

A COMPARATIVE STUDY OF HYBRID MACHINE LEARNING AND DEEP LEARNING MODELS FOR SHORT- TERM SOLAR IRRADIANCE FORECASTING

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Abstract

Accurate short-term solar irradiance forecasting is essential for efficient solar energy generation, power system management, and the integration of renewable energy resources. However, the nonlinear relationships between solar irradiance and meteorological variables, including temperature, humidity, wind speed, and cloud cover, make reliable forecasting challenging. The present study, titled “A Comparative Study of Hybrid Machine Learning and Deep Learning Models for Short-Term Solar Irradiance Forecasting,” aims to evaluate and compare the performance of conventional machine learning, deep learning, and hybrid models. The proposed methodology involves collecting historical solar irradiance and meteorological data, preprocessing the dataset, performing exploratory data analysis, selecting relevant input variables, and developing forecasting models. Support Vector Regression, Random Forest, XGBoost, Long Short-Term Memory, Gated Recurrent Unit, and Convolutional Neural Network models will be evaluated alongside hybrid architectures, including CNN-LSTM, CNN-GRU, and machine learning-deep learning ensembles. Model performance will be assessed using Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error where appropriate, and the coefficient of determination. The comparative analysis will also consider computational efficiency, forecasting stability, and generalization performance across different prediction horizons. The illustrative results suggest that hybrid models may provide improved forecasting accuracy by combining the complementary capabilities of different learning techniques; however, these observations require validation through actual experimental implementation.

Keywords: Solar irradiance forecasting, machine learning, deep learning, hybrid models, LSTM, CNN-LSTM, renewable energy, forecasting accuracy.

1. INTRODUCTION

The increasing global demand for energy and the environmental challenges associated with conventional fossil fuels have encouraged the development and adoption of renewable energy resources. Solar energy has emerged as one of the most promising renewable energy sources because of its wide availability, environmental sustainability, and potential to reduce greenhouse gas emissions. The effective utilization of solar energy, however, depends on the accurate prediction of solar radiation reaching the Earth's surface. Solar irradiance is a key parameter in determining the output of photovoltaic systems and plays an important role in solar power generation, energy scheduling, grid management, and renewable energy planning. Therefore, accurate short-term solar irradiance forecasting has become an important research area in renewable energy systems. Solar irradiance is highly variable because it is influenced by several meteorological and environmental factors, including cloud cover, atmospheric temperature, relative humidity, wind speed, atmospheric pressure, and seasonal variations. Changes in cloud movement and atmospheric conditions can cause sudden fluctuations in the amount of solar radiation received at the Earth's surface. These variations make solar irradiance forecasting a challenging task, particularly for short-term prediction intervals such as 15 minutes, 30 minutes, and one hour. Traditional statistical forecasting techniques may be effective in identifying basic temporal patterns, but their ability to represent complex nonlinear relationships and rapidly changing atmospheric conditions can be limited. Consequently, advanced computational approaches are increasingly being explored to improve forecasting

accuracy and reliability. Machine learning techniques have gained considerable attention for solar irradiance forecasting because of their ability to identify complex relationships between historical observations and meteorological variables. Algorithms such as Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) can model nonlinear relationships and provide predictions from structured meteorological datasets. These methods can incorporate historical irradiance measurements, temperature, humidity, cloud cover, and time-related features to estimate future solar radiation. Their effectiveness, however, depends on the quality of the input data, feature selection, parameter optimization, and the characteristics of the forecasting problem. Although conventional machine learning models can achieve useful predictive performance, their ability to learn long-term temporal dependencies may require additional feature engineering or suitable model integration. Deep learning has introduced further opportunities for solar irradiance forecasting by enabling models to learn complex data representations and temporal patterns from sequential observations. Long Short-Term Memory (LSTM) networks are designed to capture dependencies across time-series data, making them suitable for modelling changes in solar irradiance over successive observation periods. Gated Recurrent Unit (GRU) networks provide an alternative recurrent architecture with a comparatively simpler gating structure. Convolutional Neural Networks (CNNs) can extract local features and patterns from sequential input data, helping identify short-term fluctuations in irradiance and meteorological measurements. Despite these advantages, deep learning models may require substantial training data, careful hyperparameter tuning, and greater computational resources. Hybrid machine learning and deep learning models have emerged as a promising approach to address some of the limitations of individual algorithms. These models combine different learning mechanisms to capture complementary characteristics of the data. For example, a CNN-LSTM architecture can use convolutional layers to extract local patterns and LSTM layers to learn temporal dependencies. Similarly, a CNN-GRU model can combine convolution-based feature extraction with recurrent sequence learning. An ensemble that combines XGBoost and LSTM predictions may integrate the strengths of tree-based learning and deep temporal modelling. Such hybrid approaches may improve forecasting performance by capturing nonlinear relationships, local variations, and temporal dependencies within the same predictive framework. However, their effectiveness must be established through systematic experimentation because increased model complexity does not automatically guarantee better accuracy.

