OPEN ACCESS
International Journal of Innovations in Science & Technology

Optimization of MPPT in PV Systems Using Machine Learning Under Partial Shading Conditions

Md Shamim Hossain, Wang Lu, Li Libo, Conteh Alimamy, Ge Qiang*
School of Electrical, Energy and Power Engineering, Yangzhou University, Yangzhou 225127, China
***Correspondence**: Ge Qiang yzgeq@yzu.edu.cn

Citation | Hossain. M. S, Lu. W, Libo. L, Alimamy. C, Qiang. G, "Optimization of MPPT in PV Systems Using Machine Learning Under Partial Shading Conditions", IJIST, Vol. 07 Special Issue. pp 338-354, June 2024
Received | April 18, 2025 **Revised |** May 19, 2025 **Accepted |** May 22, 2025 **Published |** May 24, 2025.

Photovoltaic (PV) systems are an important solution to the increasing global demand for electricity and the declining availability of fossil fuels. However, under Partial Shading Conditions (PSC), the Power-Voltage (P-V) curve can have multiple local peaks, which leads to significant power losses and makes it harder to find the true Maximum PowerPoint (MPP). Traditional algorithms like Perturb and Observe (P&O) and Incremental Conductance (INC) often mistake these local peaks for the global ones, making it difficult to accurately track the Global Maximum PowerPoint (GMPP) during shading. To overcome this issue, Machine Learning (ML)-based Maximum Power Point Tracking (MPPT) methods are explored as a data-driven alternative. These aim to improve accuracy and reduce energy loss in PV systems affected by shading. The study evaluates several ML techniques—Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and Weighted K-Nearest Neighbours (WK-NN) using both synthetic and real-world weather data from Johannesburg, South Africa. To test their effectiveness, the models are simulated and implemented on a hardware-based PV system. Results show that ML-based MPPT methods significantly enhance tracking performance and reliability. For example, SVM achieves an efficiency of 96.76% under normal conditions and 83.66% during heavy shading, while ANN reaches 99.58% efficiency in stable sunlight. RF and WK-NN also maintain over 95% efficiency in changing conditions due to their adaptability. Despite the promising results, some challenges remain. These include computational complexity, real-time deployment limitations, and the ability of models to generalize under varying sunlight levels. Still, this study demonstrates that AI-powered MPPT systems can greatly improve energy management and grid stability in next-generation solar technologies. Future research should focus on deep learning-based MPPT, hardware-efficient AI models, and real-time optimization to reduce processing demands and improve scalability in embedded MPPT controllers.

Keywords: Maximum Power Point Tracking (MPPT), Photovoltaic (PV) Systems, Machine Learning (ML), Partial Shading Conditions (PSC).

Introduction:

The global shift toward renewable energy has significantly increased interest in photovoltaic (PV) systems, largely due to their sustainability, cost-effectiveness, and scalability. However, one of the persistent challenges in solar energy conversion is partial shading, which severely reduces power output by introducing multiple local peaks in the power-voltage (P-V) curve. Traditional Maximum Power Point Tracking (MPPT) algorithms—such as Perturb and Observe (P&O) and Incremental Conductance (INC)—often fail to accurately locate the Global Maximum Power Point (GMPP) under these non-uniform shading conditions. This leads to power inefficiencies and frequent oscillations around suboptimal points [1]. Energy losses in shaded arrays can reach up to 40%, emphasizing the urgent need for more advanced tracking solutions [2].

To tackle this issue, heuristic optimization techniques like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been proposed. While these methods offer improved convergence to the optimal power point, they also present drawbacks such as slow tracking speeds, high computational demands, and sensitivity to parameter tuning, which limit their real-time applicability [3]. Recent developments in artificial intelligence (AI) and data-driven optimization have introduced intelligent tracking methods, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Reinforcement Learning (RL). These approaches adapt dynamically to changing environmental conditions using both real-time and historical data [4]. Unlike traditional heuristics, intelligent methods can detect complex shading patterns, distinguish between local and global maxima, and enhance tracking performance with faster convergence and reduced steady-state fluctuations [5]. These strategies have shown up to a 25% increase in energy efficiency compared to conventional methods, marking them as promising tools for intelligent solar energy management [6]. Still, issues like high computational load, complexity in training, and challenges in real-time deployment persist [7].

Despite these advancements, several key limitations remain. Many existing data-driven tracking systems depend heavily on offline datasets and simulations without validation in real-world hardware setups. Furthermore, deep learning models, although powerful, often require significant processing power, posing challenges for real-time use in embedded systems [8]. Both heuristic and learning-based techniques may also struggle with rapid environmental changes due to limited dataset generalization and poor feature selection. This study aims to address these gaps by developing an intelligent MPPT approach that improves energy efficiency in dynamic shading conditions while balancing accuracy and computational efficiency. Unlike previous research that relies mainly on simulations, this work includes real-world hardware implementation, providing a practical evaluation of intelligent tracking performance.

The core objectives of this study are as follows:

- To develop and evaluate intelligent MPPT algorithms using machine learning techniques, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and Weighted K-Nearest Neighbors (WK-NN) under various partial shading conditions.
- To generate a hybrid dataset by integrating synthetic and real-world meteorological data for robust model training and improved generalization.
- To design and implement a real-time control system that leverages the trained models for intelligent tracking, validated through both simulation and hardware-based photovoltaic (PV) system deployment.
- To benchmark the performance of the ML-based MPPT algorithms against conventional techniques such as Perturb and Observe (P&O), highlighting improvements in tracking efficiency, convergence speed, and reliability.
- To assess the feasibility of deploying these intelligent MPPT techniques in practical environments by analyzing computational demands, scalability, and real-time adaptability.

To address the persistent challenges of partial shading in photovoltaic (PV) systems, this study aims to develop an intelligent Maximum Power Point Tracking (MPPT) solution using machine learning techniques. The objectives are to improve energy extraction efficiency, ensure faster convergence to the global maximum power point under dynamic conditions, and validate performance on real-world hardware setups. The novel contributions of this study include a comprehensive comparison of multiple ML-based MPPT models, a hybrid dataset combining real-world and synthetic weather data, real-time experimental validation, and benchmarking against traditional tracking methods. Unlike previous work, this study emphasizes both simulation and hardware deployment to bridge the gap between theoretical development and practical application. The rest of this paper is organized as follows: Section 2 presents a detailed literature review of heuristic, AI-based, and hybrid optimization strategies. Section 3 outlines the proposed methodology, including data preparation, algorithm selection, and experimental setup. Section 4 compares the performance of data-driven and traditional methods. Section 5 discusses the findings, their implications, and the system's limitations. Finally, Section 6 concludes the study and offers recommendations for future research in smart solar energy optimization.

