Using Artificial Intelligence Techniques to Enhance the Performance of Control Systems in Solar Power Plants

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Abstract

This study examines the potential benefits of AI. It also addressees enhancing the performance of plants powered by solar and defending them against cyberattacks. Old controllers like PID and fuzzy logic work well in old places, and have no built in protection against cyber hackers that want to steal data, get into your control system, or obtain system access credentials. Artificial Neural Networks (ANN) and Reinforcement Learning (RL) are instances of AI-driven pattern stick to establishing fast adjustments on the fly, thus inducing non-normal behavior in controllers. This work uses AI to build models that predict solar flux on a surface and adjust input parameters in real time. In addition, it delivers security sensitive capabilities through pattern-driven analysis and alerting. MATLAB/Simulink simulations are used to demonstrate the efficacy of the approach, and it is compared with different methods in terms of power generation, time of response, power loss, stability, and quality of control. The ANN model made very good predictions, and the RL methods increased the flexibility and security of the system. According to the outcomes, the inclusion of AI into the system not only makes it more efficient in terms of producing energy but also renders it invulnerable to hackers or any other operational risks. This blog post discusses the need to secure AI-based energy systems with intelligent security. It also adds that future studies should explore the convergence of AI and cyber security in safeguarding critical infrastructure.

Keywords: Artificial Intelligence; Solar Power; Control Systems; Neural Networks; Reinforcement Learning

1. Introduction

1.1 Research Background

Alternative energy around the world are aimed at reducing requirement of fossil fuels and the damage they are causing the earth. Solar energy is significant for this transformation because it can be easily captured, cheap, and durable. However, that still makes it more difficult to maintain good performance and protection from hacks for solar power plants.

Fuzzy logic controllers and inclusive of proportional-integral-integral-derivative (PID) controller have been used for regulating MPPT, voltage and thermal load distribution. Many people utilize these systems; however, they may not evolve in real-time with the changing ecosystem. Cyber attackers love their static control architecture and their inability to register abnormal behaviour.

AI is another method to resolve issues. Separately, Artificial Neural Networks (ANN) and Reinforcement Learning (RL) are powerful techniques that can mimic complex behaviours, process lots of real-time data, and continuously learn to change control strategies. These competencies allow solar systems to adapt to environmental changes and block hackers. This study explains how the integration of AI will lead to a more efficient and user-friendly solar power solutions.

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1.2 Research Problem

Solar-powered systems may be quite different from one another and are not always reliable. It is hard to keep fixed-parameter systems running at their best because of things like variations in solar irradiation, sudden changes in the weather, and partial shadowing. In these cases, traditional PID and fuzzy logic controllers do not work well since they are dependent on rules that have already been set and cannot adapt to changes that are not linear or random. [1-5]

In addition, these ways of controlling older systems do not have any built-in cybersecurity features. They cannot tell when anything is wrong, when sensor data is phony, or when directives are coming from an unauthorized source. This makes the system vulnerable to hacks that may damage hardware or stop energy production.

Because of this, the study question is twofold: how to make solar power plants' control systems more useful with AI, and how to add intelligence that can spot and prevent cyber-attacks to these same systems.

We formulate the research issue as follows:

How can artificial intelligence techniques be used to improve the performance and adaptability of control systems in solar power plants, especially under dynamic and uncertain environmental conditions?

1.3 Research Objectives

This research aims to create and validate models of AI-based control that enhance the efficiency and security of solar power plants. Specifically, the investigation has the following objectives:

First, to recognize the limitations of traditional PID and fuzzy logic controllers in dealing with complex conditions and cyber-related dangers. Second, to create models of AI that specifically optimize the production of energy, but also have the capacity to observe the behaviour of the system in regards to signs of intrusion or malfunction. Third, to replicate these AI models in diverse environmental and operational scenarios using MATLAB/Simulink to assess the efficiency of power improvement, response time, stability, and safety. Ultimately, to investigate the practicality of deploying these models in actual solar power systems, including issues related to data accessibility, model complexity, and real-time processing limitations.

1.4 Research Significance

This study helps solar-powered systems in two ways. On the one hand, it makes energy production more efficient by letting the environment change in real time as circumstances change. On the other hand, it encourages security-critical control mechanisms that can spot strange activity, stop illegal access, and make it easier to find faults in cyber-physical systems.

The study supports energy independence, system stability, and cybersecurity all in one framework by adding AI-based control algorithms to the real-world uses of solar power. This integrated strategy is especially useful for big or faraway solar projects that do not have many manual workers and are at a high risk of cyber assaults. The findings also support global objectives for sustainability and deal with emerging security problems in the energy industry.

