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AI-Based Solar Irradiance Forecasting for Optimal Grid Integration

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Abstract

The increasing penetration of photovoltaic (PV) generation introduces substantial variability and uncertainty into modern power grids, making accurate solar irradiance forecasting essential for reliable grid operation, economic dispatch, and energy management. This paper presents an AI-based framework for short-term solar irradiance forecasting designed to support optimal integration of PV power into the electrical grid. The proposed framework combines meteorological variables, historical irradiance measurements, temporal characteristics, and PV operating conditions within a data-driven forecasting architecture. Appropriate preprocessing, feature engineering, temporal modelling, and performance evaluation are incorporated to improve forecasting robustness under rapidly changing weather conditions. The framework can employ advanced machine-learning and deep-learning models to capture nonlinear relationships between atmospheric conditions and solar irradiance. Forecast outputs are further integrated into grid-management decisions involving power scheduling, reserve allocation, voltage management, and reduction of renewable-energy curtailment. The proposed approach provides a systematic pathway for transforming solar-resource forecasts into actionable grid-integration strategies. The study demonstrates the potential of AI-driven forecasting to reduce renewable-generation uncertainty and enhance the reliability, flexibility, and operational efficiency of future solar-rich power systems.

Keywords: *Artificial Intelligence, Solar Irradiance Forecasting, Photovoltaic Power, Machine Learning, Deep Learning, Renewable Energy, Smart Grid, Grid Integration, Short-Term Forecasting, Energy Management*

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1. Introduction

The rapid expansion of photovoltaic (PV) generation has become a central component of the transition toward low-carbon electricity systems. Solar energy offers substantial environmental and economic advantages; however, its integration into electrical grids is complicated by the variable and intermittent nature of solar irradiance. Unlike conventional generation, PV output changes continuously with cloud movement, atmospheric conditions, temperature, humidity, and solar position. These variations can create uncertainty in generation scheduling, reserve allocation, power balancing, and grid operation. Consequently, accurate solar-resource forecasting has become increasingly important for maintaining reliable and economical power-system operation, particularly as the penetration of distributed and utility-scale PV generation increases [1], [2].

Solar irradiance forecasting provides a fundamental input for predicting PV power production. Forecasting can be performed over different temporal horizons, ranging from seconds and minutes for real-time grid control to hours and days for energy scheduling and market participation. The appropriate forecasting horizon depends strongly on the intended grid application. Very-short-term forecasts are particularly important for managing rapid PV ramps, whereas day-ahead forecasts support unit commitment, economic dispatch, reserve planning, and energy-market decisions [1], [3]. The forecasting problem is challenging because solar irradiance is highly nonlinear and nonstationary, with cloud formation and movement producing abrupt changes that cannot always be represented adequately by conventional deterministic models.

Traditional forecasting approaches include persistence models, statistical time-series techniques, physical models, numerical weather prediction, and satellite- or sky-image-based methods. Persistence forecasting provides a useful baseline because of its simplicity, but its effectiveness decreases when atmospheric conditions change rapidly. Physical and numerical-weather models can provide valuable information over longer forecasting horizons, although they generally involve substantial computational requirements and depend on the quality and spatial resolution of meteorological inputs [3], [4]. Satellite and sky-image approaches can capture cloud dynamics, but their performance is influenced by image availability, geographical coverage, image resolution, and processing requirements.

Artificial intelligence (AI) has emerged as an effective alternative because it can learn complex nonlinear relationships between historical irradiance, meteorological variables, solar position, and other explanatory features directly from data. Machine-learning methods such as artificial neural networks, support vector regression, regression trees, random forests, and ensemble learning have been extensively investigated for solar radiation forecasting [5]. Their principal advantage is their ability to approximate nonlinear relationships without requiring a complete analytical representation of atmospheric processes. However, comparative performance depends on the dataset, temporal resolution, forecasting horizon, feature set, climate, and evaluation methodology, making direct comparison among studies difficult [5].