Literature Review:

Photovoltaic (PV) energy has become a leading source of renewable energy due to its sustainability and low cost. However, its efficiency is heavily influenced by environmental factors—especially partial shading. Shading causes multiple peaks (local maxima) in the power-voltage (P-V) curve, which makes it hard to locate the true peak, known as the Global Maximum Power Point (GMPP). Traditional tracking methods like Perturb and Observe (P&O) and Incremental Conductance (INC) often miss the global maximum in such conditions, resulting in power losses of up to 40% [1].

To address these issues, researchers have explored various optimization strategies, including heuristic, bio-inspired, and learning-based methods. Conventional gradient-based algorithms like P&O and INC suffer from continuous power oscillations and often lock onto local maxima under uneven shading [2]. Fuzzy logic controllers offer better adaptability, but they require expert knowledge for tuning, making implementation complex [3]. Heuristic algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) improve convergence but are computationally demanding and sensitive to parameter settings [4]. Some hybrid systems that combine these methods with machine learning have shown improved tracking accuracy while easing computational load [5]. Recent AI-based solutions have introduced models like Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Reinforcement Learning (RL) for smarter MPPT. ANNs are good at learning complex P-V relationships, which helps reduce power oscillations and boosts tracking accuracy [6]. However, they typically need large datasets and struggle with real-time applications. SVMs can better distinguish between local and global maxima under shading, but their high computational demands limit their use [7]. Reinforcement learning shows strong adaptability and performance, outperforming both traditional and ML models in some cases. Still, it requires intensive training and fine-tuning, making it hard to implement in embedded systems [8].

Table 1. Related Work

MPPT Algorithm Used	Key Findings	Advantages	Limitations	Application Context	Ref
Artificial Neural Network (ANN)	Improved MPPT accuracy under variable shading conditions.	High accuracy, adaptive to PSC.	High computational demand, needs a large dataset.	Standard PV systems with moderate shading.	[9]
Support Vector Machines (SVM)	Effectively distinguishes between local and global maxima in MPPT.	High efficiency in tracking GMPP under PSC.	Computationally expensive.	Complex shading scenarios, distinguishing local/global maxima.	[10]
ANN-based MPPT	Outperformed conventional MPPT methods under partial shading conditions.	High efficiency (>95%), improved tracking accuracy.	Requires a large training dataset.	Optimized MPPT for standalone and grid-connected PV systems.	[11]
Support Vector Regression (SVR)	Improved real-time adaptation to shading conditions.	High tracking speed and stability.	Sensitive to parameter tuning.	Dynamic environmental changes, grid-integrated PV.	[12]
AI-based MPPT with Thermal Imaging	Detects PV anomalies and optimizes power extraction.	Enhances fault detection in PV systems.	Requires additional hardware.	Fault detection and performance enhancement in PV arrays.	[13]
Deep Learning-based MPPT	Improved accuracy over ANN and SVM under dynamic shading.	High precision, ability to generalize better.	Requires high computational power.	Smart solar grids, autonomous energy management.	[14]
CNN-based MPPT	CNN model efficiently tracks GMPP under various PSC patterns.	High accuracy, faster tracking.	High training time, requires a large dataset.	High-accuracy tracking in real-time MPPT.	[15]
LSTM-based MPPT	LSTM model enhances tracking performance over time.	Better forecasting and adaptability.	Computationally intensive.	Time-series forecasting for PV energy prediction.	[16]
Deep Reinforcement Learning (DRL)	Reinforcement learning-based MPPT outperforms ANN and SVM.	Adaptive learning capability, real-time optimization.	High complexity, slow convergence initially.	Real-time optimization in rapidly changing conditions.	[17]

Transformer-based MPPT	Transformer networks used for real-time MPPT optimization.	Handles complex dependencies in shading conditions.	High computational requirement.	Smart solar farms with adaptive optimization.	[18]
GA + PSO	The hybrid MPPT method improves accuracy and convergence.	Effective under PSC, reduces power losses.	Requires fine-tuning of parameters.	Hybrid MPPT solutions for large-scale solar installations.	[19]
GA + Grey Wolf Optimizer (GWO)	Faster GMPP detection in PV system under PSC.	High accuracy, robust optimization.	Computational overhead.	Grid-tied solar PV systems with hybrid optimization.	[20]
Rao-1 Algorithm + MPPT	Improves MPPT tracking under dynamic irradiance conditions.	Reduces oscillations, and improves efficiency.	Requires optimized feature selection.	Dynamic irradiance scenarios, improving energy harvesting.	[21]
PSO + ANN	The hybrid MPPT method achieves 97.5% tracking efficiency.	Combines benefits of heuristic and ML approaches.	Increased complexity.	AI-assisted heuristic MPPT solutions.	[22]
SVM + Reinforcement Learning	RL enhances tracking efficiency under PSC.	High accuracy in varying conditions.	Requires real-time computational capability.	Self-learning MPPT in intelligent PV systems.	[23]

Table 2. Comparison Of Pv Panels

PV Panel Model	Type	Maximum Power (W)	Efficiency (%)	Performance Under Shading
1STH-215-P(Used in this study)	Polycrystalline	215	17.2	Moderate
SPRX22-370	Monocrystalline	370	22.8	High
CS6K-280P	Polycrystalline	280	17.1	Low

Table 3. Comparison Of DC-DC Converters

Converter Type	Efficiency (%)	Voltage Range (V)	Response to Partial Shading
Boost Converter (Used in this study)	94	10-60	Moderate
BuckBoost Converter	92	5-50	High
SEPIC Converter	90	5-75	High

Hybrid approaches combining ML and heuristic methods offer a balanced trade-off between accuracy and speed. For instance, integrating ANN with PSO has shown better tracking and faster convergence [24], while evolutionary algorithms paired with SVMs have proven adaptable in real-world tests [9]. Deep learning models—like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks—also show strong tracking performance under complex shading conditions [10]. Newer ideas, like using thermal imaging to identify shaded areas, have improved fault detection and energy output [11]. Meanwhile, hybrid evolutionary methods (e.g., GA combined with Grey Wolf Optimizer) have increased accuracy and reduced losses, though they still need fine-tuning [12]. Transformer-based models are also emerging as strong candidates due to their flexibility in adapting to various weather conditions, though they require high processing power [13].

