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Hybrid AI and Optimization Algorithms for Performance Enhancement of Grid-Connected Solar PV Systems

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Abstract: The increasing penetration of grid-connected solar photovoltaic (PV) systems has created significant challenges in maintaining efficiency, stability, and reliability under highly dynamic environmental conditions. Variations in solar irradiance, partial shading, temperature fluctuations, and load uncertainty degrade system performance and complicate control, forecasting, and energy management processes. In this context, hybrid artificial intelligence (AI) and optimization algorithms have emerged as a promising solution for enhancing PV system performance through intelligent, adaptive, and data-driven strategies. This study presents a comprehensive overview of hybrid AI and optimization techniques applied to key operational domains of PV systems. For Maximum Power Point Tracking (MPPT) under partial shading conditions, hybrid models such as ANN–PSO and CNN–GA are explored to improve tracking accuracy and convergence speed. In the area of real-time fault detection and predictive maintenance, deep learning frameworks using CNN and LSTM architectures enable early identification of degradation, hotspot formation, and inverter faults. Furthermore, hybrid metaheuristic optimization approaches such as PSO–GA and DE–ACO are examined for effective PV system parameter tuning, improving inverter efficiency and controller stability under varying irradiance conditions. Additionally, AI-based grid stability enhancement is addressed through reinforcement learning and adaptive control techniques aimed at mitigating voltage fluctuations, harmonics, and frequency deviations caused by PV intermittency. For energy forecasting and smart dispatch in PV-integrated smart grids, hybrid models such as LSTM–XGBoost and Transformer-based architectures are integrated to achieve accurate short-term solar power prediction and optimal energy scheduling. The findings highlight that hybrid AI and optimization frameworks significantly improve overall system efficiency, operational reliability, and smart grid performance, making them a key enabling technology for next-generation renewable energy systems.

Keywords: Hybrid Artificial Intelligence, Grid-Connected Solar PV Systems, Maximum Power Point Tracking (MPPT), Metaheuristic Optimization, Smart Grid Energy Management.

1.Introduction

Hybrid Artificial Intelligence (AI) and optimization algorithms have become a central research direction for improving the performance of grid-connected solar photovoltaic (PV) systems [1-3]. The inherent nonlinear and stochastic nature of PV systems, driven by fluctuating solar irradiance, temperature variation, and partial shading conditions, makes conventional control and optimization techniques insufficient for achieving optimal performance [4-7]. Figure 1 illustrates the role of Generative AI in solar energy: enhancing efficiency, maintenance, and grid integration. These traditional methods often struggle with slow convergence, local optima entrapment, and poor adaptability to rapidly changing environmental conditions [8-10]. In contrast, hybrid AI-based frameworks integrate data-driven learning models with global optimization strategies, enabling more intelligent and adaptive system operation. Techniques such as ANN–PSO, CNN–GA, and LSTM–based hybrid optimizers enhance Maximum Power Point Tracking (MPPT), improve dynamic response, and increase overall energy harvesting efficiency in grid-connected PV systems.

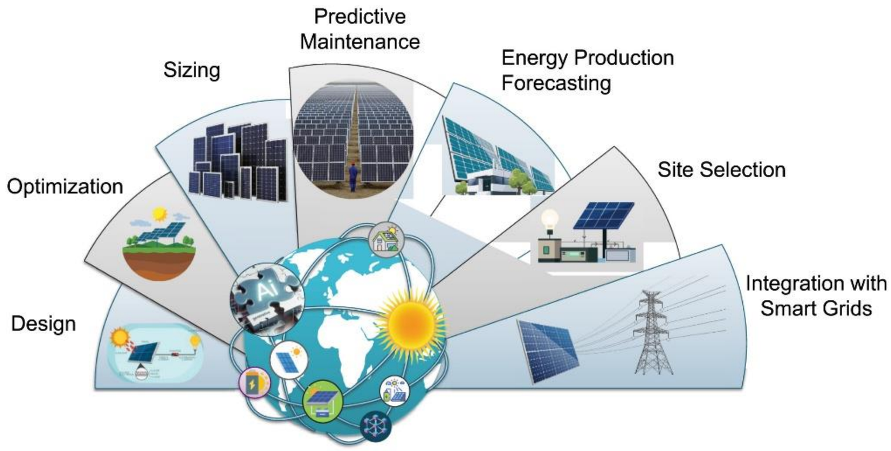

Figure 1. the role of Generative AI in solar energy: enhancing efficiency, maintenance, and grid integration [11].

Beyond MPPT enhancement, hybrid AI and optimization approaches play a crucial role in real-time fault detection and predictive maintenance of PV systems [12-15]. Deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are capable of identifying complex spatial and temporal patterns in PV performance data, enabling early detection of faults such as hotspot formation, module degradation, and inverter failures. When combined with optimization algorithms, these models not only improve classification accuracy but also reduce false alarms and enhance diagnostic reliability [16-18]. Furthermore, hybrid metaheuristic techniques such as PSO–GA and DE–ACO are widely applied for PV system parameter tuning, improving controller performance, inverter efficiency, and system stability under varying irradiance conditions. These advancements contribute significantly to reducing maintenance costs, increasing system lifespan, and ensuring continuous and reliable energy production [19-21].

In addition to control and maintenance, hybrid AI frameworks are increasingly used in energy forecasting, smart dispatch, and grid stability enhancement. Models such as LSTM–XGBoost and Transformer-based architectures provide high-accuracy short-term solar power predictions by capturing both temporal dependencies and nonlinear relationships in environmental data [22-25]. These forecasts are essential for optimal energy dispatch, battery scheduling, and demand–supply balancing in smart grids. Moreover, reinforcement learning, and adaptive optimization strategies help mitigate grid disturbances such as voltage fluctuations, frequency deviations, and harmonic distortions caused by PV intermittency [26-32]. Despite their strong advantages, challenges such as computational complexity, data dependency, and integration with legacy grid infrastructure remain critical barriers. Nevertheless, hybrid AI and optimization algorithms represent a transformative approach toward achieving efficient, resilient, and intelligent grid-connected PV systems in future smart energy networks [33-41].

