International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5755 - 5761
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0747

Artificial Intelligence In Solar Energy Forecasting and Management

Mr. Rajani Venkata Krishna[1], Mr. Syed Izaan Tirmizi[2], Mr. Mohammed Minhaj Ahmed[3], Ms. Syeda Maryam Fatima[4], Ms. Mayeda Iffath[5], Mr. Mohd. Abdullah[6], Mohammed Samad[7]
[1]Associate Professor, EEE, Lords Institute of Engineering and Technology, Himayathsagar, Hyderabad.
[2,4,5,6]UG Scholars, CSE-DS, Lords Institute of Engineering and Technology, Himayathsagar, Hyderabad, Telangana
[3,7]UG Scholar, CSE, Lords Institute of Engineering and Technology, Himayathsagar, Hyderabad, Telangana
Emails: *r.venkatakrishna@lords.ac.in[1], sdtirmizi111@gmail.com[2], minhaajahmedhyd@gmail.com[3], smaryamquadri@gmail.com[4], mayedaiffath179@gmail.com[5], mohdabdullah0421@gmail.com[6], samadmohammed704@gmail.com[7]*

Abstract
The increasing demand for clean and sustainable energy has accelerated the adoption of solar photovoltaic (PV) systems across residential, commercial, and industrial sectors. However, solar power generation is highly dependent on environmental conditions, including solar irradiance, ambient temperature, cloud cover, humidity, and wind speed. These variations create challenges in maintaining power system stability, balancing electricity demand and supply, and efficiently managing energy storage. Artificial Intelligence (AI) offers promising solutions to these challenges through advanced forecasting, intelligent decision-making, and automated energy management. This paper presents a comprehensive review of AI-based techniques for solar energy forecasting and management, focusing on machine learning (ML), deep learning, weather data integration, and smart energy systems. Methods such as Random Forest, Support Vector Regression, Artificial Neural Networks, Long Short-Term Memory networks, and hybrid forecasting models are discussed in terms of their operating principles, applications, advantages, and limitations. The paper also examines the integration of AI with smart grids, battery energy storage systems, demand-side management, and Internet of Things (IoT) technologies. Furthermore, forecasting evaluation metrics, implementation challenges, and future research directions are outlined. The review indicates that combining historical generation data with weather forecasts and real-time measurements can support more reliable solar power prediction and improve operational decision-making. The paper concludes that AI can play a significant role in developing efficient, resilient, and sustainable solar energy systems, although practical performance depends on data quality, model selection, and validation under real-world conditions.

Keywords: *Artificial Intelligence, Solar Energy Forecasting, Machine Learning, Deep Learning, Solar Photovoltaic Systems, Weather Prediction, Smart Grid, Battery Energy Storage, Energy Management.*

1. Introduction
The global transition toward renewable energy has increased the importance of solar photovoltaic technology as a sustainable source of electricity. Solar PV systems convert sunlight directly into electrical energy without producing direct operational greenhouse gas emissions. Their modular design, declining technology costs, and suitability for distributed generation have contributed to their widespread adoption. Despite these advantages, solar power generation is inherently variable. Changes in cloud cover, atmospheric conditions, solar irradiance, and temperature can produce rapid fluctuations in electricity output. These variations make it difficult for grid operators to maintain the balance between electricity generation and consumption, particularly when solar power contributes a substantial proportion of the energy mix. Traditional solar forecasting approaches commonly rely on statistical models, physical weather models, or historical averages. Although these methods remain useful, they may have limitations when relationships between environmental variables and solar generation are nonlinear or rapidly changing. AI-based forecasting techniques can learn complex patterns from historical and real-time data, making

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5755 - 5761
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0747

them valuable tools for improving prediction accuracy and supporting automated energy management. AI-based solar energy management extends beyond predicting power generation. It can also support battery charging and discharging, optimize energy consumption, identify equipment faults, and coordinate distributed energy resources. When combined with smart meters, weather stations, IoT sensors, and grid management platforms, AI can help transform conventional solar installations into intelligent energy systems.



Figure 1 AI Control Strategies

The primary objective of this paper is to review the role of AI in solar energy forecasting and management, identify suitable machine learning techniques, explain the use of weather data, and examine the integration of predictive intelligence with smart energy infrastructure.