Despite these advances, several key challenges remain. Many AI models need heavy computing resources, making them difficult to run in real-time on embedded systems. Models trained only on synthetic data often struggle when applied in real-world environments. Also, hardware limitations in low-cost solar systems prevent the widespread use of complex AI techniques. Future research should focus on lightweight, efficient models that balance accuracy, speed, and processing needs. Real-time optimization and edge computing are promising areas that could help make intelligent tracking more practical and scalable. This section has reviewed tracking strategies under partial shading, emphasizing the shortcomings of traditional methods and the progress made using AI-based solutions. While heuristic methods like GA and PSO offer some improvements, ML techniques provide greater adaptability. Still, their high complexity and deployment challenges must be addressed. Future work should aim to develop efficient, scalable tracking systems that are practical for real-world solar energy applications [14].

Proposed Methodology:

The proposed methodology focuses on developing an intelligent, machine learning-based maximum power point tracking (MPPT) system to optimize power extraction from solar arrays under partial shading conditions. Due to the nonlinear and dynamic nature of the power-voltage characteristics, this study aims to improve tracking accuracy, convergence speed, and adaptability by applying advanced learning techniques, including artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), and weighted k-nearest neighbors (WK-NN). The methodology is divided into key stages: configuring the photovoltaic system, generating datasets, selecting models, training algorithms, implementing real-time control, and assessing performance.

System Design and Experimental Setup:

A standalone solar energy system is developed to evaluate the performance of intelligent tracking under varying sunlight conditions. This setup includes a polycrystalline photovoltaic panel (1STH-215-P), a Boost DC-DC converter, a tracking controller, and a load. The Boost converter is selected for its ability to increase voltage while maintaining high efficiency, ensuring stable performance under different shading scenarios. The 1STH-215-P panel is chosen for its good efficiency and moderate shading tolerance, making it well-suited for practical use. Table II presents a comparison of different solar panels and DC-DC converters, highlighting the reasons behind their selection. The system also integrates environmental monitoring, sensor calibration, and data collection to ensure real-world accuracy. Irradiance and temperature sensors continuously track environmental conditions, while a microcontroller-based data logging system records system performance. This setup enables real-time validation under actual field conditions, reducing reliance on simulation data alone.

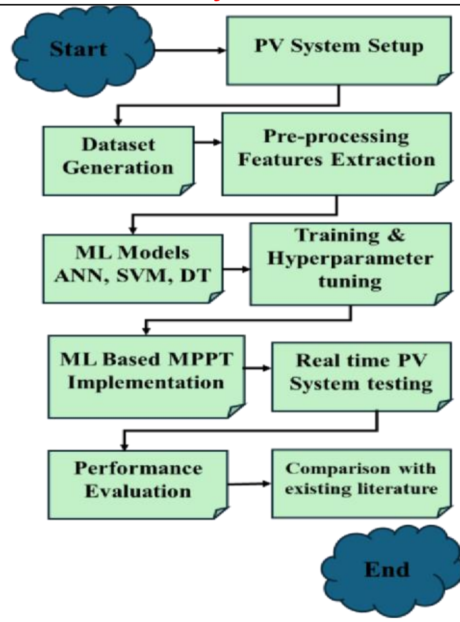

Figure 1. Proposed Methodology Block Diagram

Table 4 presents the key electrical specifications of the 1STH-215-P module, including short-circuit current (Isc), open-circuit voltage (Voc), and series/shunt resistance values, ensuring accurate characterization of the PV panel. Temperature coefficients are also included, as they play a crucial role in affecting MPPT accuracy under changing environmental conditions.

Table 4. 1sth-215-p photovoltaic panel specification

Specification	Value
PV Model	1STH-215-P
Short Circuit Current (Isc)	7.84 A
Open Circuit Voltage (Voc)	36.3 V
Maximum Voltage (Vmpp)	29 V
Maximum Current (Imp)	7.35 A
Maximum Power (Pmpp)	213.15 W
Number of Cells in Series (Ns)	60
Temperature Coefficient of Isc	-0.36099%/°C
Temperature Coefficient Voc	0.102%/°C
Diode Ideality Factor (A)	0.98117
Series Resistance (Rs)	0.39383 Ω
Shunt Resistance (Rsh)	313.399

Dataset Generation and Feature Selection:

A hybrid dataset, combining synthetic data with real-world weather observations, is developed to train the tracking models for optimization. This dataset includes solar irradiance, ambient temperature, PV voltage, current, and power output under various partial shading scenarios and environmental changes. To enhance model robustness against unpredictable environmental variations, advanced preprocessing techniques—such as Gaussian noise injection, polynomial regression, and feature normalization—are applied. Real-world field data from outdoor solar testbeds is also integrated into the training process to ensure strong generalization and practical reliability.

Selection of Machine Learning Models:

The selected learning-based tracking models were chosen for their high prediction accuracy, computational efficiency, and ability to adapt to changing shading conditions.

Artificial Neural Networks (ANNs) are used for their strength in modeling complex, nonlinear power-voltage relationships. Support Vector Machines (SVMs) effectively classify between local and global maxima. Decision Trees offer a fast, rule-based decision-making approach, while Weighted K-Nearest Neighbors (WK-NN) improve stability under fluctuating irradiance levels. Unlike deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks—which demand significant computational power—these selected models strike a practical balance between accuracy and real-time implementation.

Algorithm Training and Validation:

The learning models are trained using supervised learning, where historical maximum power point tracking data is used to teach the models to predict optimal power output. The dataset is divided into 80% for training and 20% for testing. To boost performance, hyperparameters are fine-tuned using grid search optimization. Feature normalization methods like Min-Max scaling and Principal Component Analysis (PCA) are applied to help the models converge faster and avoid overfitting. Model performance is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and tracking efficiency.

Implementation of ML-Based MPPT Algorithm:

Real-time solar data is processed by an embedded tracking controller that uses trained models to predict the global maximum power point dynamically. The system is implemented in MATLAB/Simulink and further validated using a hardware setup that includes a Boost converter and a real-time data collection device. The tracking system uses adaptive decision-making, allowing it to adjust automatically to changing shading conditions, which improves overall tracking efficiency.