In [42], an adaptive Maximum Power Point Tracking (MPPT) strategy for grid-connected photovoltaic (PV) systems was proposed using an Adaptive Neuro-Fuzzy Inference System (ANFIS) optimized through Particle Swarm Optimization (PSO) to improve energy extraction efficiency under varying environmental conditions. The developed ANFIS–PSO-based MPPT controller dynamically adjusts Pulse Width Modulation (PWM) switching to enhance tracking performance while minimizing Total Harmonic Distortion (THD). Compared with conventional Perturb and Observe (P&O) and Incremental Conductance (INC) techniques, which often experience tracking delays and difficulty identifying the global optimum under partial shading conditions, the proposed approach effectively locates the Global Maximum Power Point (GMPP), thereby improving overall energy harvesting capability. MATLAB/Simulink R2023a simulation results demonstrated that under standard operating conditions (1000 W/m² irradiance and 25 °C temperature), the controller achieved an MPPT efficiency of 99.2% while reducing THD to 2.1%, ensuring compliance with IEEE 519 grid power quality requirements.

According to [43], the paper presents a hybrid fuzzy logic proportional–integral (FLC–PI) control strategy to improve voltage stability, power quality, and inverter performance in a 26.136 MWp photovoltaic power plant connected to the Egyptian national grid. Artificial intelligence-based metaheuristic optimization techniques, including Grey Wolf Optimization (GWO), Harris Hawks Optimization (HHO), and Arithmetic Optimization Algorithm (AOA), were applied to optimize controller parameters using standard error objective functions. Simulation results in MATLAB/Simulink showed that the HHO–ISE combination achieved the best performance, reducing Total Harmonic Distortion (THD) to 3.88%, below the IEEE 519–2014 limit, thereby improving grid integration and minimizing inverter-related power quality issues.

This study by Taha et al., [44] proposed an advanced MPPT strategy for a grid-connected PV system using the Hippopotamus Optimization Algorithm (HOA) integrated with Incremental Conductance (IC) and I, PI, and FOPI controllers. The HOA was used to optimize controller parameters and compared with Arithmetic Optimization Algorithm (AOA) and Grey Wolf Optimizer (GWO). Simulation results for a 100-kW grid-connected PV system in MATLAB/Simulink showed that the HOA-based FOPI-IC-MPPT achieved superior performance, delivering 100.72 kW maximum power with a rise time of 0.0073 s, while improving dynamic response and tracking accuracy under varying operating conditions.

In [45], this paper presented an adaptive inverter control framework for grid-connected photovoltaic (PV) systems by integrating a Proportional–Integral–Derivative (PID) controller with Grey Wolf Optimization (GWO) for real-time parameter tuning. The proposed GWO–PID approach dynamically optimizes controller gains to improve transient response, voltage regulation, and power quality under varying irradiance conditions. MATLAB/Simulink results for a 50-kW grid-connected PV system demonstrated superior performance compared to conventional P and PI controllers, achieving a THD of 3.7%, stable 500 V DC-link operation, faster settling response, improved power tracking accuracy, and enhanced grid synchronization while maintaining compliance with IEEE 519–2014 standards.

This study contributes to the advancement of grid-connected solar photovoltaic (PV) systems by providing a comprehensive investigation of hybrid artificial intelligence (AI) and optimization algorithms for improving system efficiency, stability, and operational reliability under dynamic environmental conditions. The work examines AI-driven Maximum Power Point Tracking (MPPT) techniques, including ANN–PSO and CNN–GA models, to enhance tracking accuracy and convergence speed under partial shading scenarios. It further explores deep learning-based fault diagnosis frameworks using CNN and LSTM architectures for real-time detection of degradation, hotspot formation, and inverter faults, enabling predictive maintenance capabilities. Additionally, hybrid metaheuristic optimization techniques such as PSO–GA and DE–ACO are analyzed for controller parameter tuning, inverter efficiency enhancement, and stability improvement under varying irradiance conditions. The study also investigates reinforcement learning and adaptive control methods for mitigating voltage fluctuations, harmonic distortion, and frequency instability to strengthen grid stability and power quality. Furthermore, hybrid forecasting approaches including LSTM–XGBoost and Transformer-based models are discussed to improve short-term solar power prediction and intelligent energy dispatch scheduling in PV-integrated smart grids. Overall, the findings demonstrate that hybrid AI and optimization frameworks serve as an effective enabling technology for enhancing energy harvesting performance, operational intelligence, predictive maintenance capability, and grid resilience in future renewable energy systems.

2. AI-Driven Maximum Power Point Tracking (MPPT) under Partial Shading Conditions

The increasing penetration of photovoltaic (PV) systems into modern power grids has intensified the need for highly efficient and adaptive control strategies to maximize energy harvesting. Among the critical control functions in PV systems, Maximum Power Point Tracking (MPPT) plays a central role in ensuring that the PV array operates at its optimal power point under varying environmental conditions [46-48]. However, the nonlinear and dynamic nature of PV characteristics, particularly under partial shading conditions (PSC), introduces significant challenges to conventional MPPT techniques.

Traditional MPPT algorithms such as Perturb and Observe (P&O) and Incremental Conductance (IncCond) are widely used due to their simplicity and low computational requirements. Nevertheless, these methods exhibit inherent limitations, including slow convergence speed, steady-state oscillations, and failure to distinguish between local and global maximum power points when multiple peaks appear in the power–voltage (P–V) curve under PSC [49-53]. These drawbacks lead to suboptimal energy extraction and reduced overall system efficiency, especially in large-scale or urban PV installations where shading from clouds, buildings, and other obstructions is frequent and unpredictable.

To overcome these limitations, intelligent control approaches based on artificial intelligence (AI) have gained significant attention in recent years. Machine learning, and deep learning techniques offer powerful nonlinear mapping and pattern recognition capabilities, enabling more accurate estimation of the global maximum power point (GMPP). In parallel, optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and other metaheuristic methods provide robust global search capabilities that help avoid local optima traps commonly encountered in PSC environments [54-56].

More recently, hybrid AI-driven MPPT strategies, such as ANN–PSO and CNN–GA, have emerged as promising solutions by integrating learning-based prediction models with evolutionary optimization techniques. These hybrid frameworks aim to combine the strengths of both approaches, achieving faster convergence, improved tracking accuracy, and enhanced robustness under rapidly changing irradiance conditions. Such advancements are particularly important for grid-connected PV systems, where maintaining stable and efficient power output is essential for grid reliability and power quality [57-62]. Table 1 emphasizes the potential of advanced AI and optimization integration in improving PV system efficiency, reliability, and scalability in future smart grid environments.