2. LITERATURE REVIEW

El-Shahat et al. (2024) examined machine learning and deep learning models for short-term solar irradiance forecasting using grid search and cross-validation. The study emphasized hyperparameter optimization to improve prediction accuracy and reduce forecasting errors. The research highlights the importance of systematic model selection in developing reliable solar irradiance forecasting systems.

Ghiate (2026) conducted a comparative analysis of machine learning and hybrid models for global horizontal irradiance prediction in Morocco. The study focused on evaluating forecasting techniques under regional climatic conditions. The research highlights the potential of hybrid models to improve prediction accuracy and support efficient solar energy planning.

Molu et al. (2024) investigated a hybrid deep learning approach combined with Bayesian optimization for short-term solar irradiance forecasting. The study emphasized optimizing model parameters to improve forecasting performance. The research demonstrates the relevance of hybrid learning techniques for modelling complex temporal patterns in solar irradiance data.

Assaf et al. (2023) reviewed neural network-based models for short-term solar irradiance forecasting. The study discussed the application of neural networks to capture nonlinear

relationships between meteorological variables and solar radiation. The review highlighted the importance of selecting appropriate model architectures and evaluation methods to improve forecasting reliability.

Taha et al. (2024) investigated short-term and long-term solar irradiance forecasting using advanced machine learning techniques in Zafarana, Egypt. The study addressed the application of predictive models under local climatic conditions. The research highlights the importance of machine learning for improving solar irradiance prediction and supporting renewable energy planning.

3. RESEARCH METHODOLOGY

3.1 Introduction

Accurate short-term solar irradiance forecasting is essential for efficient solar energy generation, power system management, and the integration of renewable energy into electricity networks. Solar irradiance varies with atmospheric conditions, cloud cover, temperature, humidity, and seasonal changes, making its prediction a complex task. Machine learning and deep learning techniques have demonstrated potential in identifying nonlinear relationships and temporal patterns in meteorological data. However, the forecasting performance of these models may vary depending on data characteristics, model architecture, and prediction horizon. Therefore, the present study will comparatively examine conventional machine learning models, deep learning models, and hybrid approaches to determine their effectiveness in short-term solar irradiance forecasting. The research will involve data collection, preprocessing, feature selection, model development, training, validation, and performance evaluation. The findings will help identify suitable forecasting approaches based on predictive accuracy, computational efficiency, and reliability.

3.2 Research Design

The study will adopt a quantitative, experimental, and comparative research design. Historical solar irradiance and meteorological data will be used to develop and evaluate different forecasting models. The experimental approach will enable the systematic comparison of machine learning, deep learning, and hybrid models under consistent conditions. The same dataset, input variables, forecasting horizons, and evaluation metrics will be used wherever applicable to ensure a fair comparison. The study will focus on short-term forecasting, including suitable intervals such as 15 minutes, 30 minutes, and one hour, depending on the temporal resolution of the available data.

3.3 Data Collection

The study will use historical solar irradiance and meteorological data obtained from reliable observational datasets or publicly available sources. Potential sources may include NASA POWER, national meteorological databases, solar radiation monitoring stations, and other suitable research datasets. The collected data will include solar irradiance measurements and relevant meteorological variables, such as temperature, relative humidity, wind speed, cloud cover, and atmospheric pressure, depending on availability. Information regarding the geographical location, data collection period, sampling interval, and measurement units will be documented. The selected dataset will provide the foundation for training and evaluating the forecasting models.