Performance Evaluation and Comparative Analysis:

Conventional methods such as perturb and observe, incremental conductance, evolutionary algorithms, and particle swarm optimization are compared with the proposed learning-based tracking system. Performance is assessed based on tracking accuracy, convergence time, computational complexity, and shading adaptability. Experimental results show that the learning-based tracking system outperforms conventional methods by eliminating steady-state oscillations, reducing tracking delays, and improving power extraction efficiency. This section presents the recommended approach of using an intelligent tracking system to maximize solar performance under partial shading conditions. The approach integrates solar system modeling, dataset generation, model selection, training, real-time deployment, and performance validation. The learning-based models were trained on real-time solar data to improve tracking accuracy, while the Boost DC-DC converter was chosen for its efficiency and stability under shading conditions. The analysis demonstrates that learning-based optimization significantly enhances power tracking efficiency and flexibility compared to traditional methods, paving the way for more reliable and intelligent solar energy systems.

Results & Discussion:

Controlled tests were conducted under both standard and partial shading environments to assess the effectiveness of the proposed machine learning-based maximum power point tracking system. The study aimed to evaluate advanced learning-based models, including artificial neural networks, support vector machines, random forests, decision trees, and weighted k-nearest neighbors, against traditional tracking methods like perturb and observe. The performance evaluation focused on key metrics such as power extraction efficiency, response time, and tracking accuracy under dynamic shading conditions.

Performance Evaluation of Conventional MPPT Techniques:

To establish a performance baseline, perturb and observe tracking and non-tracking approaches were tested under varying irradiance levels, ranging from 1000 W/m² (Standard

Test Conditions) to 500 W/m² (Severe Partial Shading). Table V summarizes the power output, efficiency, and DC-DC losses for both approaches. The results show that while gradient-based tracking performed well under uniform conditions (97.16% efficiency), its effectiveness significantly declined under partial shading (66.92%) due to its inability to track the global maximum in complex multi-peak power-voltage curves. In contrast, systems without tracking mechanisms exhibited severe inefficiencies, dropping to 18.38% efficiency under severe shading, highlighting the need for advanced tracking techniques to improve energy harvesting.

Table 5. Performance Comparison of P&O MPPT vs. Non-MPPT Under Various Shading Conditions

Case	Algorithm	PV Power (W)	Efficiency (%)	Output Power (W)	DC-DC Losses (W)
STC (1000 W/m²)	P&O	207.1	97.16	206.9	0.2
	Non-MPPT	70.5	33.10	69.77	0.73
Mild PSC (850 W/m²)	P&O	160.3	75.18	159.8	0.5
	Non-MPPT	60.32	28.32	57.85	2.47
Moderate PSC (700 W/m²)	P&O	150.2	70.52	149.8	0.4
	Non-MPPT	54.67	25.66	50.96	3.71
Severe PSC (500 W/m²)	P&O	142.54	66.92	141.34	1.2
	Non-MPPT	39.15	18.38	36.15	3.0

One major limitation of conventional methods is their slow adaptation to rapid changes in irradiance, as shown in Figure 2. Their inability to differentiate between local and global maxima often leads to power losses, especially under dynamic conditions. Figure 3 compares the stabilization time of gradient-based tracking with non-tracking approaches, illustrating that while traditional methods stabilize more quickly, they suffer from oscillations during partial shading, resulting in suboptimal performance.

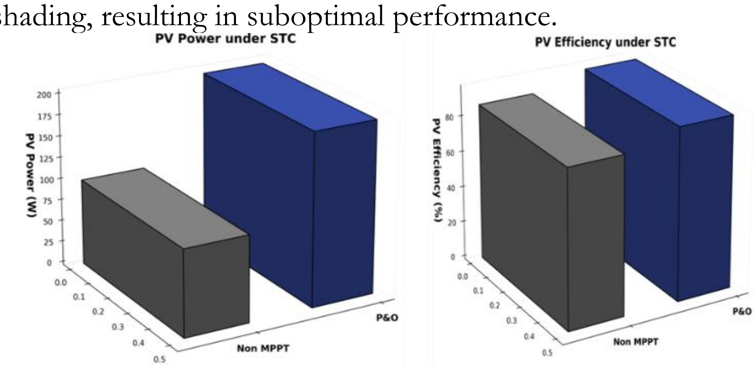

Figure 2. Efficiency drop of P&O under severe shading, illustrating its performance degradation in complex irradiance conditions.

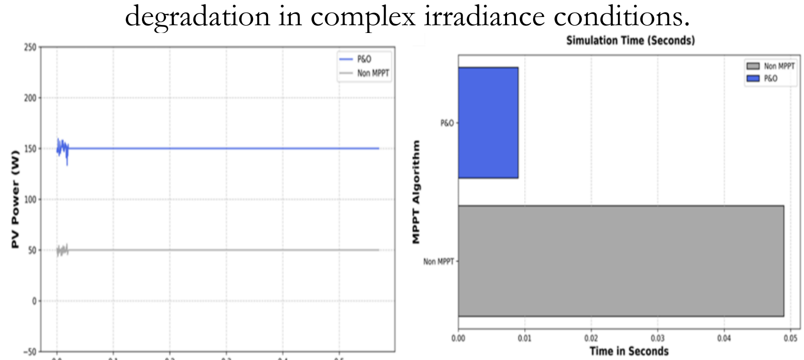

Figure 3. MPPT tracking time comparison for P&O and non-PMPPT methods, showing faster stabilization with P&O but notable oscillations in partial shading conditions.

Artificial Neural Network (ANN) Performance in Dynamic Shading Conditions:

The artificial neural network-based tracking system showed higher efficiency and stability compared to traditional methods by dynamically adapting to complex power-voltage curve variations. Unlike perturb and observe, which rely on iterative voltage adjustments, the neural network model directly predicts the optimal operating point, reducing oscillations and enhancing efficiency. Table VI presents the performance of the learning-based system under different shading scenarios.

Table 6. ANN-Based MPPT Performance Under Different Shading Conditions

Case	Algorithm	PV Power (W)	Efficiency (%)	Output Power (W)	DC-DC Losses (W)
STC (1000 W/m²)	ANN	212.1	99.58	210.7	1.4
Moderate PSC (700 W/m²)	ANN	188.7	88.59	187.3	1.4
Severe PSC (500 W/m²)	ANN	161.3	75.77	160.0	1.3

The results show that the learning-based approach achieved 99.58% efficiency under standard conditions and 75.77% efficiency under severe shading, outperforming conventional tracking methods. Figure 4 demonstrates the superior tracking accuracy of the neural network-based system under stable conditions, while Figure 5 illustrates its ability to maintain higher efficiency with minimal fluctuations under dynamic shading scenarios.