Table 1. AI-Driven Maximum Power Point Tracking (MPPT) under Partial Shading Conditions

Category	AI/Hybrid Method	Core Idea	Strengths	Suitability under Partial Shading Conditions (PSC)
Classical Machine Learning–based MPPT	SVM, k-NN, Random Forest, Decision Trees	Learns mapping between PV variables (V, I, G, T) and optimal operating point	Simple structure, fast inference, low computational cost	Moderate performance; struggles with highly dynamic shading patterns
Artificial Neural Network (ANN)-based MPPT	Feedforward ANN, MLP	Approximates nonlinear PV characteristics to estimate GMPP	Good nonlinear modeling, fast response after training	High suitability; effective in moderate PSC environments
Deep Learning-based MPPT	CNN, LSTM, DNN	Extracts spatial/temporal features from PV data for GMPP prediction	High accuracy, strong feature extraction, adaptive learning	Very high suitability; excellent for complex and rapidly changing PSC
Swarm Intelligence-based MPPT	PSO, GWO, ACO, BAT Algorithm	Uses population-based search to locate global MPP	Good global search capability avoids local maxima	High suitability; robust in multi-peak P–V curves under PSC
Evolutionary Algorithm-based MPPT	Genetic Algorithm (GA),	Optimizes duty cycle or voltage via evolutionary processes	Strong global optimization ability	High suitability; effective but may lag in real-time systems

	Differential Evolution (DE)			
Hybrid AI + Optimization MPPT	ANN–PSO, CNN–GA, LSTM–GWO	Combines learning models with metaheuristic optimization	High accuracy, fast convergence, strong robustness	Very high suitability; best performance under severe PSC
Reinforcement Learning-based MPPT	Q-Learning, Deep Q-Network (DQN)	Learns optimal control policy through reward feedback	No explicit modeling needed, adaptive learning	High suitability for dynamic and uncertain environments
Fuzzy Logic + AI-based MPPT	Neuro-fuzzy systems, Adaptive Fuzzy controllers	Uses linguistic rules combined with AI learning	Robust, interpretable, good under uncertainty	Moderate to high suitability depending on tuning
Ensemble AI-based MPPT	Hybrid stacking (ANN + RF + PSO, etc.)	Combines multiple AI models for improved decision making	High accuracy, reduced variance, strong robustness	Very high suitability for advanced smart PV systems

The comparative analysis of AI-driven Maximum Power Point Tracking (MPPT) techniques under partial shading conditions (PSC) demonstrates a clear shift from conventional deterministic algorithms toward intelligent, adaptive, and hybrid optimization frameworks. This transition is primarily driven by the intrinsic limitations of classical methods such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), which are unable to reliably track the global maximum power point (GMPP) in the presence of multiple local maxima on the PV power–voltage (P–V) characteristics.

Machine learning-based MPPT approaches, including Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN), provide improved decision-making capability by learning the relationship between environmental inputs and optimal operating points. These methods offer fast inference once trained; however, their performance is highly dependent on the quality and representativeness of training datasets. In highly dynamic PSC environments, this dependency can limit generalization capability, especially when shading patterns deviate from training scenarios. In this context, Artificial Neural Networks (ANNs) improve nonlinear mapping accuracy and are widely adopted due to their ability to approximate complex PV behavior. Nevertheless, ANN-based MPPT systems often face challenges related to training convergence and susceptibility to local minima during learning. This limitation has motivated the integration of ANN with optimization algorithms such as Particle Swarm Optimization (PSO), leading to ANN–PSO hybrid structures that enhance both parameters tuning and global search capability.

Deep learning models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, demonstrate superior performance in capturing spatial and temporal variations in irradiance and PV output. These models significantly improve prediction accuracy of the GMPP under rapidly changing conditions. However, their computational complexity and data requirements remain key barriers to real-time implementation in resource-constrained embedded PV controllers. On the optimization side, metaheuristic algorithms such as Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Differential Evolution (DE) have proven effective in avoiding local optima and enhancing global search performance. These algorithms are particularly useful under PSC where the P–V curve exhibits multiple peaks. Despite their robustness, standalone optimization methods may suffer from slower convergence speeds, making them less suitable for fast-changing environmental conditions.

Hybrid AI approaches, such as ANN–PSO and CNN–GA, represent the most promising direction for next-generation MPPT systems. These frameworks combine the predictive strength of AI models with the exploratory capability of optimization algorithms, resulting in improved tracking accuracy, faster convergence, and higher energy yield. Such hybridization effectively mitigates the weaknesses of individual methods and enhances adaptability under complex shading patterns. Moreover, Reinforcement learning-based MPPT techniques further extend adaptability by enabling systems to learn optimal control policies through interaction with the environment. While these approaches eliminate the need for explicit system modeling, they require extensive training episodes and may exhibit instability during early learning stages.

3. Real-Time Fault Detection and Predictive Maintenance Using Deep Learning in PV Systems

The reliable operation of grid-connected photovoltaic (PV) systems is increasingly critical as solar energy penetration continues to expand within modern power networks. However, PV systems are highly susceptible to a wide range of faults and performance degradation mechanisms, including partial shading effects, hotspot formation, module aging, inverter malfunctions, and sensor anomalies. These issues can significantly reduce energy yield, compromise system efficiency, and in severe cases, lead to equipment failure or safety risks. Traditional fault detection methods, which are often based on threshold limits, rule-based logic, or simple statistical analysis, are generally inadequate for capturing the complex nonlinear and time-varying behavior of PV systems operating under real-world environmental conditions [63-68].