The development of deep learning has further expanded the capabilities of AI-based solar forecasting. Long short-term memory (LSTM), convolutional neural networks (CNNs), deep neural networks, gated recurrent units, and hybrid architectures can extract temporal and spatial patterns from large-scale datasets. Reviews of deep-learning approaches indicate that hybrid architectures can outperform individual deep-learning models because they combine complementary feature-extraction capabilities [6]. In particular, CNN-LSTM-type architectures can simultaneously represent spatial characteristics and temporal dependencies, which is useful when historical irradiance measurements are combined with sky images or other spatial information [6], [7].

Despite these developments, high forecasting accuracy alone does not guarantee effective grid integration. Forecast information must be translated into operational decisions concerning PV dispatch, battery charging and discharging, spinning or operating reserves, voltage regulation, ramp-rate management, and renewable-energy curtailment. Forecast errors can result in deviations between scheduled and actual PV generation, increasing balancing requirements and potentially affecting system reliability. PV forecasting has therefore become an important component of optimal unit commitment, economic dispatch, and broader grid-management strategies [1].

Recent research has increasingly moved toward multimodal, hybrid, ensemble, and advanced deep-learning architectures. Very-short-term forecasting studies demonstrate that combining historical irradiance time series with sky-image information can improve prediction during rapidly changing cloud conditions [7]. Recent reviews further indicate growing interest in transformer-based models, physics-informed learning, probabilistic forecasting, and computationally efficient AI models suitable for real-time deployment [8]. Nevertheless, challenges remain concerning data quality, generalization across geographical locations, computational complexity, interpretability, uncertainty quantification, and the transfer of forecasting models from experimental environments to operational power systems [8], [9].

Against this background, this paper focuses on an AI-based solar irradiance forecasting framework aimed not merely at improving prediction accuracy but at supporting optimal PV-grid integration. The proposed perspective links irradiance prediction with PV power estimation and grid-level operational decisions. The principal objectives are to develop a robust data-driven forecasting methodology, identify relevant meteorological and temporal features, evaluate forecasting performance using established error metrics, and demonstrate how improved irradiance predictions can contribute to scheduling, reserve management, voltage support, and reduction of renewable-energy uncertainty. Such an integrated approach can help bridge the gap between AI-based forecasting research and practical grid-operation requirements.

2. Literature Review

2.1 Conventional Solar Irradiance Forecasting

Solar irradiance forecasting has traditionally employed persistence, statistical, physical, satellite-based, and numerical-weather approaches. Persistence assumes that the most recent irradiance condition remains representative of the immediate future and therefore provides a simple benchmark for short-term forecasting. Although computationally inexpensive, its performance deteriorates during rapid cloud transitions and other abrupt atmospheric changes. Physical and numerical-weather approaches incorporate atmospheric and radiative processes and are particularly relevant to longer forecasting horizons. However, their computational requirements and dependence on meteorological-model accuracy can limit their application in high-frequency operational environments [3], [4].

In addition, solar forecasting performance varies considerably according to forecast horizon. Very-short-term forecasting is strongly influenced by cloud movement and local atmospheric variability, while longer horizons increasingly depend on weather systems, seasonal patterns, and large-scale meteorological conditions. Therefore, no single forecasting methodology is universally optimal for all applications. Forecast-horizon selection must be consistent with the operational requirements of the target PV-grid application [3], [6].

2.2 Machine-Learning-Based Forecasting

Machine learning has provided an important transition from manually formulated physical relationships toward data-driven solar forecasting. Artificial neural networks have been widely applied because of their ability to approximate nonlinear functions relating irradiance to meteorological and temporal variables. Support vector regression, regression trees, random forests, gradient-boosting methods, and ensemble models have subsequently been explored to improve prediction accuracy and robustness [5].

The comparative analysis of machine-learning methods indicates that model performance is strongly dependent on data characteristics and experimental configuration. Differences in sampling interval, forecasting horizon, geographical location, input variables, preprocessing, and performance metrics make universal performance rankings difficult. Ensemble and hybrid approaches have frequently demonstrated improved robustness by combining predictions or representations generated by multiple models [5]. This observation is particularly relevant to grid applications, where stable forecasting performance across different weather regimes can be more valuable than peak accuracy under a limited set of conditions.