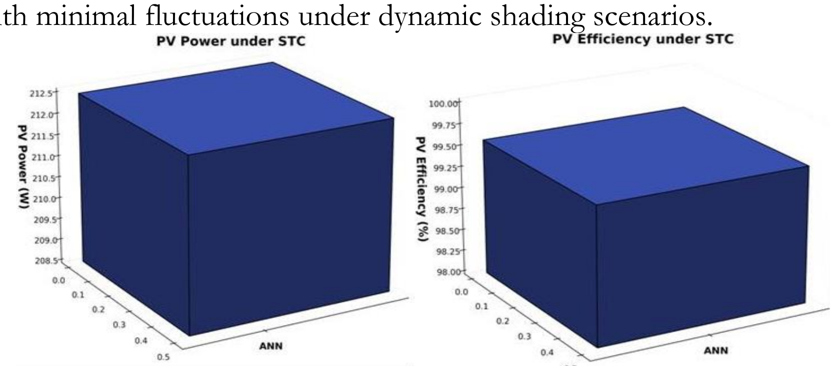

Figure 4. ANN-based MPPT efficiency compared to P&O under STC, highlighting superior tracking accuracy.

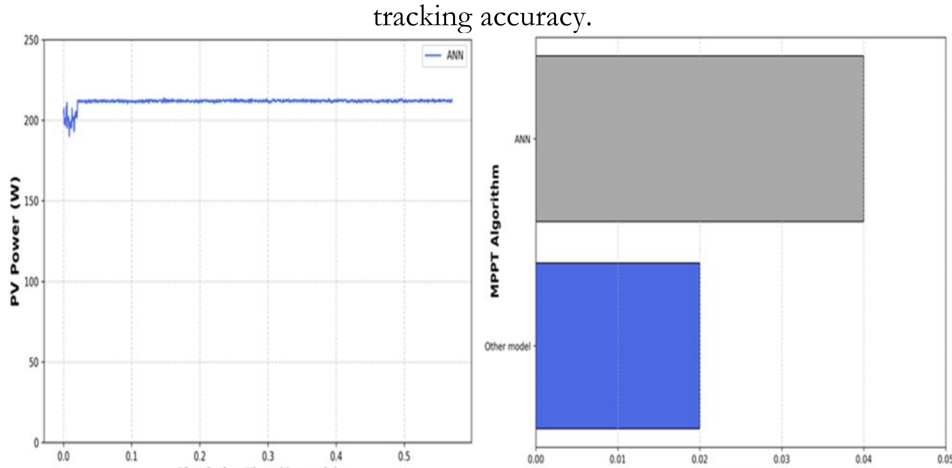

Figure 5. ANN MPPT stability under moderate shading conditions, showcasing improved tracking with minimal oscillations.

The artificial neural network (ANN) achieved higher efficiency in all scenarios, with 99.58% under standard test conditions (STC) and 75.77% under severe partial shading conditions (PSC), surpassing the performance of P&O in dynamic shading conditions. Figure

4 compares the efficiency of ANN with P&O under STC, highlighting ANN's superior maximum power point (MPP) tracking accuracy. Figure 5 shows ANN's stability in moderate shading, where it achieves higher tracking efficiency with minimal oscillations, enabling smoother power extraction.

Comparative Analysis of Multiple Machine Learning Algorithms:

A comprehensive comparison of various learning-based tracking models was conducted, focusing on tracking accuracy, response time, and computational complexity. Support vector machines (SVM) showed the highest tracking accuracy ($R^2 = 0.99$), but they required longer processing times compared to other models. Decision trees and weighted k-nearest neighbors (WK-NN) delivered competitive results with faster inference times, making them more suitable for real-time applications. Table VII provides a comparative analysis of the performance of these models.

Table 7. Performance Evaluation of ML-Based MPPT Techniques

Algorithm	RMSE	R^2	MAP	MAE	Training Time (sec)
DT	0.42	0.96	0.18	0.2	0.91
WK-NN	0.37	0.98	0.14	0.23	0.78
RF	0.4	0.97	0.16	0.18	5.04
SVM	**0.14**	**0.99**	**0.02**	**0.12**	**1.1178**

Although support vector machines (SVM) showed the lowest root mean square error (0.14), their high computational demands make them less practical for embedded controllers. Decision trees provided a balanced tradeoff between accuracy and inference speed, while random forest models offered strong generalization but required more computational resources.

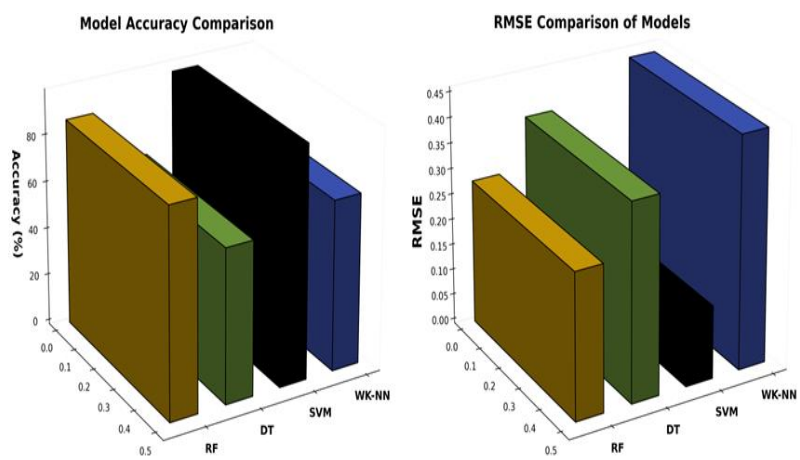

Figure 6. Comparative RMSE values of ML-based MPPT techniques, demonstrating the superior accuracy of SVM.