In recent years, deep learning techniques have emerged as a powerful solution for real-time fault detection and predictive maintenance in PV systems due to their superior ability to learn hierarchical representations from large-scale data. Models such as Convolutional Neural Networks (CNNs) are effective in extracting spatial features from electrical signatures and thermal images, while Long Short-Term Memory (LSTM) networks are particularly suited for modeling temporal dependencies and forecasting degradation trends. Hybrid architectures, such as CNN–LSTM and autoencoder-based frameworks, further enhance diagnostic accuracy by combining spatial–temporal learning with anomaly detection capabilities [69-74]. Table 2 shows types of Real-Time Fault Detection and Predictive Maintenance Using Deep Learning in PV Systems

Table 2. Types of Real-Time Fault Detection and Predictive Maintenance Using Deep Learning in PV Systems

Type	Core Function	Detected Faults	Key Strengths	Application Role in PV Systems
CNN-based Fault Detection	Extracts spatial features from PV signals, thermal images, or IV curves	Extracts spatial features from PV signals, thermal images, or IV curves	High feature extraction capability, strong image-based diagnosis	Visual inspection and signal-based fault classification
LSTM-based Predictive Maintenance	Models temporal dependencies in PV performance data for forecasting degradation	Gradual degradation, aging, performance drift	Excellent time-series prediction, early fault forecasting	Long-term health monitoring and failure prediction
CNN–LSTM Hybrid Models	Extracts spatial features (CNN) and temporal patterns (LSTM) simultaneously	Hotspots, inverter faults, degradation, shading effects	High accuracy, robust spatial-temporal learning	Comprehensive real-time fault diagnosis and prediction
Autoencoder-based Anomaly Detection	Learns normal operating behavior and detects deviations	Unknown faults, sensor anomalies, inverter malfunctions	Works without labeled fault data, unsupervised learning capability	Early-stage anomaly detection in PV systems
RNN-based Fault Detection	Processes sequential PV data for pattern recognition	Voltage fluctuations, current instability, transient faults	Suitable for sequential data, simpler than LSTM	Short-term monitoring of PV performance

GAN-based Fault Simulation & Detection	Generates synthetic fault data and improves detection robustness	Rare faults, complex shading patterns	Enhances dataset diversity, improves model generalization	Data augmentation and rare fault identification
GAN-based Fault Simulation & Detection	Generates synthetic fault data and improves detection robustness	Rare faults, complex shading patterns	All major PV faults including inverter and module faults	Data augmentation and rare fault identification
Hybrid Deep Learning + Optimization Models	Optimizes model parameters and improves prediction accuracy	All major PV faults including inverter and module faults	High accuracy, adaptive performance, optimized learning	Advanced predictive maintenance in smart PV grids
Transformer-based Models	Captures long-range dependencies in PV data	Complex degradation patterns, multi-source faults	State-of-the-art accuracy, scalable architecture	Next-generation predictive maintenance systems

The analysis of deep learning-based approaches for real-time fault detection and predictive maintenance demonstrates their significant potential for improving the operational reliability and efficiency of grid-connected photovoltaic (PV) systems. Conventional diagnostic methods, including threshold-based monitoring and rule-driven algorithms, often struggle to identify early-stage degradation and complex fault patterns due to the nonlinear and dynamic operating conditions of PV installations. Environmental variability, irradiance fluctuations, temperature changes, and component aging further complicate fault identification, creating a need for intelligent frameworks capable of adaptive learning and robust decision-making.

Hybrid deep learning architectures, particularly CNN–LSTM models, provide a more comprehensive solution by integrating spatial feature extraction with temporal pattern recognition. These frameworks demonstrate improved detection accuracy for inverter faults, hotspot formation, degradation mechanisms, and shading-induced abnormalities. The fusion of multiple learning mechanisms enhances model robustness under highly dynamic operating conditions and contributes to more reliable predictive maintenance scheduling. In addition, advanced techniques such as autoencoders and transformer-based models further strengthen anomaly detection capability and improve adaptability to previously unseen fault scenarios.

Despite these advantages, several challenges remain for practical implementation. Large-scale labeled datasets are often required for effective model training, while computational complexity can limit deployment in low-cost monitoring hardware. Model interpretability and cybersecurity considerations also represent emerging concerns as intelligent PV monitoring platforms become increasingly interconnected within smart grid environments. Future developments should focus on lightweight deep learning architectures, transfer learning approaches, federated learning frameworks, and edge AI deployment to improve scalability and real-time applicability. Overall, deep learning-driven fault diagnosis and predictive maintenance represent a transformative direction for modern PV systems. Intelligent monitoring frameworks enable earlier fault identification, reduce maintenance costs, minimize energy losses, and improve long-term operational stability. As computational capabilities continue to advance, hybrid deep learning models are expected to play a central role in enabling resilient, autonomous, and high-performance photovoltaic energy infrastructures.

4. Hybrid Metaheuristic Optimization Techniques for PV System Parameter Tuning

The rapid expansion of photovoltaic (PV) power generation has intensified the demand for intelligent optimization techniques capable of improving system efficiency, operational stability, and power quality under dynamic environmental conditions [75-81]. Grid-connected PV systems operate in highly nonlinear environments where solar irradiance fluctuations, temperature variations, partial shading, and load uncertainties continuously influence system performance. Conventional optimization methods often struggle to identify optimal operating parameters in real time due to limited exploration capability and susceptibility to local optima [82-93]. Consequently, enhancing controller tuning, inverter performance, and system stability has become a major research focus for achieving higher energy conversion efficiency and reliable PV integration into modern power networks. Figure 2 demonstrates block diagram of hybrid optimization and MPPT for solar input to grid integration