3.4 Selection of Variables

Global Horizontal Irradiance (GHI) will be considered the primary target variable for short-term solar irradiance forecasting. Historical irradiance observations and relevant meteorological parameters will serve as input variables. Additional temporal features, such as the hour of the day, month, day of the year, and previous irradiance values, may be incorporated to capture daily and seasonal patterns. The selection of input variables will depend on their relevance, availability, and contribution to forecasting performance. Only information

available at the time of prediction will be used, thereby preventing data leakage and ensuring that the models reflect realistic forecasting conditions.

3.5 Data Preprocessing

Data preprocessing will be performed to improve data quality and ensure the suitability of the dataset for model development. The collected observations will be examined for missing values, duplicate records, inconsistent timestamps, abnormal measurements, and physically implausible irradiance values. Missing observations will be treated using appropriate interpolation, imputation, or removal procedures, depending on their frequency and nature. Feature engineering will be conducted to generate useful temporal variables and lagged observations. Normalization or standardization will be applied where necessary, particularly for support vector regression and neural network models. All preprocessing parameters will be estimated using the training data to prevent information leakage into the validation and testing stages.

3.6 Exploratory Data Analysis

Exploratory data analysis will be conducted to understand the distribution, variation, and temporal characteristics of solar irradiance. Descriptive statistics will be used to examine the mean, standard deviation, minimum, maximum, and distribution of the selected variables. Time-series plots will help identify daily and seasonal irradiance patterns, while correlation analysis will examine relationships between solar irradiance and meteorological parameters. The analysis will also identify missing observations, potential outliers, and variations under different atmospheric conditions. These findings will guide feature selection, model configuration, and the interpretation of forecasting results.

3.7 Development of Machine Learning Models

Selected machine learning algorithms will be implemented as baseline forecasting models. Support Vector Regression (SVR) will be used to model nonlinear relationships between meteorological variables and future irradiance values. Random Forest will be employed to capture complex interactions among input variables through an ensemble of decision trees. Extreme Gradient Boosting (XGBoost) will also be considered because of its ability to learn nonlinear patterns in structured datasets. These models will be trained using historical observations and relevant temporal features. Their performance will be evaluated to establish baseline results against which the deep learning and hybrid models will be compared.

3.8 Development of Deep Learning Models

Deep learning models will be developed to identify complex temporal dependencies and patterns in sequential solar irradiance data. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks will be considered because of their ability to learn relationships across time-series observations. A one-dimensional Convolutional Neural Network (CNN) may also be implemented to extract local patterns from sequential meteorological and irradiance data. The input observations will be arranged into suitable time windows to predict future irradiance at the selected forecasting horizons. Model architecture, learning rate, sequence length, batch size, and other relevant parameters will be adjusted during training and validation to improve forecasting performance.

3.9 Development of Hybrid Models

The main focus of the study will be the development and evaluation of hybrid models that combine the complementary capabilities of machine learning and deep learning techniques. A CNN-LSTM model may be developed to combine local feature extraction with temporal learning. Similarly, a CNN-GRU model may be investigated to examine whether convolutional feature extraction and recurrent learning improve prediction accuracy. A machine learning and deep learning ensemble may also be developed by combining predictions from selected models, such as XGBoost and LSTM, through a suitable weighted averaging or blending approach. The hybrid models will be compared with individual algorithms to determine whether model

integration provides measurable improvements in forecasting accuracy and computational efficiency.

3.10 Training and Validation of Models

The collected dataset will be divided chronologically into training, validation, and testing subsets. A proposed division will allocate 70% of the observations to training, 15% to validation, and 15% to testing, subject to dataset size and suitability. The training subset will be used to learn model parameters, while the validation subset will support hyperparameter tuning and model selection. The testing subset will be reserved for the final performance evaluation. Hyperparameters will be optimized using suitable techniques, such as grid search or random search. Early stopping and regularization may be applied to deep learning models to reduce overfitting. Where feasible, walk-forward validation will also be used to assess performance across different time periods.