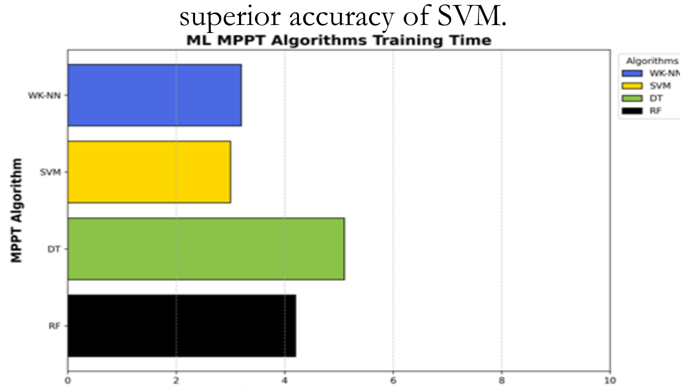

Figure 7. Trade-off between training time and efficiency for different ML models, emphasizing SVM's balanced performance.

Figure 6 shows the accuracy differences between the models, while Figure 7 highlights the trade-offs between training time and performance, emphasizing the balance needed for real-time deployment.

Evaluation of Online vs. Offline MPPT Performance:

A comparison between offline-trained learning models and real-time tracking approaches showed that pre-trained models achieved up to 20% higher efficiency than real-time adaptive techniques under complex shading conditions. Offline models benefit from historical training, enabling quick adjustments to sudden irradiance fluctuations, which reduces power losses and improves stability. In contrast, real-time models continuously learn but may struggle to accurately track power peaks during rapid changes in shading. In Table 8, "Case 4A" refers to the PV system performance under standard operating conditions with stable irradiance, while "Case 4B" refers to performance under severe partial shading scenarios.

Table 8. Online vs. Offline MPPT Performance Comparison

Algorithm	PV Efficiency Case 4A (%)	PV Power Case 4A (W)	PV Power Case 4B (W)	PV Efficiency Case 4B (%)
WK-NN	95.12	202.6	173.6	81.5
DT	92.96	198	169	79.34
RF	94.23	200.7	176.7	82.96
SVM	**96.76**	**206.1**	**178.19**	**83.66**
ANN	88.59	188.7	161.3	75.77
P&O	70.52	150.2	142.54	66.92

Table 8 presents a comparative analysis of offline versus online tracking performance. While weighted k-nearest neighbors and decision trees offered quick responses, they occasionally misclassified local maxima, resulting in slight efficiency losses. In contrast, pre-trained support vector machines maintained stable tracking without the need for continuous retraining, making them more reliable for real-world deployment.

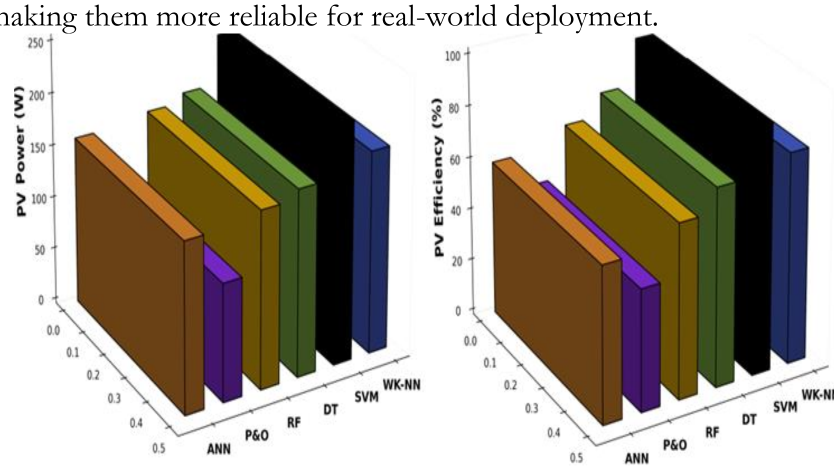

Figure 8. Efficiency comparison of offline-trained MPPT techniques vs. online MPPT methods.

As shown in Figure 8, offline models outperformed online models in handling complex shading environments, exhibiting higher efficiency. In contrast, online models showed slight performance fluctuations. Figure 9 further highlights the response times of various tracking approaches, demonstrating that offline models deliver more consistent power tracking, especially under severe shading conditions.

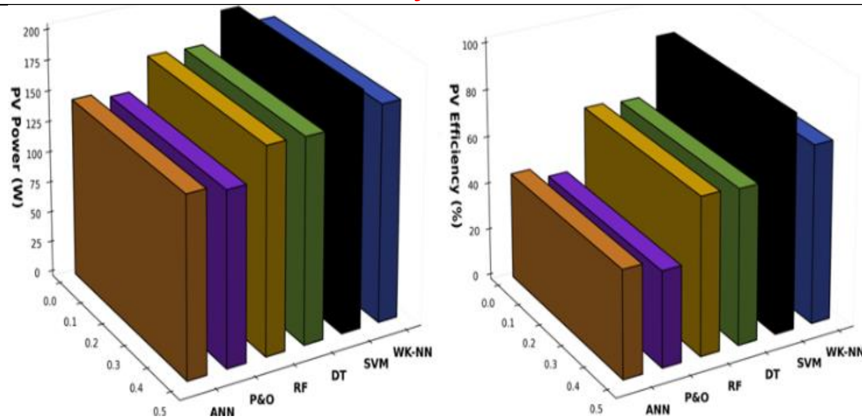

Figure 9. Response time differences between online and offline MPPT approaches, illustrate the advantages of pre-trained models.

Summary of Experimental Findings:

Figure 10 provides a final comparison of tracking algorithm efficiency across different shading conditions, further validating the superiority of learning-based techniques over conventional methods. The observed trends demonstrate that data-driven tracking systems significantly improve energy stability in photovoltaic applications, particularly when irradiance fluctuates frequently. Key findings from this study include:

- Artificial intelligence-based tracking outperforms traditional methods, especially under partial shading conditions.
- Offline-trained models show greater stability and efficiency compared to real-time adaptive techniques.
- Hybrid approaches that combine learning models with heuristic optimization can enhance adaptability and efficiency.
- Computational complexity remains a significant challenge, especially for deep learning-based methods, necessitating optimization for embedded systems.