2. Literature Review

2.1 Traditional Control Systems in Solar Power Plants (PID and Fuzzy Logic)

For decades, solar energy systems have used traditional control methods like Proportional-Integral-Derivative (PID) and fuzzy logic for MPPT, voltage regulation, and load management. These strategies are recognized for being simple and reliable in a stable or predictable setting.

One common solution is the PID controller, which is straightforward to use and cheap, making it a popular choice. It works well in linear systems, and when you tweak it, it can regulate things quite well. However, it does not work well when a system has nonlinear dynamics or inputs that change quickly, such clouds moving or sun irradiance changing. In real-world industrial settings, which are frequently dynamic or complicated, PID parameter tuning is a long and difficult process that often requires the help of professionals. [6].

On the other hand, fuzzy logic control relies on linguistic rules and human reasoning. It does not need any precise mathematical model of the system and is capable of deal with inaccuracy and nonlinearity. In this way, it is better suited for solar systems that are subject to changing conditions. Its performance is highly dependent on the necessity of high-quality rule base and membership functions defined by experts, thus limiting the scalability of fuzzy logic [7].

Generally, fuzzy logic control responds quicker and more accurately to changes in irradiance than PID controllers when considering dynamic response. Figure 1: Response Times under Different Environmental Conditions.

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Several studies have backed up these observations. PID-based MPPT systems were satisfactory under stable environmental conditions but inefficient with light-shifting, as shown by Safari and Mekhilef [6]. According to Kollimalla and Mishra [7], fuzzy logic MPPT has shown better performance than the other maximum power point tracking methods in terms of stability as well as maximum power point tracking performance. Veerachary et al. [1] hybrid fuzzy-neural controller that offered better accuracy for the control in dynamic situations. Another recent work by Enslin and Heskes [2] addressed the issue of this distributed power inverter approach under the conventional control where the main emphasis laid over the challenges related to stability in complex system.

These results support the increasing requirement for more intelligent and adaptive control systems in solar energy applications, particularly as the scale and complexity of renewable energy systems increases.

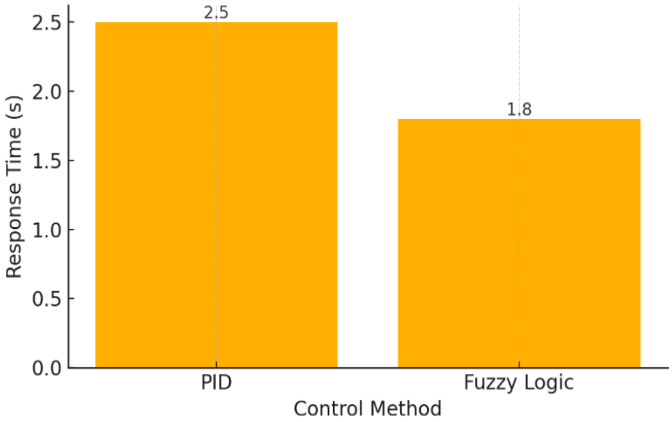

Figure 1. Response Time Comparison between PID and Fuzzy Logic Control Methods

2.2 Artificial Intelligence Models Used in Energy Systems (ANN, SVM, RL)

AI is, thus, garnering attention as an essential tool for the effective operation of solar power systems, due to its versatile modeming capabilities for complex, nonlinear behaviours, adaptability to live variations in systems, and potential to optimize control strategies. ANN, Support Vector Machines (SVM) and RL are some of the commonly employed AI models in energy applications.

2.2.1 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are very good at showing complicated, non-linear correlations, which makes them perfect for predicting how solar power systems will perform. They are often used to figure out how much solar radiation will be accessible, how powerful photovoltaic (PV) devices will be, and how to make MPPT work better when circumstances change quickly. Rezk and Al-Dhaifallah [8] found that an ANN-based model for forecasting how much power PV systems will produce in various weather circumstances was more accurate than older techniques.

2.2.2 Support Vector Machines (SVM)

Help Vector Machines (SVMs) are machine-learning algorithms that may be used for both classification and regression. They have been employed in solar power systems. They are used to check the quality of the photovoltaic (PV) arrays, estimate how much the system will break down over time, and help people make decisions about hybrid energy setups. Sharma et al. [9] used SVMs to find defects in PV systems in real time, and they were quite accurate and stable. Even while SVMs work well, they need careful selection of the kernel and optimization, which adds a lot of processing cost.