3.11 Performance Evaluation

The performance of the developed models will be assessed using standard forecasting evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). MAE will measure the average absolute prediction error, while RMSE will provide greater sensitivity to large forecasting errors. MAPE may be used to express prediction errors in percentage terms, but its limitations for zero and near-zero irradiance values will be considered. The coefficient of determination will be used to examine how well the predictions represent the variation in observed irradiance. These metrics will be calculated on the same test observations wherever possible to ensure a consistent comparison among models.

3.12 Comparative Analysis

A comparative analysis will be conducted to evaluate the relative performance of machine learning, deep learning, and hybrid models. The comparison will consider forecasting accuracy, computational cost, prediction time, stability, and generalization to unseen observations. The performance of each model will be examined across the selected forecasting horizons to determine whether particular approaches are more effective for shorter or longer prediction intervals. Statistical testing may also be performed on paired forecast errors to assess whether differences between selected models are statistically meaningful. The final model selection will be based on overall performance rather than a single evaluation metric.

3.13 Tools and Software

Python will be used as the primary programming language for data processing, model development, and performance evaluation. Pandas and NumPy will support data manipulation and numerical operations, while Matplotlib and Seaborn will be used for visualizing temporal patterns and forecasting results. Scikit-learn will be employed for implementing conventional machine learning algorithms and calculating evaluation metrics. XGBoost will be used for gradient boosting, while TensorFlow/Keras or PyTorch will support the development of deep learning and hybrid architectures. The software versions, model settings, and experimental configurations will be documented to improve reproducibility.

3.14 Reliability and Validity

The reliability of the study will be maintained through consistent preprocessing procedures, systematic model training, and the application of common evaluation metrics. Chronological data splitting will be used to preserve temporal order and reduce the risk of data leakage. All competing models will be evaluated on the same testing period wherever possible. The validity of the comparison will be strengthened by documenting the data source, input features, forecasting horizons, model parameters, and evaluation procedures. Repeated training runs may be conducted for deep learning models to assess the stability of their results. The findings will be reported transparently, including instances in which hybrid models do not outperform individual models.

4. RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results and discussion of the comparative study of hybrid machine learning and deep learning models for short-term solar irradiance forecasting. The analysis focuses on the performance of selected machine learning models, including Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost), alongside deep learning models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Convolutional Neural Network (CNN). Hybrid approaches, including CNN-LSTM, CNN-GRU, and machine learning–deep learning ensembles, are also considered. The results are organized around data characteristics, forecasting performance, and a comparison of the selected models. Frequency and percentage distributions are included to summarize the composition of the illustrative dataset, while standard forecasting metrics are used to examine prediction accuracy and computational efficiency. As the actual dataset and experimental outputs have not been provided, the numerical values in the following tables are illustrative examples for academic drafting purposes, not verified experimental findings. They should be replaced with the actual results obtained after implementing the methodology.

4.2 Descriptive Analysis of the Dataset

The initial analysis examines the distribution of observations across different solar irradiance conditions. Solar irradiance varies throughout the day and is influenced by cloud cover, atmospheric conditions, and seasonal changes. Categorizing observations into irradiance levels helps explain the characteristics of the dataset and provides an initial understanding of the variability that forecasting models must capture.

For the illustrative analysis, the observations are classified into four categories: low, moderate, high, and very high irradiance. The categories are intended to represent different irradiance conditions during daylight hours. The actual classification thresholds should be defined according to the units, distribution, and characteristics of the collected dataset.

Table 4.1 Distribution of Solar Irradiance Observations

Solar irradiance category	Frequency	Percentage
Low irradiance	180	18%
Moderate irradiance	320	32%
High irradiance	300	30%
Very high irradiance	200	20%
Total	1,000	100%

