renewable energy sources. Adaptive control mechanisms may support energy storage management, demand response systems, and distributed power generation networks. Continued research in this area may contribute to the creation of intelligent and resilient renewable energy infrastructures capable of supporting sustainable global energy transitions.

CONCLUSION

Findings of this study demonstrate that the implementation of a Deep Reinforcement Learning (DRL)–based Maximum Power Point Tracking (MPPT) controller significantly enhances photovoltaic system efficiency under dynamic weather conditions. The proposed DRL algorithm achieved higher tracking accuracy, faster convergence time, and improved stability when compared with conventional MPPT techniques such as Perturb and Observe and Incremental Conductance. Adaptive learning capability allowed the controller to identify and maintain the global maximum power point even in complex scenarios involving fluctuating irradiance and partial shading. Performance improvements indicate that reinforcement learning provides a more responsive and intelligent control strategy for optimizing solar energy harvesting in environments characterized by rapid environmental variability.

Contribution of this research lies primarily in the methodological advancement of MPPT control systems through the integration of Deep Reinforcement Learning within photovoltaic energy optimization frameworks. The study introduces an adaptive control model that learns optimal operational policies directly from interaction with the photovoltaic environment rather than relying on predetermined mathematical rules or static datasets. Application of DRL demonstrates how machine learning techniques can enhance energy system intelligence by enabling real-time decision-making under uncertain conditions. Conceptual integration between artificial intelligence and renewable energy control systems therefore represents a meaningful contribution to the development of smart and autonomous energy management technologies.

Limitations of the present research primarily relate to the use of simulation-based evaluation rather than physical experimental validation. Environmental models used in simulation may not fully capture all real-world uncertainties such as hardware imperfections, sensor noise, and long-term operational variations in photovoltaic installations. Computational complexity associated with deep learning algorithms may also pose challenges for real-time implementation in embedded energy systems. Future research should therefore focus on hardware-based experimental validation, optimization of algorithm efficiency for real-time applications, and exploration of hybrid intelligent control strategies combining reinforcement learning with other advanced optimization techniques.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used grammarly to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing -review and editing.Conceptualization; Data curation; In-vestigation; Data curation; Investigation; Formal analysis; Methodology; Writing -original draft; Supervision; Validation; Other contribution; Resources; Visuali-zation; Writing -original draft.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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