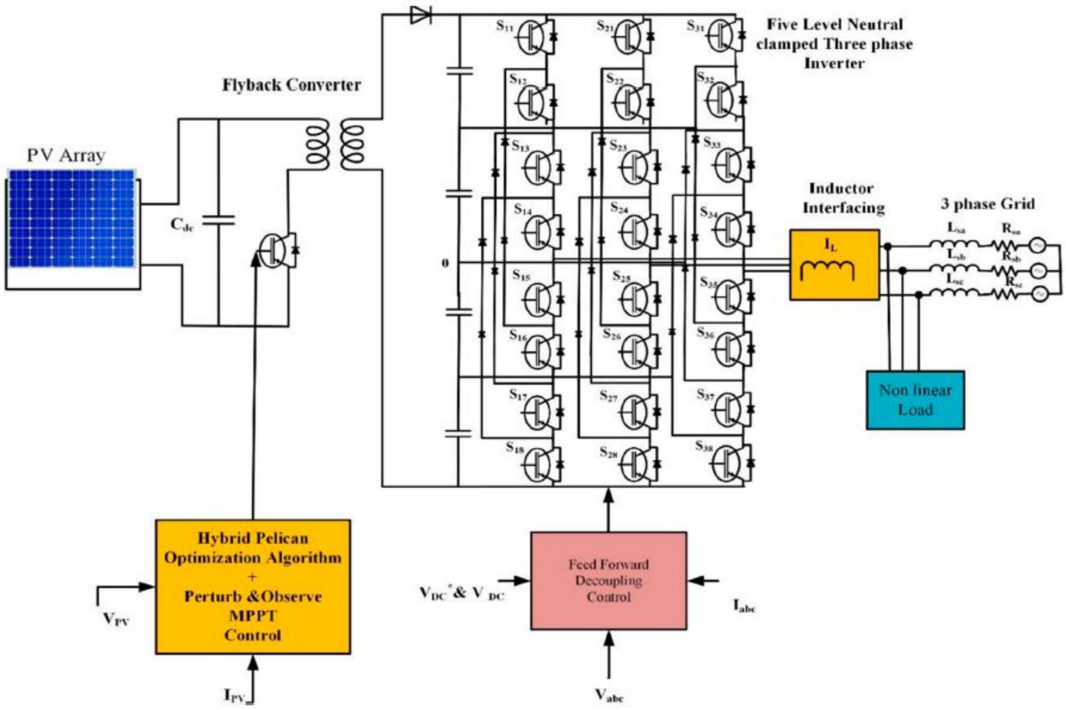

Figure 2. Block diagram of hybrid optimization and MPPT for solar input to grid integration [94].

Hybrid metaheuristic optimization techniques have emerged as a promising solution by combining the strengths of multiple optimization algorithms to overcome the limitations of standalone approaches. Methods such as Particle Swarm Optimization–Genetic Algorithm (PSO–GA), Differential Evolution–Ant Colony Optimization (DE–ACO), and Grey Wolf Optimizer–Particle Swarm Optimization (GWO–PSO) integrate global exploration and local exploitation mechanisms to improve convergence speed, parameter optimization accuracy, and system robustness. These hybrid frameworks have demonstrated strong potential for applications including Maximum Power Point Tracking (MPPT), controller parameter tuning, inverter efficiency enhancement, and dynamic energy management under varying irradiance conditions. By enabling adaptive optimization and intelligent control, hybrid metaheuristic strategies contribute significantly to improving the reliability, efficiency, and long-term operational performance of next-generation grid-connected PV systems. **Table 3** illustrates hybrid metaheuristic optimization techniques for PV system parameter tuning.

Table 3. Hybrid Metaheuristic Optimization Techniques for PV System Parameter Tuning

Hybrid Optimization Method	Combined Algorithms	Optimization Objective	Application in PV Systems	Key Advantages
PSO–GA Hybrid Optimization	Particle Swarm Optimization (PSO) + Genetic Algorithm (GA)	Optimize controller gains, MPPT parameters, and inverter operation	PV controller tuning, maximum power extraction, grid-connected inverter optimization	Fast convergence, strong global search capability, reduced local optimum trapping

DE–ACO Hybrid Optimization	Differential Evolution (DE) + Ant Colony Optimization (ACO)	Improve parameter adaptation and system stability	PV inverter control, voltage regulation, and energy management	Better exploration–exploitation balance, improved optimization accuracy
PSO–DE Optimization	Particle Swarm Optimization + Differential Evolution	Enhance convergence speed and optimization precision	MPPT tuning, DC–DC converter control, PV array optimization	Improved search diversity, reduced premature convergence
GA–ACO Hybrid Optimization	Genetic Algorithm + Ant Colony Optimization	Optimize power flow and controller parameters	Grid-interactive PV systems and smart inverter coordination	Robust optimization performance, improved solution quality
GWO–PSO Hybrid Optimization	Grey Wolf Optimizer (GWO) + Particle Swarm Optimization	Improve global search efficiency and stability	PV converter parameter tuning and dynamic control optimization	Faster convergence and strong exploration capability
PSO–Fuzzy Optimization	Particle Swarm Optimization + Fuzzy Logic	Adaptive controller parameter adjustment	MPPT enhancement and inverter control under irradiance variations	Improved robustness under uncertainty
GA–ANN Optimization	Genetic Algorithm + Artificial Neural Network	Optimize neural network weights and prediction accuracy	Intelligent PV power forecasting and adaptive control	Higher prediction precision and adaptive learning
ACO–ANN Optimization	Ant Colony Optimization + Artificial Neural Network	Enhance learning parameter selection	Fault diagnosis and predictive maintenance in PV systems	Improved model accuracy and feature optimization
Hybrid Multi-Objective Optimization	PSO–GA–DE or combined metaheuristics	Simultaneous optimization of efficiency, stability, and power quality	Smart grid-integrated PV systems	Better trade-off management among multiple objectives
Adaptive Hybrid Metaheuristic Frameworks	Dynamic combination of multiple algorithms	Real-time optimization under varying irradiance and environmental conditions	Next-generation intelligent PV energy management systems	Self-adaptive performance and enhanced operational resilience

Hybrid metaheuristic optimization techniques have demonstrated substantial potential for enhancing the performance, stability, and operational efficiency of grid-connected photovoltaic (PV) systems operating under dynamic environmental conditions. Conventional optimization approaches frequently encounter challenges related to nonlinear PV behavior, irradiance variability, and complex parameter interactions, which can limit system responsiveness and energy conversion performance. By integrating complementary optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Differential Evolution (DE), Ant Colony Optimization (ACO), and Grey Wolf Optimizer (GWO), hybrid metaheuristic frameworks provide improved exploration and exploitation capabilities, enabling more accurate and adaptive parameter tuning.

The analysis indicates that hybrid optimization approaches contribute significantly to controller parameter adjustment, inverter efficiency enhancement, Maximum Power Point Tracking (MPPT) improvement, and overall grid stability. Their ability to accelerate convergence speed, avoid local optimum trapping, and maintain robust operation under varying irradiance conditions makes them highly suitable for intelligent PV energy management applications. Moreover, combining multiple optimization mechanisms improves system adaptability and resilience in highly dynamic operating environments.

Despite these advantages, practical implementation challenges remain, including computational complexity, algorithm tuning requirements, and real-time deployment constraints in embedded PV control systems. Future developments should focus on lightweight hybrid optimization architectures, adaptive self-learning mechanisms, and integration with artificial intelligence techniques to further improve scalability and operational intelligence. As smart grid technologies continue to evolve, hybrid metaheuristic optimization is expected to become an essential enabling technology for achieving highly efficient, resilient, and autonomous photovoltaic energy systems.