2. Literature Review

Research on AI-based solar forecasting has progressed from conventional statistical techniques toward machine learning, deep learning, hybrid architectures, and intelligent energy management. The following studies provide a foundation for understanding this development. First, conventional machine learning models remain valuable when data are structured and the forecasting task is well defined. Algorithms such as Random Forest and SVR can offer a useful balance between predictive capability and computational cost. Second, deep learning models are particularly relevant when the data contain temporal or spatial dependencies. LSTMs can model sequential information, [1] while CNNs can extract features from sky images and weather maps. Hybrid models can combine these capabilities, although greater complexity does not guarantee better performance in every application. Third, integrating weather forecasts with historical PV output can improve the information available to prediction models. However, [2] weather forecasts themselves contain uncertainty, and their errors can propagate into power predictions. Fourth, a strong prediction model is not sufficient on its own to ensure better energy management. Its forecasts must be incorporated into a decision-making process that considers electricity demand, battery [3] constraints, operating costs, and grid requirements. Finally, cross-location validation, reproducible datasets, and uncertainty-aware evaluation remain important research priorities. Recent reviews emphasize that differences in datasets, forecast horizons, and evaluation methods complicate direct comparisons between published results [4].

3. Methodology

3.1.Solar Energy Forecasting: Fundamentals and Classification

Solar energy forecasting estimates the electrical power or solar irradiance expected at a particular location and future time. It helps power system operators schedule resources, plan maintenance, manage storage, and respond to changes in electricity demand.

3.1.1. Types of solar forecasting

Very-short-term forecasting: Used for real-time control, cloud-induced power fluctuations, inverter operation, and rapid battery response.

Short-term forecasting: Supports intraday scheduling, local energy balancing, and battery charge planning.

Day-ahead forecasting: Helps grid operators schedule conventional generation, procure electricity, and plan reserves.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5755 - 5761
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0747

Long-term forecasting: Supports energy planning, resource assessment, maintenance scheduling, and investment decisions.

Forecasting horizons should be selected according to the operational objective and data availability. Short-term prediction often benefits from local sensor measurements [5] and cloud information, whereas day-ahead prediction relies more heavily on numerical weather predictions and historical observations. These distinctions are consistent with reviews of solar forecasting techniques.

3.1.2. Factors affecting solar power generation

The principal environmental and operational factors include:

- Solar irradiance: The amount of solar radiation reaching the PV modules; a primary determinant of power generation.
- Temperature: High module temperatures generally reduce the efficiency of conventional silicon PV modules.
- Cloud cover: Clouds can rapidly reduce or fluctuate incoming solar radiation.
- Humidity and atmospheric conditions: These can be associated with cloud formation, haze, and changes in solar transmission.
- Wind speed: Wind can cool PV modules and influence their operating temperature.
- Time and season: Solar elevation, day length, and seasonal weather patterns affect available solar energy [6].
- System condition: Dust, shading, inverter efficiency, module degradation, and equipment faults influence actual output.

Consequently, an effective forecasting model should account for both weather conditions and the physical characteristics of the solar installation.

3.2.Artificial Intelligence Techniques for Solar Power Prediction

AI algorithms identify relationships between historical observations, meteorological conditions, and solar power output. Different algorithms are suitable for different datasets, forecast horizons, and computational requirements. As shown in Figure 2 Solar Forcating.