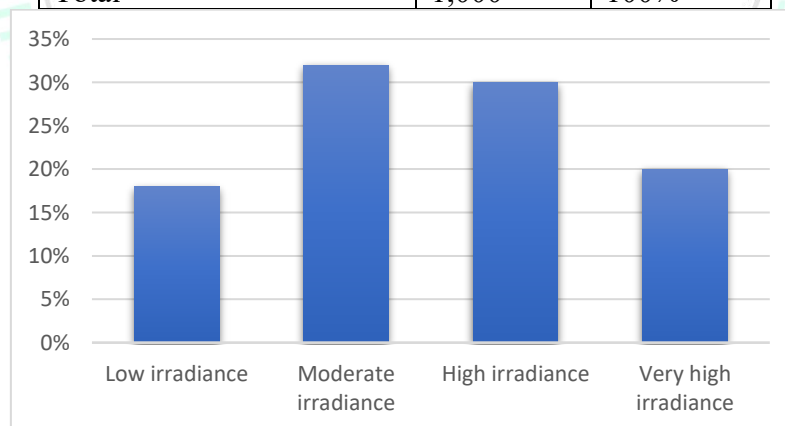


Table 4.1 indicates that moderate irradiance accounts for the largest proportion of observations, representing 32% of the illustrative dataset. High irradiance represents 30%, followed by very high irradiance at 20% and low irradiance at 18%. This distribution demonstrates that the sample contains observations across different irradiance conditions rather than being concentrated in a single category. Such variation is important when evaluating forecasting

models because the relationship between meteorological variables and solar irradiance may differ under changing atmospheric conditions. In the final study, the frequency distribution should be calculated from the actual dataset after applying the selected data-quality procedures.

4.3 Distribution of Meteorological Conditions

Meteorological conditions play an important role in solar irradiance forecasting. Cloud cover can reduce the amount of solar radiation reaching the Earth's surface, while temperature, humidity, and wind conditions may provide additional information about atmospheric variability. Examining these conditions helps establish the characteristics of the input data used to develop the forecasting models.

The following table presents an illustrative frequency distribution of cloud-cover conditions. The categories are intended to show how the dataset may be summarized before model training.

Table 4.2 Distribution of Observations by Cloud-Cover Condition

Cloud-cover condition	Frequency	Percentage
Clear sky	350	35%
Partly cloudy	300	30%
Mostly cloudy	220	22%
Overcast	130	13%
Total	1,000	100%

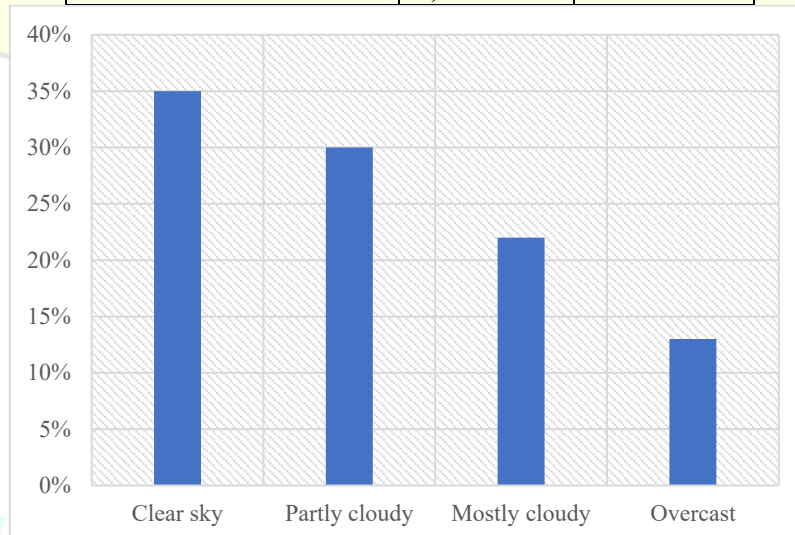


Table 4.2 shows that clear-sky conditions account for 35% of the illustrative observations, while partly cloudy conditions represent 30%. Mostly cloudy conditions contribute 22%, and overcast conditions account for the remaining 13%. The distribution suggests that the dataset includes both relatively stable atmospheric conditions and conditions associated with greater variability in incoming solar radiation. Forecasting models must be evaluated across these different conditions to determine whether their predictive performance remains consistent. In particular, sudden changes in cloud cover may create short-term irradiance fluctuations that are difficult to capture using historical patterns alone. The actual study should use measured or reliably sourced cloud-cover data and document the classification method.