5. Energy Forecasting and Smart Dispatch Methods in PV-Integrated Smart Grids Using Hybrid AI Models

The increasing penetration of photovoltaic (PV) systems into modern smart grids has introduced significant challenges in maintaining reliable power balance and efficient energy management due to the intermittent and weather-dependent nature of solar energy generation [95-97]. Variations in solar irradiance, cloud movement, temperature fluctuations, and seasonal environmental conditions can cause substantial uncertainty in PV power output, directly affecting grid stability, energy dispatch planning, and operational reliability. Conventional forecasting techniques based on statistical methods and deterministic models often exhibit limited predictive capability when dealing with nonlinear and highly dynamic renewable energy systems [98-102]. Consequently, advanced forecasting and intelligent dispatch strategies have become essential for enabling stable and efficient integration of large-scale PV generation into next-generation smart grid infrastructures. Figure 3 highlights energy forecasting and smart dispatch methods.

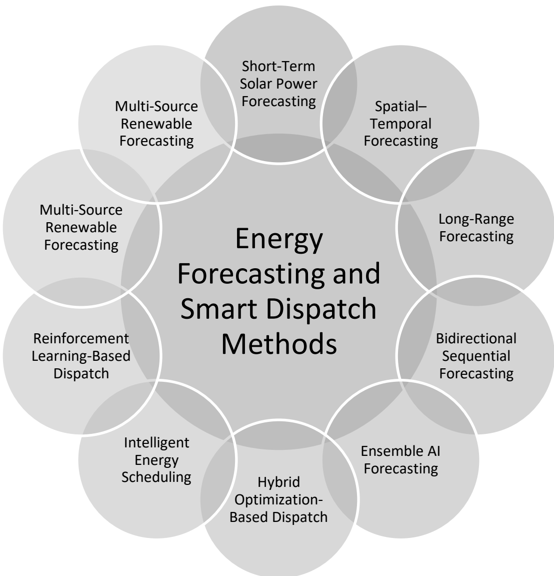

Figure 3. Energy Forecasting and Smart Dispatch Methods.

Recent advancements in artificial intelligence (AI) and hybrid machine learning techniques have created new opportunities for improving solar power prediction accuracy and optimizing energy dispatch scheduling. Deep learning approaches such as Long Short-Term Memory (LSTM) networks effectively capture temporal dependencies in historical PV generation data, while advanced machine learning methods such as Extreme Gradient Boosting (XGBoost) improve nonlinear feature learning and forecasting precision. Furthermore, Transformer-based architectures have demonstrated exceptional capability in modeling long-range temporal relationships through attention mechanisms, enhancing forecasting performance under complex operating conditions [103-114]. The integration of these hybrid AI forecasting models with intelligent dispatch scheduling frameworks enables more accurate short-term solar power prediction, optimized battery energy management, improved demand–

supply balancing, and enhanced grid resilience. Table 4 shows energy forecasting and smart dispatch methods in PV-Integrated smart grids using hybrid ai models.

Table 4. Energy Forecasting and Smart Dispatch Methods in PV-Integrated Smart Grids Using Hybrid AI Models

Type	Hybrid AI Model / Technique	Core Function	Application in PV-Integrated Smart Grids	Key Advantages
Short-Term Solar Power Forecasting	LSTM–XGBoost	Combines temporal sequence learning with nonlinear regression for accurate PV generation prediction	Hour-ahead and day-ahead solar power forecasting	High forecasting accuracy, captures temporal variability
Spatial–Temporal Forecasting	CNN–LSTM	CNN extracts weather-related features, while LSTM captures time-series dependencies	PV generation prediction under dynamic weather conditions	Strong feature extraction and temporal modeling
Long-Range Forecasting	Transformer-Based Models	Uses attention mechanisms to capture long-term temporal relationships	Utility-scale PV forecasting and grid scheduling	Handles long sequences efficiently, high prediction precision
Bidirectional Sequential Forecasting	BiLSTM–Attention Models	Processes historical information in both forward and backward directions with attention learning	Smart grid demand–generation balancing	Improved sequence dependency modeling
Ensemble AI Forecasting	Random Forest–LSTM	Combines machine learning and deep learning for robust forecasting	Multi-variable solar power prediction	Improved robustness and reduced forecasting variance
Hybrid Optimization-Based Dispatch	LSTM–PSO	Integrates forecasting with optimization for energy dispatch scheduling	Battery charging/discharging coordination and PV dispatch	Better operational efficiency and dispatch optimization
Intelligent Energy Scheduling	Transformer–Genetic Algorithm (GA)	Combines advanced forecasting with optimal dispatch control	Smart grid energy management and resource allocation	Enhanced scheduling efficiency
Reinforcement Learning-Based Dispatch	Deep Reinforcement Learning (DRL)	Learns adaptive dispatch strategies from operational environments	Real-time grid balancing and demand response	Adaptive control capability
Multi-Source Renewable Forecasting	Hybrid CNN–Transformer	Integrates multiple renewable energy inputs and weather variables	PV–wind hybrid energy forecasting	High forecasting reliability
Advanced Smart Grid Dispatch Systems	Ensemble Hybrid AI Frameworks	Combines multiple AI models for forecasting and scheduling decisions	Integrated PV-storage-grid operation	High flexibility, strong decision capability

The integration of photovoltaic (PV) systems into smart grid infrastructures has increased the importance of accurate energy forecasting and intelligent dispatch scheduling for maintaining reliable and efficient power system operation. Due to the stochastic nature of solar irradiance and environmental variability, PV power generation exhibits significant fluctuations that introduce uncertainty into grid operation. These uncertainties can lead to voltage instability, power imbalance, increased operating costs, and challenges in demand–supply coordination. Consequently, advanced forecasting frameworks combined with intelligent dispatch mechanisms have become essential components for enhancing renewable energy utilization and ensuring stable smart grid performance.

Traditional forecasting approaches based on statistical regression models and deterministic methods often struggle to capture the nonlinear relationships between meteorological variables and PV power generation. Their predictive accuracy tends to deteriorate under rapidly changing weather conditions, limiting their effectiveness in short-term energy management applications. In contrast, artificial intelligence (AI)-based forecasting techniques provide stronger nonlinear modeling capability and adaptive learning characteristics that improve prediction reliability. Machine learning algorithms can identify hidden patterns in historical operational data, enabling more accurate estimation of future PV output.