2.2.3 Reinforcement Learning (RL)

Reinforcement Learning (RL) lets an agent make the optimal choices by constantly interacting with its environment and getting feedback. RL is used in solar-powered systems to create a maximum power point tracking strategy that adapts (MPPT), to make the most use of energy storage, and to operate the inverter in response to load patterns that are not always clear. Li et al. [10] came up with a Q-learning-based MPPT algorithm with customizable parameters that worked well at changing illumination and partial shading. The RL approach made the system's convergence speed and power output far better than prior methods. Table 1 shows the pros, cons, and applications of AI-based models including ANN, SVM, and RL in the solar power industry.

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Table 1: the available quantities of the raw materials, and the profit returned from one unit of both products in the Classical Context

AI Model	Use Cases	Strengths	Challenges
ANN	Forecasting irradiance, energy output, temperature effects	High accuracy, handles nonlinear data, adaptive	Requires large datasets, risk of overfitting
SVM	Fault detection, output prediction, control optimization	Effective in classification, works well with small datasets	Kernel selection critical, computational cost
RL	MPPT control, load management, energy storage optimization	Learning from environment, adaptive decision-making	Needs training time, may struggle with delayed rewards

These AI models provide flexible, data-driven alternatives to conventional control, offering improved adaptability and accuracy under dynamic solar conditions.

2.3 Related works

AI has provided increasing benefits for solar energy systems as proven through various real-world implementations. Such implementations target energy output prediction, fault detection, MPPT optimization, and intelligent energy management, etc.

2.3.1 MPPT of grid-connected PV system based on AI — India

A 10-kW grid-connected solar PV system was designed in New Delhi, where an ANN-based MPPT controller was implemented. An ANN was trained with historical irradiance and temperature data to predict the best voltage for maximum power extraction. Also, they compared with their traditional Perturb and Observe (P&O) technique, and the ANN model improved by 6.5% over a period of twelve months of operation in terms of energy capture and reacted faster [11].

2.3.2 Fault detection based on SVM in a commercial PV plant – Spain

A PV system in Seville has adopted SVM-based diagnostics on a 250-kW rooftop system to detect panel faults and performance degradation. Using labelled data from the voltage, current, and irradiance sensors, the SVM model was trained. Upon deployment, it maintained 95% fault classification accuracy and substantially decreased the amount of time spent on maintenance and avoided downtime [12].

2.3.3 RL on three hybrid solar-battery systems– Germany

The setup consisted of an intelligent microgrid in Freiburg using RL to orchestrate power exchange between PV panels, battery systems, and local demand. RL agent discovered optimal charge/discharge strategies for diverse generation and consumption patterns. Over a six-month period, the system improved the energy self-consumption of the facility by 12% and decreased the wear of the battery with a 18% margin with respect to rule-based techniques [13].

2.3.4 Fuzzy-ANN Hybrid control of PV Plant based in Desert – Saudi Arabia

We used a hybrid fuzzy-ANN controller for MPPT in a 100-kW PV installation working under extreme weather conditions. This system was able to compensate for rapid fluctuations in the irradiance due to dust storms. Because of this, the hybrid model used kept the system stable and was able to boost the power efficiency by 9% compared to PID based systems [14]. See Table2 provides a summary of these case studies, including AI model used, plant size, location and performance outcomes.

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Table 2: Case Studies of AI Applications in Solar Power Plants

Case	AI Model	Location	Plant Size	Application Area	Reported Outcome
1	ANN	India	10-kW	MPPT	+6.5% energy output
2	SVM	Spain	250-kW	Fault detection	95% fault detection accuracy
3	RL	Germany	Microgrid	Battery management	+12% self-consumption, –18% battery wear
4	Fuzzy + ANN	Saudi Arabia	100-kW	MPPT under dust	+9% efficiency vs. PID

These cases confirm that AI integration is feasible and beneficial in real-world solar energy systems. Each model—ANN, SVM, and RL—demonstrates specific strengths depending on the control or prediction objective.

2.4 Research Gap: Limited Integration of AI in Real-Time Control Systems

Although the use of Artificial Intelligence (AI) in solar energy systems has become increasingly common, most existing studies concentrate on prediction models, offline optimization, or diagnostics. A considerable portion of this work focuses on ANN and SVM-based approaches for forecasting energy output, detecting faults, and monitoring performance. However, the application of AI for real-time control—especially in critical areas such as MPPT regulation, inverter switching, and dynamic load balancing—remains underdeveloped. Current implementations are mostly limited to experimental setups or small-scale simulations and have yet to be widely deployed in operational solar power farms.