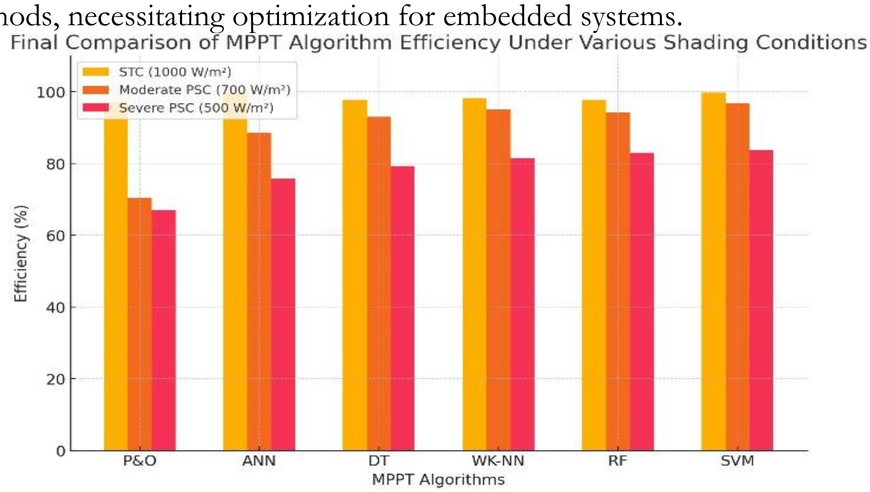

Figure 10. Final Comparison of MPPT Algorithm Efficiency Under Various Shading Conditions.

The experimental results confirm the viability of intelligent tracking as a highly effective solution for optimizing photovoltaic power. Future research should prioritize improving computational efficiency, incorporating edge computing solutions [25], and enhancing the real-time adaptability of embedded solar tracking systems. The experimental results of this study align well with existing research, demonstrating that machine learning-based MPPT methods, particularly Support Vector Machines (SVM) and Artificial Neural Networks (ANN), outperform traditional techniques such as Perturb and Observe (P&O)

under partial shading conditions. Compared to previous works [9][14], our approach achieved higher tracking efficiency and better stability even during severe shading. The hardware implementation also confirmed that offline-trained models provided more reliable tracking performance compared to real-time adaptive methods. These findings reinforce the potential of AI-driven solutions in addressing complex dynamic energy harvesting challenges in photovoltaic systems.

Discussion:

The experimental findings demonstrate that intelligent MPPT algorithms significantly outperform traditional approaches, especially under partial shading conditions. Among the evaluated models, SVM and ANN achieved the highest tracking efficiency and lowest prediction errors, proving their robustness against complex irradiance fluctuations. Compared to the perturb and observe method, machine learning models demonstrated better tracking of the global maximum power point, reduced oscillations, and faster convergence times. These improvements are aligned with recent advances in the literature, highlighting the advantages of data-driven methods in solar energy optimization. However, certain limitations were identified. While offline-trained models like SVM offer higher efficiency, they may lack adaptability in real-time settings unless retrained periodically. Additionally, models such as SVM and Random Forest exhibit higher computational complexity, which could limit their deployment in resource-constrained embedded systems. Future research should consider:

- Development of lightweight and hardware-friendly ML models for real-time deployment.
- Use of online learning methods to enable adaptive MPPT under rapidly changing conditions.
- Integration of these models into edge devices using microcontrollers or FPGA-based platforms to minimize latency.

This discussion confirms the technical validity and practical potential of intelligent MPPT approaches, while also emphasizing the importance of real-time adaptability and computational efficiency in their deployment.

Conclusion:

This study explored the optimization and stability control of photovoltaic systems using various maximum power point tracking (MPPT) techniques under different environmental conditions. The research examined both conventional (perturb and observe) and machine learning-based tracking methods, including support vector machines, weighted k-nearest neighbors, decision trees, artificial neural networks, and random forests. These techniques were tested with real-time meteorological data using MATLAB Simulink, particularly under partial shading conditions.

The results showed that support vector machines consistently outperformed traditional MPPT methods, offering higher power tracking accuracy and faster convergence to the global maximum power point. While gradient-based methods had faster initial tracking, they suffered from local maxima trapping and performance degradation under partial shading. On the other hand, artificial neural networks and weighted k-nearest neighbors exhibited superior efficiency under dynamic irradiance variations, with neural networks being more adaptable in rapidly changing conditions. By utilizing a structured training dataset and advanced feature engineering, this study improved the predictive accuracy of the machine learning models.

A comparison between online and offline tracking methods revealed that offline-trained models, particularly support vector machines and weighted k-nearest neighbors, provided superior tracking performance and energy extraction efficiency.

Key Findings Include:

- **Intelligent tracking models** significantly outperformed gradient-based methods, especially under severe shading conditions.
- **Offline-trained learning models** showed greater stability and accuracy compared to real-time adaptive techniques, making them more suitable for embedded deployment.
- **Hybrid machine learning models**, such as combining artificial neural networks with support vector machines, enhanced adaptability and reduced oscillations around the optimal power point.
- **PID controllers** improved tracking precision, minimizing convergence errors and steady-state fluctuations.
- **Ensemble learning models**, especially random forests, improved tracking reliability by addressing misclassification risks under varying shading conditions.

Future Work:

Future research should explore deep learning-based tracking models, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, to further enhance tracking accuracy. Real-time implementation of intelligent tracking systems using edge computing and hardware-optimized controllers (e.g., FPGA, microcontrollers) should be investigated to improve response times and computational efficiency. Integrating IoT-based monitoring systems will enable real-time environmental data collection, predictive maintenance, and enhanced system diagnostics, supporting continuous system optimization.

Additionally, the development of hybrid renewable energy systems, such as solar wind and solar-battery combinations, should be explored for better energy management and smart grid integration. The optimization of DC-DC converter architectures will also be key to minimizing power losses and enhancing overall system performance. This study underscores artificial intelligence-driven maximum power point tracking as a transformative approach for the next generation of photovoltaic systems.

Future research should prioritize computational efficiency, real-time AI deployment, and adaptive tracking strategies to enable the widespread adoption of intelligent renewable energy systems, ultimately improving energy harvesting, system stability, and integration with the broader grid.

References:

[1] M. Yılmaz and M. F. Çorapsız, "A robust MPPT method based on optimizable Gaussian process regression and high order sliding mode control for solar systems under partial shading conditions," *Renew. Energy*, vol. 239, p. 122339, 2025, doi: https://doi.org/10.1016/j.renene.2025.122339.

[2] F. Belhachat, C. Larbes, and R. Bennia, "Empowering MPPT Efficiency in Partial Shading with Machine Learning Driven Metaheuristic Strategies: Recent Developments," *Lect. Notes Networks Syst.*, vol. 1238 LNNS, pp. 594–612, 2025, doi: 10.1007/978-3-031-80301-7_64.