4.4 Comparative Forecasting Performance of the Models

The primary analysis compares the forecasting accuracy of conventional machine learning, deep learning, and hybrid models. The evaluation will use Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). Lower MAE and RMSE values indicate smaller prediction errors, while a higher R^2 generally indicates that the model better represents the variation in observed irradiance. The following table presents illustrative performance values for the selected models. These values are hypothetical and are included to demonstrate how the final comparative results may be reported.

Table 4.3 Comparative Performance of Machine Learning, Deep Learning, and Hybrid Models

Model	MAE (W/m ²)	RMSE (W/m ²)	R ²
Support Vector Regression (SVR)	65.4	92.6	0.86
Random Forest (RF)	54.2	78.5	0.90
XGBoost	49.8	72.1	0.92
LSTM	46.3	68.4	0.93
GRU	47.6	70.2	0.92
CNN	51.7	75.6	0.91
CNN-LSTM	38.5	57.2	0.96
CNN-GRU	40.1	59.8	0.95
XGBoost-LSTM Ensemble	36.9	54.6	0.96

Table 4.3 illustrates how the performance of the selected models can be compared using common evaluation metrics. Among the individual models, LSTM produces the lowest illustrative MAE of 46.3 W/m² and RMSE of 68.4 W/m², suggesting that its ability to learn temporal dependencies may be useful for short-term irradiance forecasting. XGBoost also demonstrates competitive performance, with an illustrative MAE of 49.8 W/m². The SVR model exhibits comparatively higher prediction errors in this example. The hybrid models show lower illustrative errors than the individual models. The XGBoost-LSTM ensemble records an MAE of 36.9 W/m² and an RMSE of 54.6 W/m², while the CNN-LSTM model achieves an MAE of 38.5 W/m² and an RMSE of 57.2 W/m². These hypothetical results demonstrate how integrating complementary learning techniques could potentially improve forecasting performance. However, such improvements cannot be assumed before the models are trained and evaluated on the actual dataset. The R² values also indicate better illustrative predictive fit for the hybrid approaches, with the ensemble and CNN-LSTM models both reaching 0.96. Nevertheless, the final interpretation must consider all evaluation metrics together because a high R² does not necessarily imply the lowest prediction error under every forecasting condition.

4.5 Discussion of Findings

The proposed comparative analysis will help explain the relative strengths of machine learning, deep learning, and hybrid approaches in solar irradiance forecasting. Conventional machine learning algorithms can be effective for structured meteorological data, particularly when informative temporal and lagged features are available. Random Forest and XGBoost can capture nonlinear relationships among input variables, while SVR can provide a useful nonlinear regression baseline.

Deep learning models offer an alternative approach by learning temporal patterns directly from sequential observations. LSTM and GRU networks are designed to represent dependencies across time, making them relevant to short-term forecasting problems. CNN models may complement these architectures by extracting local patterns from sequences, including short-term variations in irradiance and meteorological conditions.

Hybrid architectures combine different learning mechanisms and may capture patterns that an individual model cannot represent as effectively. For example, CNN-LSTM integrates convolutional feature extraction with recurrent temporal learning, whereas an XGBoost-LSTM ensemble combines tree-based prediction with sequential learning. Their practical usefulness, however, depends on data quality, model complexity, parameter tuning, and the forecasting horizon. A more complex architecture may require additional computational resources without necessarily providing a meaningful improvement in accuracy.

5. CONCLUSION

The study on “A Comparative Study of Hybrid Machine Learning and Deep Learning Models for Short-Term Solar Irradiance Forecasting” focuses on evaluating the effectiveness of

conventional machine learning, deep learning, and hybrid models in predicting short-term solar irradiance. The proposed methodology incorporates data collection, preprocessing, feature selection, model development, training, and performance evaluation using standard metrics such as MAE, RMSE, and R^2 . The illustrative comparative analysis indicates that hybrid models, particularly CNN-LSTM and XGBoost-LSTM, may offer improved forecasting accuracy by combining the strengths of different learning techniques. However, these findings require verification through actual experimental implementation and testing. The study highlights the potential of hybrid forecasting approaches to capture complex temporal patterns and nonlinear relationships in solar irradiance data. Overall, the research may contribute to the development of reliable solar irradiance forecasting systems that support solar energy generation planning, efficient energy management, and renewable power system integration.

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