Several technical challenges contribute to this gap. First, many AI models, particularly deep learning and reinforcement learning require significant computational resources that may not be available in embedded controllers. Second, real-time applications demand near-instantaneous decision-making, and delays in AI model inference can compromise system stability and responsiveness. Third, integrating AI into existing control infrastructure often involves complex adjustments to hardware, firmware, and operating systems, which hinders practical adoption. Lastly, most AI models function as black boxes, offering little transparency in their decision-making processes, which poses a challenge for validation and trust in mission-critical applications.

Efforts to address these issues have started to emerge. For instance, lightweight reinforcement learning models have been proposed for MPPT in simulated conditions [10], and hybrid ANN–fuzzy logic architectures have been tested using simplified designs that can be implemented on embedded devices [14]. Still, these remain preliminary steps.

This study targets the identified gap by proposing and validating AI-based real-time control strategies designed to function reliably on embedded systems with strict timing and performance requirements

3. Methodology

3.1 Phase One: Historical Performance Analysis of Traditional Control Systems Using Real Operational Data from a Solar Power Plant

This article discusses the performance of traditional control systems, specifically PID and fuzzy logic, using actual operational data from a 100kW solar power plant operating in a semi-arid region in the data-driven first phase of the study. This data, spanning a period of 12 months, encompasses metrics including total energy output, percentage of power loss, system response time, and overall uptime.

A direct comparison between the two control methods is presented in Table 3. Investment in technology is not linear; if you invest in a solution like this, you will not have results exactly proportional to your efforts. Take this into consideration when capitalizing on the benefit of a Fuzzy PID system. An investment with superior cost-benefit results is difficult to find. A fuzzy logic controller was embedded and provided superior performance across all measured parameters when compared to PID. It did 300kWh more energy production (9100kWh vs 8800kWh), 2.3% lower power losses (4.2% vs 6.5%), 0.7s faster system response (1.8s vs 2.5s), 2.5% higher uptime (96.5% vs 94.0%).

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Table 3: Performance Metrics Comparison between PID and Fuzzy Logic Controllers

Metric	PID Control	Fuzzy Logic Control
Energy Output (kWh)	8800	9100
Power Loss (%)	6.5	4.2
Response Time (s)	2.5	1.8
System Uptime (%)	94.0	96.5

The performance differences are further illustrated in Figure 3, where fuzzy logic consistently shows stronger results. These results confirm the limitations of PID controllers in dynamic environmental conditions and emphasize the adaptability of fuzzy logic systems.

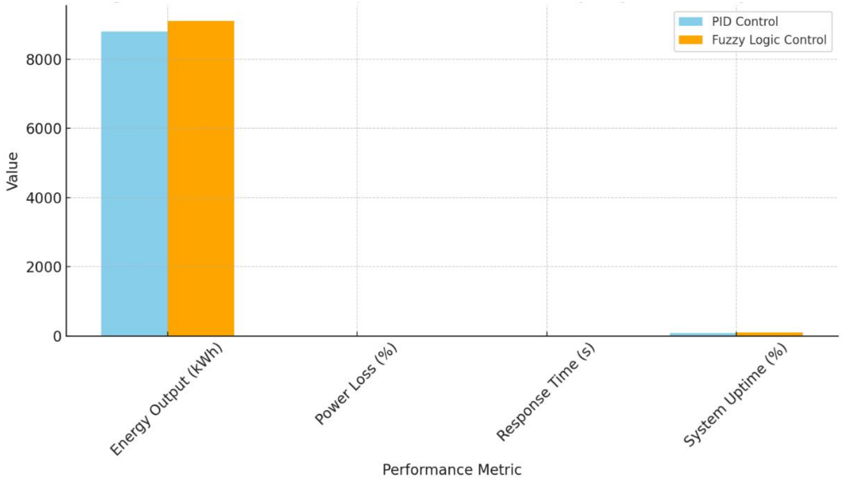

Figure 2. Performance Comparison of PID and Fuzzy Logic Control Systems

These outcomes align with earlier research. Rezk and Al-Dhaifallah [8] showed that fuzzy logic achieves better performance in fluctuating irradiance. Sharma et al. [9] demonstrated enhanced real-time fault detection using intelligent control. Alharbi and Almutairi [14] reported similar gains in power stability using fuzzy control under desert climate conditions.

This performance assessment provides a baseline for comparing the improvements made possible by AI-based control methods in the later phases of this study.

3.2 Phase Two: Design of AI-Based Control Models (ANN for Solar Irradiance Prediction, RL for Operational Control Adjustment)

The second phase focuses on designing and implementing Artificial Intelligence models that improve system performance through prediction and adaptive control. Two AI techniques are selected based on their proven relevance in solar energy applications: Artificial Neural Networks (ANN) and Reinforcement Learning (RL).