Among deep learning techniques, Long Short-Term Memory (LSTM) networks have demonstrated strong capability for short-term solar forecasting due to their ability to capture temporal dependencies in sequential PV generation data. LSTM models effectively process historical irradiance patterns and environmental information, making them highly suitable for time-series prediction problems. However, standalone LSTM models may exhibit limitations when handling highly complex nonlinear feature interactions. Hybrid frameworks such as LSTM–XGBoost address this issue by combining temporal learning capability with advanced regression performance, leading to improved forecasting precision and reduced prediction errors.

Transformer-based architectures have recently emerged as a highly promising approach for renewable energy forecasting because of their attention mechanisms and ability to model long-range dependencies. Unlike recurrent neural networks, Transformers process sequential information more efficiently and capture complex temporal relationships with higher scalability. These advantages make Transformer-based forecasting particularly valuable for utility-scale PV installations and smart grid environments where large volumes of operational data are continuously generated.

Accurate forecasting alone is insufficient without intelligent dispatch scheduling mechanisms capable of translating predictions into operational decisions. Smart dispatch frameworks utilize forecasted PV generation data to optimize battery charging and discharging schedules, balance electricity demand and supply, reduce renewable energy curtailment, and improve grid stability. Hybrid AI-driven dispatch strategies further enhance operational flexibility by integrating forecasting outputs with optimization algorithms, enabling adaptive energy allocation under uncertain operating conditions.

Despite significant advancements, several challenges remain for large-scale deployment of AI-based forecasting and dispatch systems. Data quality issues, computational complexity, model interpretability limitations, and real-time implementation constraints continue to influence system performance. Furthermore, extreme weather conditions and unexpected operating events may reduce forecasting reliability, highlighting the need for more resilient and adaptive learning architectures. Future research should focus on lightweight hybrid AI frameworks, federated learning approaches, uncertainty quantification methods, and edge intelligence deployment to improve scalability and practical applicability.

6. Opportunities and Challenges

The rapid expansion of grid-connected solar photovoltaic (PV) systems has intensified the need for advanced control, monitoring, and optimization strategies to ensure high efficiency, stability, and reliability under highly variable environmental conditions. PV systems inherently exhibit nonlinear and stochastic behavior due to fluctuations in solar irradiance, temperature variations, and partial shading effects. These uncertainties significantly affect key performance aspects such as Maximum Power Point Tracking (MPPT), energy forecasting, fault detection, and grid interaction. Traditional control and optimization techniques often struggle to maintain optimal performance in such dynamic environments because of limited adaptability and poor global search capability. Figure 4 shows opportunities. Figure 5 outlines challenges.

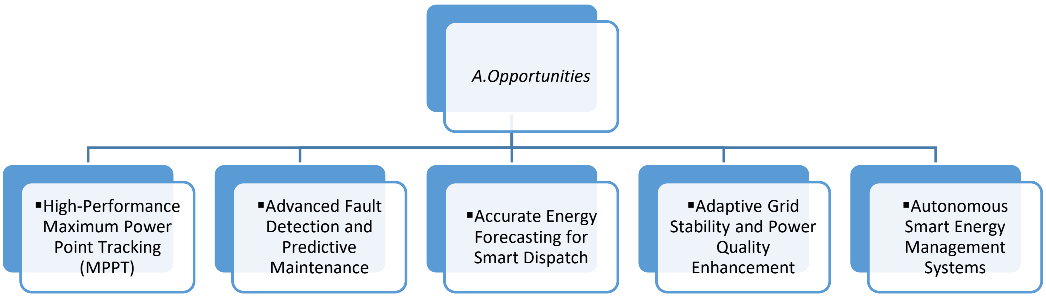

Figure 4. Opportunities

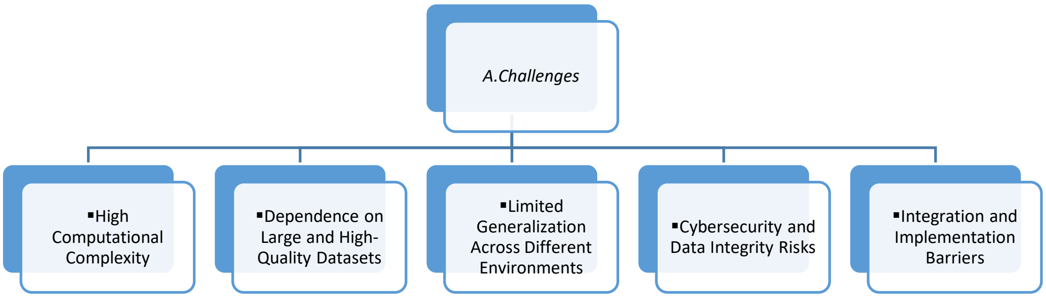

Figure 5. Challenges

In this context, hybrid artificial intelligence (AI) and optimization algorithms have emerged as a powerful solution for enhancing PV system performance. By integrating machine learning and deep learning models with metaheuristic optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Differential Evolution (DE), and Ant Colony Optimization (ACO), these hybrid frameworks enable intelligent, adaptive, and data-driven decision-making. Applications such as ANN–PSO for MPPT, LSTM–XGBoost for energy forecasting, and CNN–GA for fault diagnosis demonstrate significant improvements in accuracy, convergence speed, and operational robustness. Consequently, hybrid AI-based approaches are becoming a key enabler for next-generation smart grid-integrated PV systems.

A. Opportunities

- High-Performance Maximum Power Point Tracking (MPPT)

Hybrid AI and optimization algorithms significantly enhance Maximum Power Point Tracking (MPPT) performance in grid-connected PV systems, particularly under partial shading conditions. Classical MPPT methods often fail due to multiple local maxima in the PV characteristic curve, leading to suboptimal energy extraction. In contrast, hybrid approaches such as ANN–PSO, CNN–GA, and LSTM-based optimization frameworks combine the learning capability of AI with the global search strength of metaheuristic algorithms. This integration enables accurate identification of the global maximum power point with faster convergence and reduced oscillations, resulting in improved overall energy harvesting efficiency.