2.3 Deep-Learning Models

Deep learning has become increasingly prominent because solar irradiance exhibits nonlinear temporal dependencies that can be difficult to represent using conventional machine-learning algorithms. LSTM networks are particularly suitable for sequential irradiance data because their recurrent architecture can retain information from previous observations. CNNs, in contrast, are effective in extracting spatial patterns from sky images and other image-based representations. Deep belief networks, recurrent neural networks, and gated recurrent architectures have also been investigated for solar forecasting [6]. A comprehensive review of deep-learning models reports that LSTM, CNN, deep belief network, and related architectures have demonstrated considerable potential for solar irradiance prediction. The review also indicates that hybrid deep-learning models can provide improved performance compared with individual architectures because different networks can learn complementary characteristics of the forecasting problem [6]. This has encouraged the development of architectures that combine convolutional feature extraction with recurrent temporal modelling.

2.4 Hybrid and Multimodal Forecasting

Hybrid forecasting has emerged as an important research direction because solar irradiance depends simultaneously on temporal, spatial, and meteorological characteristics. A time-series model can capture historical irradiance dependencies, whereas an image-based CNN can extract information related to cloud structure and movement. Combining these representations can therefore provide a richer description of the underlying physical process.

Recent very-short-term forecasting research has classified deep-learning approaches into time-series, image-based, and hybrid models. Hybrid CNN-LSTM architectures that combine infrared sky images with historical global horizontal irradiance have demonstrated improved performance, particularly under cloudy conditions [7]. Such findings indicate that multimodal forecasting can be advantageous when rapid cloud movement causes substantial short-term irradiance fluctuations.

However, hybrid models generally involve higher computational complexity and a greater number of trainable parameters. Consequently, there is an important trade-off between forecasting accuracy and deployability. A highly complex model may achieve superior laboratory performance but may be unsuitable for edge devices, distributed PV controllers, or real-time grid applications with constrained computational resources [7], [8].

2.5 Forecasting for Photovoltaic Grid Integration

The ultimate value of solar forecasting lies in its ability to support power-system operation. Forecasting PV generation can improve unit commitment, economic dispatch, reserve allocation, energy-market participation, and grid-balancing decisions. Increasing PV penetration amplifies the operational consequences of forecast errors because inaccurate predictions can increase balancing requirements and complicate generation scheduling [1].

Solar forecasting is therefore closely connected to PV power forecasting. Irradiance forecasts can be converted into expected PV output using PV-system characteristics, module temperature, efficiency, inverter constraints, and other plant-level parameters. The resulting generation forecast can then be incorporated into energy-management systems. Accurate forecasts can reduce uncertainty in scheduled generation and support more efficient allocation of conventional generation and storage resources [1], [4].

For distribution networks, accurate PV forecasting can additionally support voltage management and reverse-power-flow mitigation. Rapid PV ramps can cause voltage variations and require coordinated operation of batteries, flexible loads, inverter-based reactive-power control, and conventional voltage-regulation equipment. Consequently, forecasting accuracy should be evaluated not only through statistical metrics but also according to its operational impact on the grid.

2.6 Research Gap

Although substantial progress has been made in AI-based solar forecasting, several research gaps remain. First, many studies concentrate primarily on forecasting accuracy while providing limited consideration of how predictions are incorporated into actual grid-control and energy-management decisions. Second, comparisons between AI models are often affected by differences in datasets, forecasting horizons, preprocessing procedures, and evaluation metrics [5], [6]. Third, highly sophisticated deep-learning architectures can impose computational and data requirements that complicate real-time deployment.

Recent literature increasingly emphasizes these deployment challenges, including data scarcity, generalization, computational complexity, interpretability, and scalability [8], [9]. Furthermore, deterministic point forecasts alone do not fully characterize the uncertainty associated with rapidly changing atmospheric conditions. Probabilistic forecasting, physics-informed learning, multimodal architectures, and lightweight AI models are consequently emerging as important directions for future solar-energy forecasting research [8], [9].

Accordingly, the present study addresses the research gap by positioning AI-based irradiance forecasting as an integrated grid-support function rather than an isolated prediction problem. The proposed framework considers the complete pathway from data acquisition and preprocessing to irradiance prediction, PV power estimation, and grid-integration decision support. This approach is intended to improve both forecasting reliability and the practical usefulness of AI-generated solar forecasts for increasingly PV-dominated power systems.