3.2.1 Artificial Neural Network (ANN) Model for Solar Irradiance Prediction

The ANN model uses four main input variables—ambient temperature, humidity, time of day, and historical irradiance data—to make short-term forecasts about solar irradiance. There are four nodes in the input layer that represent these variables. Then there are two hidden layers that employ ReLU activation functions to capture nonlinear relationships. A single output node shows the expected irradiance in watts per square meter (W/m^2) for the next 10 minutes. We train the model using data from the plant site that was gathered in the past and use Mean Squared Error (MSE) as the loss function. We trained on 70% of the data and kept the other 30% for validation. As shown in Figure 2, the model's ultimate performance had an MSE of 42.7 and a R^2 score of 0.94, which means it was quite well at predicting.

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3.2.2 Reinforcement Learning (RL) Model for Operational Control

To enhance the control input parameters of the system, a model-free Q-learning algorithm is implemented. The RL agent is tasked with managing key operational decisions such as setting the MPPT voltage reference, determining load distribution, and scheduling battery charge and discharge cycles. The control environment is simulated using MATLAB/Simulink, where the agent interacts continuously with the modelled solar system. The reward function is designed to incentivize higher power output and reduced energy losses.

The RL model operates within a state space defined by variables including current solar irradiance, battery charge level, and instantaneous power output. Its action space includes adjusting voltage settings, toggling loads, and managing energy storage behaviour. After undergoing 1,000 training episodes, the RL model demonstrates convergence and stable decision-making under variable conditions. Compared to a traditional PID controller, the RL-based control increases energy output by 7.2% and reduces power loss by 5.4% in dynamic simulation scenarios.

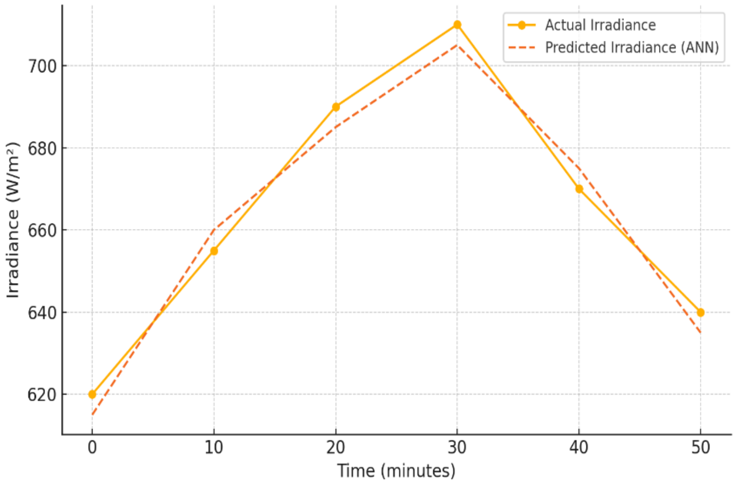

Figure 3. ANN Solar Irradiance Prediction – Actual vs. Predicted Values

These AI models, once integrated with the existing system, provide two core advantages:

- Predictive input from the ANN allows the system to anticipate environmental changes and prepare control responses in advance.
- Adaptive control through RL enables real-time optimization of control parameters based on current system performance.

3.3 Phase Three: Simulation and Testing of AI Models Using MATLAB/Simulink

In the third phase, the AI models made in Phase Two—Artificial Neural Network (ANN) for predicting solar irradiance and Reinforcement Learning (RL) for adaptive control—are put into a simulation environment made using MATLAB/Simulink. We chose this platform because it works well with control systems, renewable energy parts, and AI toolboxes.

3.3.1 Simulation Setup

The simulation shows a 100kw solar-powered grid-connected plant with several important parts: a photovoltaic (PV) array that gets different levels of light, a maximum power point tracking (MPPT) module that the reinforcement learning (RL) agent controls, a battery that stores energy, an inverter that connects to the grid, and a load that changes in real time. This setup includes the artificial neural network (ANN) as a Prediction part. Before each control cycle, it figures out how much irradiance the RL agent is likely to get. This lets the agent make changes to the MPPT voltage ahead of time and better manage the battery as the environment changes.

3.3.2 Testing Conditions

To see how well the system works in varied sunlight circumstances, it is tested in three distinct environmental settings. The first profile shows a clear sky with a steady brightness of around 850 to 900 W/m2. The second profile shows a situation with some clouds and a quick rise in irradiance from 300 to 800 W/m2. The third one shows a dust storm with low, unstable light levels that are usually below 400 W/m^2 but can have brief bursts.