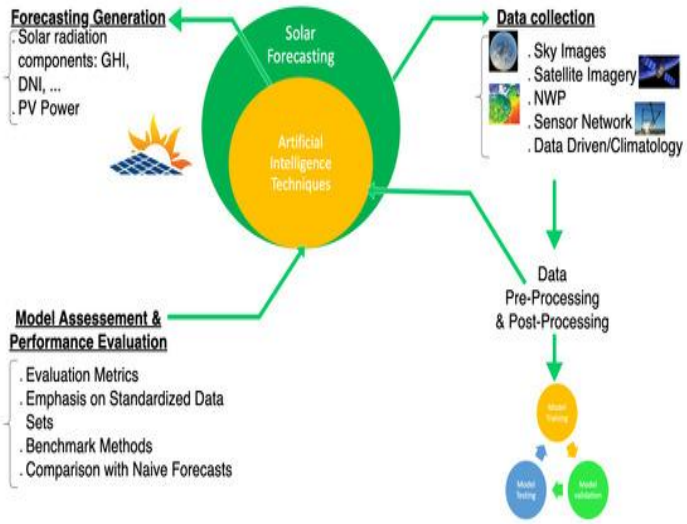


Figure 2 Solar Forcating

3.2.1. Linear regression and statistical models

Linear regression estimates solar output from a combination of input variables. For example, a model may use solar irradiance, temperature, and time of day to estimate PV power. Here, Pt is predicted power, Gt is solar irradiance, Tt is temperature, Ht is a humidity-related input, and et represents unexplained variation. Linear regression is computationally efficient and relatively easy to interpret. However, it may not adequately represent complex nonlinear relationships. Statistical time-series methods can serve as useful baselines against which more advanced AI models are evaluated.

3.2.2. Random Forest

Random Forest is an ensemble learning algorithm that combines predictions from multiple decision trees. Each tree learns relationships between weather variables, historical power output, and the forecasting target. For regression, the final prediction can be represented as: Where N is the number of trees and Pt,i is the prediction from the i-th tree.

3.2.3. Support Vector Regression

Support Vector Regression (SVR) uses a regression framework based on support vectors and a

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5755 - 5761
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0747

specified error tolerance. With an appropriate kernel, SVR can model nonlinear relationships between weather conditions and PV output. It is particularly useful for small- to medium-sized datasets when suitable [7] hyper parameters and input scaling are selected. Its main limitations include sensitivity to parameter selection, potentially expensive training on large datasets, and reduced practicality for very large, continuously updated forecasting systems.

3.2.4. Artificial Neural Networks

Artificial Neural Networks (ANNs) contain interconnected processing units that learn patterns from training examples. A typical feed-forward network receives [8] weather measurements and historical power observations and produces a power forecast.

A simplified hidden-layer relationship is:

$$h = f(Wx + b)$$

ANNs can represent nonlinear relationships and support multivariable forecasting. However, they require appropriate data preparation, hyperparameter tuning, and protection against overfitting.

3.3.Comparison of forecasting methods

As shown in Table 2 Main Limitation and strength [9].

Table 2 Main Limitation and strength

Algorithm	Main strength	Main limitation	Suitable application
Linear regression	Simple and interpretable	Limited nonlinear modeling	Baseline forecasting
Random Forest	Handles nonlinear relationships	Limited temporal extrapolation	Tabular weather data
SVR	Flexible nonlinear regression	Parameter-sensitive	Small- to medium-sized datasets
ANN	Learns complex input-output relationships	Requires careful tuning	General PV prediction
LSTM	Learns temporal dependencies	Higher training cost	Time-series forecasting
CNN-LSTM	Combines spatial and temporal learning	Requires richer data and computing	Cloud-image-based forecasting
Transformer	Models long-range dependencies	Data and compute intensive	Multistep forecasting

No algorithm is universally superior. The most appropriate model depends on forecast horizon, climate, dataset size, sensor availability, and the consequences of forecast errors. Recent reviews similarly emphasize the importance of evaluation under consistent conditions rather than ranking algorithms using results from unrelated studies [10].

4. Ai-Based Solar Energy Management

Solar forecasting and energy management are complementary functions. Forecasting estimates future generation; energy management determines

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5755 - 5761
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0747

how the available energy should be used, stored, or exported.

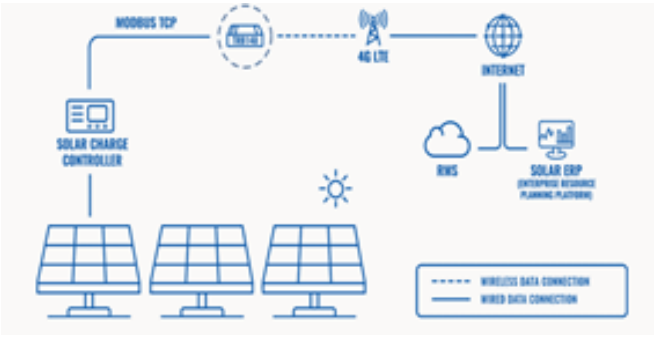


Figure 3 Solar Energy management

4.1.Battery energy storage management

Battery energy storage systems help compensate for differences between solar generation and electricity demand. AI can use expected PV output, battery state of charge, electricity prices, and load forecasts to plan charging and discharging. For example, when solar generation is expected to exceed daytime demand, the controller may charge the battery. If generation is expected to fall during the evening, stored energy can be used to reduce grid imports, subject to battery limits and operating costs.