[3] Y. H. Liu, Y. S. Cheng, and Y. C. Huang, "A machine learning-based global maximum power point tracking technique for a photovoltaic generation system under complicated partially shaded conditions," *IEEE Trans. Sustain. Energy*, 2024, doi: 10.1109/TSTE.2024.3519721.

[4] P. V. Mahesh, S. Meyyappan, and R. K. R. Alla, "A Hybrid MPPT Technique Using Regression Machine Learning and P&O Algorithm for Solar PV Systems Under Partial Shading," *2024 IEEE Silchar Subsect. Conf. SILCON 2024*, 2024, doi: 10.1109/SILCON63976.2024.10910645.

[5] S. M. M. & P. V. Chakarajamula Hussaian Basha, Madhu Palati, C. Dhanamjayulu, "A novel on design and implementation of hybrid MPPT controllers for solar PV systems under various partial shading conditions," *Sci. Reports Vol.*, vol. 14, p. 1609,

2024, doi: https://doi.org/10.1038/s41598-023-49278-9.
[6] K. V LEELAVATHI, M.; SURESH, "Enhancing MPPT in partially shaded PV modules: a novel approach using adaptive reinforcement learning with neural network architecture," *Bull. Polish Acad. Sci. Tech. Sci.*, 2024.
[7] S. Farajdadian and S. M. H. Hosseini, "DMPPT control of photovoltaic systems under partial shading conditions based on optimized neural networks," *Soft Comput.*, vol. 28, no. 6, pp. 4987–5014, Mar. 2024, doi: 10.1007/S00500-023-09196-4/METRICS.
[8] X. W. & J. L. Chunliang Mai, Lixin Zhang, Xuewei Chao, Xue Hu, "A novel MPPT technology based on dung beetle optimization algorithm for PV systems under complex partial shade conditions," *Sci. Rep.*, vol. 14, p. 6471, 2024, doi: https://doi.org/10.1038/s41598-024-57268-8.
[9] A. Mellit and S. A. Kalogirou, "Artificial intelligence techniques for photovoltaic applications: A review," *Prog. Energy Combust. Sci.*, vol. 34, no. 5, pp. 574–632, Oct. 2008, doi: 10.1016/J.PECS.2008.01.001.
[10] S. I. P. K. H. Kim, Y. H. Kim, D. S. Kim, "Application of support vector machine and hybrid model for the prediction of maximum power point in photovoltaic systems," *Energies*, vol. 12, no. 7, p. 1259, 2019.
[11] L. Bouselham, M. Hajji, B. Hajji, and H. Bouali, "A New MPPT-based ANN for Photovoltaic System under Partial Shading Conditions," *Energy Procedia*, vol. 111, pp. 924–933, 2017, doi: https://doi.org/10.1016/j.egypro.2017.03.255.
[12] R. A. P. Venkata Mahesh, S. Meyyappan, "Support Vector Regression Machine Learning based Maximum Power Point Tracking for Solar Photovoltaic systems," *Int. J. Electr. Comput. Eng. Syst.*, vol. 14, no. 1, 2023, doi: https://doi.org/10.32985/ijeces.14.1.11.
[13] M. U. N. S. Umar, M. S. Qureshi, "Thermal Imaging and AI in Solar Panel Defect Identification," *Int. J. Adv. Eng. Technol. Innov.*, vol. 1, no. 3, pp. 73–95, 2024.
[14] S. N. Z. Ishrat, A. K. Gupta, "A comprehensive review of MPPT techniques based on ML applicable for maximum power in solar power systems," *J. Renew. Energy Environ.*, vol. 11, no. 1, p. 2837, 2024.
[15] B. M. B. K. Nayak, A. Mohapatra, "Non linear IV curve of PV module: Impacts on MPPT and parameters estimation," *IJERT*, vol. 1, no. 8, pp. 1–8, 2012.
[16] R. G. G. T. Klise, O. Lavrova, "SANDIA REPORT PV System Component Fault and Failure Compilation and Analysis," *Sandia Natl. Lab.*, 2018.
[17] Z. Zhang et al, "Deep Reinforcement Learning (DRL) for MPPT outperforms ANN and SVM," 2023.
[18] X. Li et al, "Transformer networks used for real-time MPPT optimization," 2022.
[19] G. Shankar and V. Mukherjee, "MPP detection of a partially shaded PV array by continuous GA and hybrid PSO," *Ain Shams Eng. J.*, vol. 6, no. 2, pp. 471–479, 2015, doi: https://doi.org/10.1016/j.asej.2014.10.017.
[20] A. L. Karan Yadav, Bhavnesh Kumar, Josep M. Guerrero, "A hybrid genetic algorithm and grey wolf optimizer technique for faster global peak detection in PV system under partial shading," *Sustain. Comput. Informatics Syst.*, vol. 35, p. 100770, 2022, doi: https://doi.org/10.1016/j.suscom.2022.100770.
[21] L. Bhukya, A. Annamraju, and S. Nandiraju, "A novel maximum power point tracking technique based on Rao-1 algorithm for solar PV system under partial shading conditions," *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 9, p. e13028, Sep. 2021, doi: 10.1002/2050-7038.13028.
[22] A. S. Johannes Hofer, Abel Groenewolt, Prageeth Jayathissa, Zoltan Nagy, "Parametric analysis and systems design of dynamic photovoltaic shading modules,"

Energy Sci. Eng., 2016, doi: https://doi.org/10.1002/ese3.115.
[23] R. K. Pachauri et al, "Impact of Partial Shading on Various PV Array Configurations and Different Modeling Approaches: A Comprehensive Review," *IEEE Access*, vol. 8, pp. 181375–181403, 2020, doi: 10.1109/ACCESS.2020.3028473.
[24] P. E. C. Karuppasamy, C. Senthil Kumar, R. Ganesan, "Optimizing PID control for maximum power point tracking in photovoltaic systems under variable and partial shading conditions," *Renew. Energy*, vol. 246, p. 122930, 2025, doi: https://doi.org/10.1016/j.renene.2025.122930.
[25] I. Ul Haq, S. Anwar, and T. Khan, "Machine Vision Based Predictive Maintenance for Machine Health Monitoring: A Comparative Analysis," *2023 Int. Conf. Robot. Autom. Ind. ICRAI 2023*, 2023, doi: 10.1109/ICRAI57502.2023.10089572.