- Advanced Fault Detection and Predictive Maintenance

Hybrid AI systems provide a powerful framework for real-time fault detection and predictive maintenance in PV installations. Deep learning models can identify complex patterns associated with hotspot formation, module degradation, and inverter malfunctions, while optimization techniques enhance classification accuracy and reduce false alarms. This combination enables early detection of system anomalies before they evolve into critical failures. As a result, maintenance strategies shift from reactive to predictive, reducing downtime, minimizing operational costs, and extending the lifespan of PV system components.

- Accurate Energy Forecasting for Smart Dispatch

Energy forecasting is another key area where hybrid AI models offer significant benefits. Techniques such as LSTM–XGBoost and Transformer-based architectures improve short-term solar power prediction by capturing both temporal dependencies and nonlinear relationships in environmental data. When integrated with optimization algorithms, these forecasting outputs are transformed into optimal energy dispatch strategies. This leads to better scheduling of battery storage systems, improved demand–supply balancing, reduced energy curtailment, and enhanced stability in grid operations.

- Adaptive Grid Stability and Power Quality Enhancement

Hybrid AI and optimization algorithms also contribute to improved grid stability and power quality in PV-integrated systems. Intelligent controllers continuously adjust inverter parameters and system operating points in response to fluctuations in irradiance, load demand, and grid disturbances. Optimization techniques help maintain voltage and frequency within acceptable limits while reducing harmonic distortion. This adaptive capability ensures smoother grid integration of renewable energy sources, particularly in weak or highly variable grid conditions.

- Autonomous Smart Energy Management Systems

The integration of AI with optimization algorithms enables the development of autonomous and self-learning energy management systems. These systems coordinate PV generation, energy storage, and load demand without continuous human intervention. Over time, they improve decision-making efficiency through continuous learning from operational data. This leads to more intelligent, flexible, and resilient smart grid operations capable of maximizing renewable energy utilization while minimizing system inefficiencies.

B. Challenges

- High Computational Complexity

One of the major challenges of hybrid AI and optimization frameworks is their high computational complexity. The combination of deep learning models and metaheuristic algorithms requires significant processing power, especially when implemented in real-time PV control systems. This becomes a critical limitation for embedded devices and inverter-level controllers, where hardware resources are constrained. As a result, achieving real-time performance without sacrificing accuracy remains a key challenge.

- Dependence on Large and High-Quality Datasets

Hybrid AI models rely heavily on large volumes of high-quality data for training and validation. However, PV systems often experience issues such as missing data, sensor noise, and inconsistent measurements due to environmental and operational factors. These data limitations can significantly affect model accuracy and robustness. In many cases, insufficient or biased datasets reduce the generalization capability of the system when deployed in real-world conditions.

- Limited Generalization Across Different Environments

Another important challenge is the limited ability of trained models to generalize across different geographic and climatic conditions. PV systems behave differently depending on irradiance levels, temperature variations, and shading patterns. A model trained in one environment may not perform effectively in another without retraining or adaptation. This limits scalability and increases the complexity of deploying AI-based solutions across diverse PV installations.

- Cybersecurity and Data Integrity Risks

As PV systems become more digitally connected, cybersecurity risks become increasingly significant. Hybrid AI-based control systems depend on continuous data communication between sensors, controllers, and cloud platforms. This creates vulnerabilities to cyberattacks such as false data injection, spoofing, and communication disruptions. Any compromise in data integrity can lead to incorrect control decisions, potentially affecting grid stability and system safety.

- Integration and Implementation Barriers

Despite their advantages, integrating hybrid AI and optimization systems into existing power infrastructure remains challenging. Many legacy grid systems are not designed to support advanced

AI-based control architectures. Compatibility issues with SCADA systems, communication protocols, and regulatory frameworks can slow down implementation. Therefore, practical deployment requires careful system redesign, standardization, and gradual integration strategies.

Hybrid AI and optimization algorithms represent a transformative advancement in improving the performance of grid-connected solar PV systems. Their ability to combine predictive intelligence with global optimization strategies enables superior solutions for MPPT, fault detection, energy forecasting, and grid stability enhancement. Compared to conventional methods, hybrid frameworks offer faster convergence, higher accuracy, improved adaptability, and stronger resilience under partial shading and dynamic environmental conditions, making them highly suitable for modern smart grid applications. However, despite these advantages, several challenges still limit their large-scale deployment, including high computational complexity, dependence on large datasets, limited generalization across different environments, cybersecurity risks, and integration difficulties with existing grid infrastructure. Addressing these challenges will require future research focused on lightweight AI models, edge computing solutions, transfer learning, and secure intelligent control architectures. Overall, hybrid AI and optimization-based systems are expected to play a central role in enabling efficient, reliable, and autonomous solar PV energy systems in future sustainable energy networks.

7. Conclusion

Hybrid AI and optimization algorithms provide a powerful and flexible framework for enhancing the performance of grid-connected solar PV systems across multiple operational domains. Their integration enables significant improvements in Maximum Power Point Tracking (MPPT), particularly under partial shading conditions, where traditional methods fail to achieve global optimization. Similarly, the use of deep learning-based fault detection systems enhances the reliability of PV installations by enabling early identification of degradation, hotspot formation, and inverter malfunctions, thereby supporting predictive maintenance strategies and reducing system downtime.

Moreover, hybrid metaheuristic optimization techniques contribute effectively to PV system parameter tuning, ensuring improved inverter efficiency, controller stability, and robust operation under fluctuating irradiance conditions. In parallel, AI-driven grid stability solutions based on reinforcement learning and adaptive control help mitigate power quality issues such as voltage fluctuations, harmonics, and frequency deviations, ensuring smoother integration of PV systems into modern power grids. Additionally, hybrid forecasting models, including LSTM–XGBoost and Transformer-based approaches, significantly enhance short-term solar power prediction accuracy, enabling intelligent energy dispatch and optimal utilization of storage and grid resources.

Despite these advantages, challenges such as high computational complexity, data dependency, generalization limitations, and integration with existing grid infrastructure remain critical barriers to large-scale deployment. Future research should focus on developing lightweight hybrid models, edge-based AI implementations, federated learning approaches, and secure intelligent control architectures. Overall, hybrid AI and optimization algorithms represent a key technological pathway toward highly efficient, resilient, and autonomous grid-connected PV systems, aligning strongly with the goals of future smart and sustainable energy networks.

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