International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

AI Applications in the Solar Renewable Energy Sector: A Research Synthesis

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Abstract— The rapid growth of the solar renewable energy sector is driving the need for smarter and more efficient system operation. However, challenges such as intermittent energy generation, forecasting inaccuracies, and high operation and maintenance costs continue to limit its full potential. This study presents a comprehensive synthesis of international research on the application of Artificial Intelligence (AI) in the solar energy domain, highlighting its role in improving performance, reliability, and decision-making across the value chain.

The paper examines key AI applications including solar irradiance and power forecasting, fault detection and predictive maintenance, maximum power point tracking (MPPT), solar tracking optimization, and smart grid integration with energy storage systems. Advanced techniques such as deep learning (CNN-LSTM, Transformers), reinforcement learning, and federated learning are analyzed for their effectiveness in real-world scenarios. Furthermore, the study identifies critical research gaps, particularly in the context of Indian climatic conditions, edge AI deployment, and model interpretability. The findings suggest that AI-driven approaches can significantly enhance energy yield, reduce operational costs, and enable the transition toward intelligent, data-driven solar power systems.

Index Terms — Artificial Intelligence, Solar Energy, Photovoltaic Systems, Machine Learning, Solar Forecasting, Predictive Maintenance, MPPT.

I. INTRODUCTION

The global solar energy sector is undergoing a rapid and transformative shift as countries across the world move toward cleaner and more sustainable energy sources. With increasing concerns over climate change and rising energy demands, solar photovoltaic (PV) technology has emerged as one of the most promising solutions. The global solar PV market is expected to witness substantial growth, with new installations projected to reach around 655 GW by 2025 and further expand to nearly 930 GW by 2029. This growth reflects not only technological advancements but also strong policy support and declining costs of solar infrastructure.

However, despite its rapid expansion, the solar sector still faces critical challenges that limit its full potential. One of the primary issues is the intermittent nature of solar energy, as power generation is highly dependent on weather conditions and sunlight availability. Additionally, high operation and maintenance (O&M) costs, along with inefficiencies in monitoring and fault detection, continue to impact overall system performance and reliability.

In this context, Artificial Intelligence (AI) has emerged as a powerful enabler across the entire solar value chain. From improving energy forecasting and optimizing system performance to enabling predictive maintenance and smart grid integration, AI is transforming traditional solar power systems into intelligent and data-driven infrastructures. Industry studies indicate that AI has over 50 potential applications in the energy sector, with more than 100 companies already integrating AI

F. Site Selection

AI-based site selection uses GIS data and machine learning models to identify optimal locations for solar installations. These models analyze factors such as solar irradiance, land availability, temperature, shading, and proximity to grid infrastructure. By processing large datasets, AI ensures that solar plants are installed in locations that maximize energy generation.

G. Fault Detection

AI-driven fault detection systems use models like LSTM, SVM, and image analysis to continuously monitor system performance and identify anomalies. These systems analyze parameters such as voltage, current, and temperature to detect deviations from normal operation. Image-based techniques further help in identifying physical defects like cracks or hotspots. Early fault detection prevents energy losses and improves system reliability.

H. Energy Storage

AI optimizes energy storage systems using reinforcement learning and hybrid optimization techniques to manage battery charging and discharging. These systems consider factors such as solar generation forecasts, energy demand, electricity prices, and battery health to make optimal decisions.

I. Material Discovery

AI is increasingly used in the discovery and optimization of new solar materials, such as perovskite-based solar cells. Machine learning models analyze chemical and physical properties of materials to identify combinations that offer higher efficiency into their solutions, contributing to investments exceeding $13 billion.

II. OVERVIEW OF PHOTOVOLTAIC ENERGY GENERATION SYSTEMS

A. Traditional Solar Power Systems:

Traditional solar power systems operate using fixed settings and predefined control methods, which means they do not adapt much to changing weather or operating conditions. Power generation is typically managed using conventional MPPT techniques, and monitoring is done through basic SCADA systems that mainly show real-time data without deeper analysis. Forecasting is relatively simple and often less accurate, especially when weather conditions change quickly. Maintenance is usually either scheduled or reactive, meaning issues are addressed only after they occur.

B. AI-Integrated Solar Power Systems:

AI-integrated solar systems are designed to be smarter and more adaptive. They use advanced algorithms to analyze real-time and historical data, allowing them to predict power generation more accurately and respond effectively to changing weather conditions. AI helps optimize MPPT and solar tracking in real time, ensuring maximum energy output even in challenging conditions like partial shading. It also enables predictive maintenance by identifying potential faults before they become serious problems, reducing downtime and repair costs.

III. KEY APPLICATION DOMAINS OF AI IN SOLAR ENERGY

Here is a structural map of how AI integrates across the solar value chain:

IV. METHODOLOGIES

A. Solar Forecasting

Solar forecasting uses AI models such as CNN-LSTM, GRU, and Transformer to predict solar irradiance and power output by analyzing historical weather data, satellite inputs, and real-time sensor data. These models capture both time-based and spatial patterns, making them significantly more accurate than conventional statistical approaches. For example, traditional methods may have forecasting errors of 15–20%, whereas AI-based models can reduce this to around 5–8% using metrics like RMSE (Root Mean Square Error) and MAE (Mean Absolute Error).