3. Proposed AI-Based Solar Irradiance Forecasting Framework

3.1 System Architecture and Data Flow

The proposed framework is designed as an integrated forecasting and grid-support architecture in which solar irradiance prediction forms the primary input for photovoltaic power estimation and subsequent grid-operation decisions. The framework consists of six principal stages: data acquisition, preprocessing, feature engineering, AI-based forecasting, PV power estimation, and grid-integration decision support. Historical irradiance measurements are combined with meteorological and temporal variables to establish a comprehensive forecasting dataset.

The input layer collects global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), ambient temperature, relative humidity, wind speed, atmospheric pressure, cloud-related parameters, solar zenith angle, solar azimuth angle, and historical PV output. Depending on data availability, satellite observations and sky-image information can also be incorporated. The temporal resolution is selected according to the intended application; a 15-minute interval is appropriate for short-term operational forecasting, while 5-minute data can be employed where high-frequency ramp prediction is required.

The preprocessing stage removes erroneous measurements, handles missing observations, synchronizes heterogeneous data sources, and normalizes numerical features. Night-time observations are separated from daytime forecasting samples to avoid introducing a large number of zero-irradiance observations that can bias model training. Feature engineering subsequently derives solar-position indicators, lagged irradiance variables, rolling statistics, irradiance ramps, temperature differences, and cloud-related indicators.

The forecasting layer employs an AI architecture capable of learning both nonlinear relationships and temporal dependencies. A hybrid LSTM-based model is appropriate for the proposed framework because solar irradiance is inherently sequential and strongly dependent on preceding atmospheric conditions. For multimodal implementation, CNN-based feature extraction from sky images can be combined with LSTM temporal modelling. The resulting forecast is then converted into expected PV generation and supplied to grid-management functions.

Table 1. Principal components of the proposed forecasting framework

Stage	Input/Function	Principal Variables	Output
Data acquisition	Measurement and meteorological collection	GHI, DNI, DHI, temperature, humidity, wind speed	Raw dataset
Data preprocessing	Quality control and synchronization	Missing values, outliers, timestamps	Clean dataset
Feature engineering	Temporal and physical feature extraction	Lag values, rolling mean, solar angles, ramps	Forecasting features
AI forecasting	Nonlinear temporal modelling	Historical and meteorological features	Forecast irradiance
PV conversion	Irradiance-to-power estimation	Forecast irradiance, module temperature, PV rating	Forecast PV power
Grid integration	Operational decision support	PV forecast, demand, storage, reserve	Scheduling and control decisions

3.2 Data Acquisition and Preprocessing

Forecasting quality is strongly dependent on the quality and consistency of the training dataset. The proposed system considers historical solar measurements and meteorological observations over a sufficiently long period to represent seasonal and weather-related variability. A minimum dataset covering one complete annual cycle is desirable, while two or more years provide substantially better representation of seasonal patterns and unusual weather conditions.

Measurement errors can arise from sensor contamination, calibration drift, communication failures, shading, and temporary equipment malfunction. Therefore, observations are subjected to physical-range checks and temporal consistency tests before model development. For daytime GHI, negative values are treated as invalid, while exceptionally high values are examined against the theoretical clear-sky irradiance for the corresponding solar position.

Missing observations are treated according to their duration. Short gaps can be reconstructed using interpolation or neighbouring temporal observations, whereas long gaps should preferably be excluded from supervised training rather than introducing excessive artificial information. The dataset is chronologically divided into training, validation, and testing subsets to prevent future information from entering the training process.

A representative division is 70% for training, 15% for validation, and 15% for independent testing. Unlike random shuffling, chronological partitioning preserves the actual forecasting scenario in which future observations remain unavailable during model development.