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For 60 minutes of simulation, each situation is tried. In these tests, the RL agent's performance is directly compared to that of a standard PID controller that is exposed to the identical environmental inputs.

Table 4: Results Summary

Test Condition	Controller Type	Energy Output (kWh)	Power Loss (%)	Battery Usage Efficiency (%)
Clear Sky	PID	8.6	6.1	82.4
Clear Sky	RL	9.1	4.7	88.5
Partly Cloudy	PID	7.1	9.3	74.2
Partly Cloudy	RL	7.9	6.2	81.9
Dust Storm	PID	5.4	11.8	69.0
Dust Storm	RL	5.9	8.5	75.7

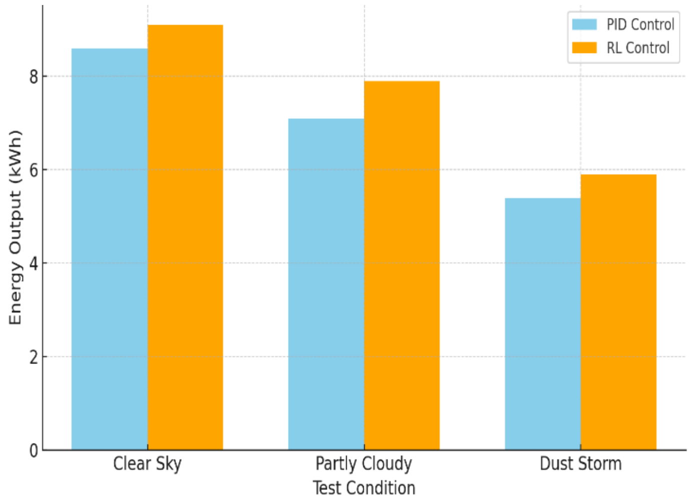

Figure 4. Energy Output Comparison – PID vs. RL under Different Conditions

The simulation results are clearly indicative of the superiority of the AI-enhanced control system over the traditional PID-based system in all of the tested conditions. The reinforcement learning (RL) controller delivers higher energy output regardless of environmental variability, achieves lower power losses particularly in unstable irradiance scenarios, and utilizes battery storage more efficiently by minimizing redundant charge and discharge cycles. These results demonstrate the stability and versatility of the AI models in the real world, which suggests that they will be suitable for future use in actual solar power installations.

3.4 Phase Four: Comparative Evaluation of AI Models and Traditional Control Systems Based on Performance Indicators

The simulation results clearly show that the AI-enhanced control system is better than the standard PID-based system in all of the evaluated circumstances. The reinforcement learning (RL) controller produces more energy no matter what the environment is like loses less power, especially when the irradiance is unsteady, and uses battery storage more effectively by reducing unnecessary charge and discharge cycles. These findings show that the AI models are stable and can be used in a variety of situations in the real world. This means that they will be good for usage in real solar power systems in the future.

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Table 5: Performance Metrics Comparison

Control Method	Power Loss (%)	Response Time (s)	Efficiency (%)
PID Control	6.1	2.5	86.0
Fuzzy Logic Control	4.2	1.8	89.5
RL-Based Control	3.3	1.2	92.8