B. Predictive Maintenance

Predictive maintenance leverages AI techniques such as SVM, Random Forest, and computer vision to continuously monitor system performance and detect faults before they occur. These models analyze SCADA data (voltage, current, temperature) and image data from thermal cameras or drones to identify issues like hotspots, inverter faults, and module degradation. Anomaly detection algorithms can identify deviations in current-voltage (I-V) characteristics, which indicate early-stage faults.

C. Solar Tracking

AI-based solar tracking uses reinforcement learning to dynamically adjust panel orientation based on real-time environmental conditions such as solar irradiance, cloud movement, and shading. Unlike traditional fixed or pre- and stability. This significantly reduces the time and cost required for experimental research.

V. CALCULATION AND NUMERICAL ANALYSIS

A. Solar Forecasting using CNN–LSTM

The output power of a PV system is given by:

$$P = \eta \cdot A \cdot G$$

Where P is output power, η is efficiency, A is panel area, and G is solar irradiance.

For Area = 10,000 m², Efficiency = 18%:

Traditional forecasting (20% error): P = 0.18 × 10000 × 640 = 1.15 MW

AI forecasting (5% error): P = 0.18 × 10000 × 760 = 1.37 MW

This results in improved scheduling accuracy and better grid integration.

B. Predictive Maintenance using SVM & Random Forest

Annual energy loss: Loss = Downtime × Daily Energy Loss

Without AI: = 10 × 5 = 50 MWh

With AI (40% reduction): = 6 × 5 = 30 MWh ⇒ Savings: 20 MWh annually.

C. Solar Tracking using Reinforcement Learning

For 1 MW plant: E_a^I = 1500 × 1.2 = 1800 MWh

AI tracking increases generation by 300 MWh/year.

D. MPPT Optimization using ANN

Energy Gain = $(P_a^I - P^{con}t)$ × t = (92 − 80) × 6 = 72 kWh/day

Annual gain: 72 × 365 = 26,280 kWh

E. Smart Grid Integration using Edge AI

Without AI: 2000 × 0.08 = 160 MWh; With AI: 2000 × 0.05 = 100 MWh

Savings = 60 MWh annually.

F. Site Selection using GIS & ML

Higher irradiance improves generation ≈ 20%; For 1 MW plant: 1500 → 1800 MWh

G. Fault Detection using LSTM

Without AI: 1500 × 0.1 = 150 MWh; With AI: 1500 × 0.02 = 30 MWh

Savings = 120 MWh.

H. Energy Storage Optimization

Utilization Gain = 450 − 350 = 100 kWh/day ⇒ Annual: 36,500 kWh

VII. CONCLUSION

This study shows how Artificial Intelligence (AI) can make solar power systems smarter and more efficient. Unlike traditional systems that depend on fixed settings and react only after problems occur, AI helps in predicting, optimizing, and improving system performance in real time.

Applications like solar forecasting, MPPT optimization, and predictive maintenance clearly demonstrate better accuracy, lower losses, and higher energy output. Overall, AI not only improves efficiency but also reduces operational issues and costs.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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programmed tracking systems, RL algorithms continuously learn the optimal angle to maximize incident solar radiation on the panel surface.

AI-optimized dual-axis tracking can increase energy generation by 15–25%. In a 1 MW plant, this could translate to an additional 150–250 MWh annually, depending on location.

D. MPPT Optimization

AI-based MPPT techniques, using ANN and deep learning models, improve the extraction of maximum power from PV systems under varying conditions such as partial shading and temperature fluctuations. Traditional MPPT algorithms like Perturb & Observe (P&O) or Incremental Conductance can get stuck at local maxima during partial shading, leading to power losses. AI models overcome this by learning the global maximum power point through pattern recognition.

E. Smart Grid Integration

AI enhances smart grid integration by combining Edge AI, IoT, and advanced analytics to manage energy flow in real time. These systems collect and process data from multiple sources, including solar plants, loads, and storage systems, to optimize energy distribution. AI algorithms can predict demand, adjust supply, and even enable automated energy trading. AI-based demand response systems can reduce peak load by 10–15%, while intelligent energy dispatch can reduce overall system losses by 5–8%.

VI. SUMMARY TABLE OF AI APPLICATIONS

Application	AI Tool Used	Improvement	Numerical Benefit
Forecasting	CNN-LSTM	Error ↓ 5%	+0.22 MW
Maintenance	SVM, RF	Downtime ↓ 40%	+20 MWh
Tracking	RL	Efficiency ↑ 20%	+300 MWh/yr
MPPT	ANN	Power ↑	+26,280 kWh
Smart Grid	Edge AI	Loss ↓ 3%	+60 MWh
Site Select.	GIS+ML	Output ↑ 20%	+300 MWh
Fault Det.	LSTM	Loss ↓ 8%	+120 MWh
Storage	RL	Utilization ↑	+36,500 kWh
Materials	ML	Efficiency ↑	+70 W/mod

In simple terms, AI is playing an important role in transforming conventional solar systems into more reliable and intelligent energy solutions for the future.

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