A simplified energy balance is:

$$P_{PV} + P_{grid} + P_{dis} = P_{load} + P_{ch} + P_{export}$$

4.1.1. Smart grid integration

AI-based forecasts help utilities estimate the contribution of solar generation to total electricity supply. This information can improve generator scheduling, reserve planning, voltage management, and coordination of distributed energy resources. Forecast errors cannot be eliminated completely. Therefore, grid operators should combine point forecasts with uncertainty estimates and operational reserves rather than depend on a single predicted value.

4.1.2. Demand-side management

AI can forecast both solar production and consumer demand. Smart energy systems can then schedule flexible loads, such as water heating, electric vehicle charging, or selected industrial processes, during periods when solar electricity is more abundant. Fault detection and predictive maintenance An AI system can compare expected power output with measured generation under similar environmental conditions. A persistent difference may indicate panel soiling, shading, inverter malfunction, sensor errors, or equipment degradation. Such alerts should trigger verification rather than automatically assume that every deviation is a hardware fault. Weather uncertainty and incorrect sensor measurements can also produce prediction errors.

4.1.3. IoT-enabled energy management

IoT devices can collect real-time data from solar panels, inverters, smart meters, batteries, and environmental sensors. This information can be transmitted to local controllers or cloud-based analytics platforms. Edge computing can support low-latency decisions near the installation, while cloud computing can provide larger-scale model training, monitoring, and coordination across multiple sites. AI-based control should retain safe fallback mechanisms if communication or model services become unavailable. Research on AI for renewable power system operation highlights the broader role of forecasting, dispatch optimization, and intelligent control in managing variable renewable resources.

4.2.Performance Evaluation Metrics

A forecasting model must be evaluated using suitable metrics and a test dataset that was not used during training. Common evaluation measures include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R2)

4.2.1. Mean Absolute Error

MAE calculates the average absolute difference between actual and predicted power.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - \hat{P}_i|$$

A lower MAE indicates that predictions are closer to the observed values on average.

4.2.2. Root Mean Square Error

RMSE gives greater weight to larger prediction errors.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2}$$

This metric is useful when large forecasting errors are particularly undesirable for grid balancing or battery scheduling.

Mean Absolute Percentage Error

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5755 - 5761
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0747

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{P_i - \hat{P}_i}{P_i}\right|$$

MAPE is easy to interpret as a percentage but becomes undefined when actual power is zero and unstable when actual values are close to zero. For solar systems, this is particularly relevant around sunrise and sunset.

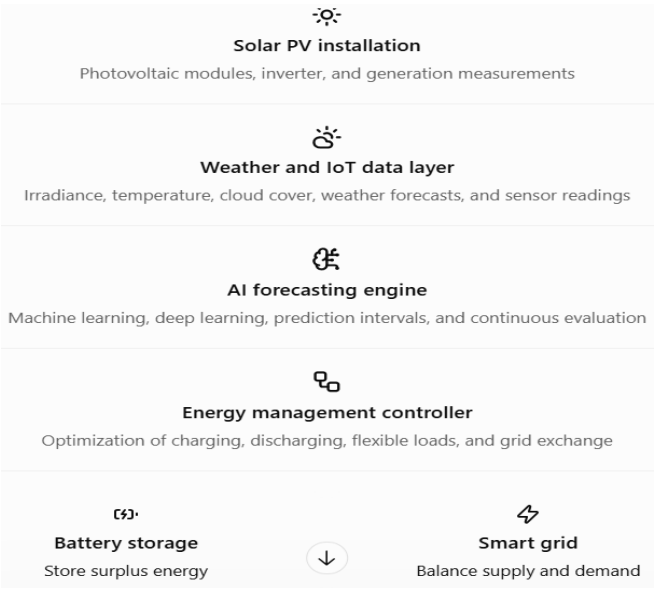
Coefficient of determination

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - \hat{P}_i)^2}{\sum_{i=1}^{n}(P_i - \bar{P})^2}$$

Here, P is the mean observed power. R2 measures how well the predictions explain variation in the observations relative to a mean-based reference. It should be interpreted alongside error metrics because a high R2 does not necessarily imply small operational errors.