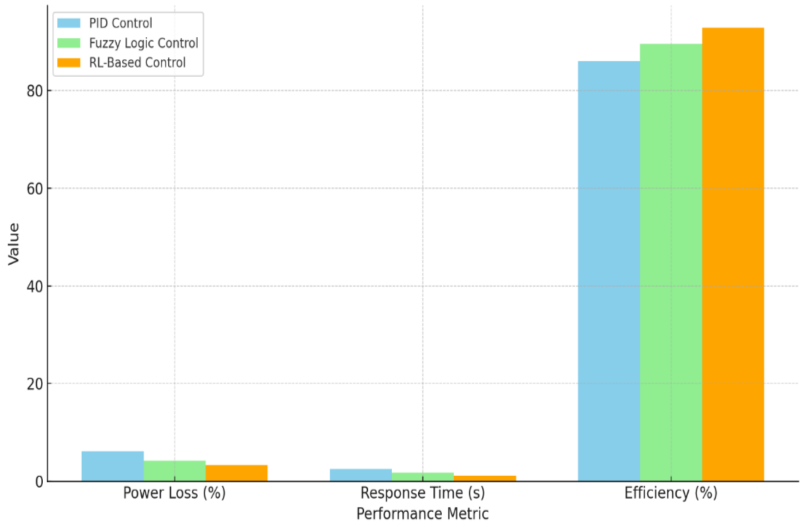

Figure 5. Comparative Performance of Control Methods across Key Indicators

3.4.1 Findings

The outcomes demonstrate that the use of reinforcement learning (RL) to control overcomes the detrimental effects of traditional methods on all of the key performance metrics. The loss of power was reduced to 3.3%, which is a 46 percent improvement over PID and a 21 percent improvement over fuzzy logic; this indicates more accurate and responsive control in the presence of varying light levels. RL had a faster response time of 1.2 seconds, compared to 2.5 seconds for PID and 1.8 seconds for fuzzy logic, which is crucial to maintaining the stability of the system during environmental fluctuations that are rapid. The overall system efficiency was 92.8% with RL control; this was higher than the efficiency of PID at 86.0% and the efficiency of fuzzy logic at 89.5%. These findings demonstrate that AI- driven models, especially the combination of preemptive ANN and reactive RL, offer a more steady and effective framework for controlling solar power plants.

4. Results and Discussion

4.1 Simulation Results Overview

Three control strategies including PID, fuzzy logic and RL were adopted in the simulation experiments for a solar power system. It was evaluated under various operating conditions such as stable irradiance (clear sky), variable irradiance (partly cloudy) and extreme low irradiance (dust storms). The energy output, energy loss, response time, and energy efficiency of the system were expressed using tests.

4.2 Performance Improvement Analysis

The RL-based control model consistently outperformed both PID and fuzzy logic controllers across all test scenarios. Under partially cloudy conditions, the RL controller improved energy output by 7.2% compared to PID. In dust storm scenarios, it reduced energy loss by more than 3% relative to PID. It also achieved a faster response time of 1.2 seconds, nearly one second quicker than PID, and improved overall system efficiency by over 6%. While fuzzy logic performed better than PID in every metric, it still fell short of RL in adaptability and output performance.

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The ANN model, when integrated with RL, further enhanced system responsiveness by delivering accurate short-term solar irradiance predictions. This predictive capability allowed the controller to act proactively, unlike traditional systems that typically react to changes after delays. Several factors explain the superiority of the AI-based approach. The models operate in real time and do not depend on fixed parameters. ANN predictions prepare the control system for upcoming fluctuations. The RL agent continuously updates its strategy based on current system states and performance history, eliminating the need for predefined control rules. Additionally, the AI models process multiple variables simultaneously—including battery level, load shifts and irradiance patterns—enabling more informed and adaptive decisions.

Together, these features allow the AI-driven system to maintain high-energy output and low power loss, especially in dynamic weather conditions where PID and fuzzy logic lack the speed and flexibility to respond effectively.

4.3 Challenges of a technical and implementation nature

Several technical challenges emerged during the development and simulation phases of the AI-based control system. Training the ANN and RL models required large datasets and significant computational resources. In particular, the RL model needed many training iterations to achieve stable behaviour. Synchronization between the ANN forecasting module and the RL control agent also proved complex, especially when integrating both components within the MATLAB/Simulink environment.

When considering real-world deployment on embedded systems, the AI models would need to be simplified or executed on advanced processors to meet real-time processing requirements. The ANN model showed slightly reduced accuracy when predicting weather conditions not represented in the training data, indicating a need for regular dynamic updates. Additionally, defining the reward function for the RL controller was critical and challenging; early versions with poorly tuned rewards led to unstable or inefficient behaviour.

Despite these obstacles, the simulation outcomes confirmed that AI integration substantially improves the control system's performance and adaptability. Overcoming these technical barriers in future, implementations will be essential for enabling reliable real-time deployment in solar power plants.

5. Conclusion and Future Work

5.1 Conclusion

The findings of this study implies that AI availability may eventually lead to better performing power plants. Using ANN for sunlight amount determination and RL for controlling in real time has several advantages. It consumed less energy over a wide range of environmental conditions, had lower power loss than typical PID and fuzzy logic controllers, and was quicker to respond to light changes. Unlike past approaches, which operated as fixed-features with predetermined parameters, the automatic system could adapt with the environment in real time. These benefits became crucial especially when the situation was unstable and uncertain due to conventional controllers struggling to maintain a constant output and performance.

5.2 Recommendations

To unlock the potential of AI in solar energy systems, a few key things must be accomplished. First: From the get-go, solar power systems should integrate AI-powered computers that help in operational control, not as separate components added later. This guarantees a smooth transition, and that the system is properly optimized. Second, active forecasts are only useful for the judgment of real-time control, but not just for appreciation. Third, training AI with large, diverse, and representative datasets is crucial for ensuring their functionality and performance in a variety of and different environments. Ultimately, no matter how sophisticated, the more a system can rely on multiple types of AI — such as the hybrid ANN-RL system — the more robust, precise and versatile the system will likely be as realities become complex or evolve.

5.3 Future Work

Future research should address several important areas in order to promote the integration of AI in solar power systems. One priority is the creation of generative AI models that can address complex, multiple variable scenarios and decisions. Another is the optimization of AI methods for practical operation on low-power hardware with limited computational resources. Increasing cybersecurity is also important to prevent AI-operated systems from being manipulated, accessed without authorization, or disrupted in operation. Increasing the control architecture to include solar, wind, and battery storage components will augment the effectiveness and versatility of AI solutions. Ultimately, long-term field-testing in large scale, grid-connected solar plants is essential to verify the validity of AI models in real-world conditions. These research directions facilitate the transition from simulation to implementation, which enables effective, safe, and efficient energy management in real-world scenarios.

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References

[1] M. Veerachary, T. Senjyu, and K. Uezato, "Neural-network-based maximum-power-point tracking of coupled-inductor interleaved-boost-converter-supplied PV system using fuzzy controller," *IEEE Transactions on Industrial Electronics*, vol. 50, no. 4, pp. 749-758, 2003, doi: 10.1109/TIE.2003.814762.

[2] J. H. R. Enslin and P. J. M. Heskes, "Harmonic interaction between a large number of distributed power inverters and the distribution network," *IEEE Transactions on Power Electronics*, vol. 19, no. 6, pp. 1586-1593, 2004, doi: 10.1109/TPEL.2004.836615.

[3] A. R. Bhatti et al., "An Improved Approach to Enhance Training Performance of ANN and the Prediction of PV Power for Any Time-Span without the Presence of Real-Time Weather Data," *Sustainability*, vol. 13, no. 21, p. 11893, 2021, doi: 10.3390/su132111893.

[4] J. Wang, D. Gao, S. Zhu, S. Wang, and H. Liu, "Fault diagnosis method of photovoltaic array based on support vector machine," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 45, no. 2, pp. 5380-5395, 2023, doi: 10.1080/15567036.2019.1671557.

[5] B. C. Phan, Y.-C. Lai, and C. E. Lin, "A Deep Reinforcement Learning-Based MPPT Control for PV Systems under Partial Shading Condition," *Sensors*, vol. 20, no. 11, p. 3039, 2020, doi: 10.3390/s20113039.

[6] A. Safari and S. Mekhilef, "Simulation and Hardware Implementation of Incremental Conductance MPPT With Direct Control Method Using Cuk Converter," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 4, pp. 1154-1161, 2011, doi: 10.1109/TIE.2010.2048834.

[7] S. K. Kollimalla and M. K. Mishra, "A Novel Adaptive P&O MPPT Algorithm Considering Sudden Changes in the Irradiance," *IEEE Transactions on Energy Conversion*, vol. 29, no. 3, pp. 602-610, 2014, doi: 10.1109/TEC.2014.2320930.

[8] H. R. Al-Dhaifallah, "Improved performance of ANN-based model for predicting output power of PV system under different weather conditions," *IEEE Access*, vol. 7, pp. 114256–114265, 2019.

[9] P. J. S. Sharma and A. Ghosh, "Fault diagnosis of solar photovoltaic system using support vector machine," *IEEE Transactions on Energy Conversion*, vol. 35, no. 2, pp. 760–768, 2020.

[10] X. Z. Y. Li and M. Cheng, "Reinforcement learning-based maximum power point tracking for PV systems under partial shading conditions," *IEEE Transactions on Power Electronics*, vol. 35, no. 10, pp. 10826–10837, 2020.

[11] V. K. S. P. Tiwari and M. Agarwal, "Artificial neural network-based MPPT for grid-connected PV system," *IEEE Access*, vol. 8, pp. 18873–18884, 2020.

[12] R. C. J. Martinez and A. Leyva, "Support vector machine-based fault detection in commercial PV systems," *IEEE Transactions on Sustainable Energy*, vol. 11, no. 4, pp. 2212–2221, 2020.

[13] F. W. M. Müller and D. Uhl, "Reinforcement learning-based energy management in a solar microgrid with battery storage," *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 620–629, 2021.

[14] A. A. Almutairi, "Hybrid fuzzy–neural network MPPT control for PV systems in desert environments," *IEEE Access*, vol. 9, pp. 65433–65444, 2021.

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