4.3.Proposed AI-Based Solar Energy Management Framework

Based on the reviewed approaches, this paper proposes a conceptual framework that integrates forecasting and intelligent energy management.



Conclusion

Artificial Intelligence is an important enabling technology for improving solar energy forecasting and management. By learning patterns from historical PV generation, meteorological observations, and weather predictions, AI models can support more informed estimates of future solar power output. Machine learning algorithms such as Random Forest and Support Vector Regression offer practical solutions for structured datasets, while deep learning methods such as LSTM, CNN-LSTM, and transformer architectures provide additional capabilities for temporal and spatial modeling. The integration of forecasting with smart grids, IoT devices, battery storage, and demand-side management extends the benefits of AI beyond prediction. Such integration can support improved energy scheduling, more effective use of stored electricity, predictive maintenance, and coordination of distributed energy resources. Nevertheless, the practical value of AI depends on data quality, model validation, uncertainty handling, cybersecurity, computational cost, and compatibility with real-world operating constraints. No single forecasting algorithm is optimal for all locations and prediction horizons. This review therefore recommends an application-oriented approach in which models are selected according to the data available and the intended energy management task. Future research should prioritize reproducible evaluation, cross-climate validation, uncertainty-aware forecasting, and field-tested control strategies. With these developments, AI-based solar energy systems can contribute to more efficient, flexible, and sustainable electricity infrastructure.

Future Research Directions

Future work should focus on making AI-based solar forecasting more reliable, explainable, and suitable for deployment.

- Hybrid AI models: Combine complementary algorithms, such as CNN-LSTM or statistical-ML approaches, when the data justify their added complexity.
- Weather-image integration: Combine satellite imagery, sky cameras, numerical weather predictions, and local PV measurements.
- Transfer learning: Investigate whether models trained on data-rich sites can be adapted to locations with limited observations.
- Edge AI and IoT: Develop

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 10 October 2026
Page No: 5755 - 5761
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0747

computationally efficient models for local, real-time control with reduced dependence on cloud connectivity.

- AI-driven battery optimization: Couple generation forecasts with battery degradation, state-of-charge limits, tariffs, and demand prediction.

References

[1]. Barhmi, K., Heynen, C., Golroodbari, S., and van Sark, W. (2024). "A Review of Solar Forecasting Techniques and the Role of Artificial Intelligence." Solar, 4(1), 99–135.

[2]. Khouili, O., Hanine, M., Louzazni, M., López Flores, M. A., García Villena, E., and Ashraf, I. (2025). "Evaluating the Impact of Deep Learning Approaches on Solar and Photovoltaic Power Forecasting: A Systematic Review." Energy Strategy Reviews, 59, 101735.

[3]. "Machine Learning Forecasting of Solar PV Production Using Single and Hybrid Models over Different Time Horizons." (2024). Heliyon, 10(7), e28898.

[4]. Gupta, M., Arya, A., Varshney, U., Mittal, J., and Tomar, A. (2025). "A Review of PV Power Forecasting Using Machine Learning Techniques." Progress in Engineering Science, 2(1), 100058.

[5]. Jadapalli, S., Datta, G., Swati, G. V., Maitra, S. K., Choudhury, U., Biramo, M. L., et al. (2026). "Scoping Review of Artificial Intelligence Approaches for Solar Energy Forecasting Addressing Methodological Developments, Data Practices and Operational Implications." Discover Applied Sciences, 8, Article 665.

[6]. "Artificial Intelligence-Based Methods for Renewable Power System Operation." (2024). Nature Reviews Electrical Engineering, 1, 163–179.

[7]. "A Review of Distributed Solar Forecasting with Remote Sensing and Deep Learning." (2024). Renewable and Sustainable Energy Reviews, 198, 114391.

[8]. "Machine Learning for Photovoltaic Power Forecasting Integrated with Energy Storage Systems: A Scientometric Analysis, Systematic Review, and Meta-Analysis." (2025). Energies, 18(23), 6291.

[9]. "Machine Learning for Renewable Energy Forecasting: Advances, Challenges, and Future Directions." (2026). Sustainable Energy Research, 13, Article 14.

[10]. "A Review on Data-Driven Methods for Solar Energy Forecasting." (2025). Applied Energy, 400, 126631.