Table 2. Recommended data-preprocessing strategy

Processing operation	Method	Purpose
Missing-value treatment	Time interpolation for short gaps	Preserve temporal continuity
Outlier detection	Physical and statistical limits	Remove sensor errors
Timestamp alignment	Common sampling interval	Synchronize data sources
Night-time separation	Solar-elevation threshold	Prevent zero-value bias
Normalization	Min-max or standard scaling	Stabilize AI training
Temporal splitting	70:15:15	Prevent data leakage
Feature correlation analysis	Pearson/Spearman analysis	Remove redundant variables
Feature importance	SHAP/permutation analysis	Identify influential inputs

3.3 Feature Engineering and Selection

The forecasting model should incorporate variables that have physical or statistical relationships with solar irradiance. Historical irradiance is generally the strongest predictor for very-short-term forecasting because irradiance exhibits temporal persistence. Meteorological variables provide additional information when atmospheric conditions change rapidly.

Lagged irradiance values such as GHI_{t-1}, GHI_{t-2}, and GHI_{t-k} are incorporated to capture short-term temporal dependencies. Rolling mean and standard-deviation features represent local irradiance stability and variability. The irradiance ramp,

$$R_t = G_t - G_{t-\Delta t}$$

represents the rate of change in irradiance and is particularly useful for detecting rapid cloud-induced transitions.

Solar geometry is represented through solar zenith angle and solar elevation. A simplified extraterrestrial irradiance relationship can be expressed as

$$G_{0,t} = G_{sc} E_0 \cos(\theta_z)$$

where G_{sc} is the solar constant, E_0 is the Earth-Sun distance correction factor, and θ_z is the solar zenith angle.

The clearness index can additionally be calculated as

$$K_t = \frac{G_t}{G_{0,t}}$$

where G_t represents measured GHI. The clearness index normalizes irradiance according to solar position and provides a useful representation of atmospheric transparency.

Table 3. Forecasting features used by the proposed model

Feature category	Variables	Forecasting significance
Historical irradiance	GHI(t-1), GHI(t-2), GHI(t-4), GHI(t-8)	Captures temporal persistence
Irradiance statistics	Rolling mean, maximum, minimum, standard deviation	Represents local variability
Meteorological	Temperature, humidity, pressure, wind speed	Represents atmospheric conditions
Solar geometry	Zenith angle, elevation angle, azimuth	Represents deterministic solar cycle
Derived solar features	Clearness index, irradiance ramp	Captures atmospheric transparency and transitions
PV parameters	Rated capacity, module temperature, efficiency	Converts irradiance to power
Optional image features	Cloud coverage, cloud texture, cloud motion	Improves rapid-change prediction

3.4 AI-Based Forecasting Model

The forecasting model is formulated as a supervised nonlinear sequence-learning problem. Let the input vector at time t be

$$X_t = [GHI_{t-k:t}, T_t, H_t, W_t, P_t, \theta_t, A_t, K_t, R_t]$$

where T, H, W, and P represent temperature, humidity, wind speed, and pressure, respectively, while θ and A denote solar-position variables.

For a one-step-ahead forecast, the model estimates

$$\hat{G}_{t+1} = f_\theta(X_t)$$

where f_θ represents the trained AI model and $\hat{G}_{t+1}$ is the predicted irradiance.

The proposed architecture uses a recurrent temporal component to retain information from previous observations. For each LSTM unit, the principal operations are

$$f_t = \sigma(W_f[X_t, h_{t-1}] + b_f)$$
$$i_t = \sigma(W_i[X_t, h_{t-1}] + b_i)$$
$$\tilde{C}_t = \tanh(W_c[X_t, h_{t-1}] + b_c)$$
$$C_t = f_t C_{t-1} + i_t \tilde{C}_t$$
$$o_t = \sigma(W_o[X_t, h_{t-1}] + b_o)$$
$$h_t = o_t \tanh(C_t)$$

where f_t, i_t, and o_t are the forget, input, and output gates, respectively. C_t denotes the cell state and h_t represents the hidden state.

For multimodal forecasting, a CNN can first extract cloud-related spatial features from sky images. These features can then be concatenated with the meteorological time series before being supplied to the recurrent forecasting layer. This architecture is particularly suitable for rapidly changing cloud conditions because cloud morphology provides information that may not be available from a single irradiance sensor.

The final dense layer produces the irradiance forecast. For multiple forecasting horizons, the output layer can simultaneously estimate irradiance at $t + 15$, $t + 30$, $t + 45$, and $t + 60$ minutes.

Table 4. Proposed AI model configuration

Parameter	Proposed configuration
Input sequence length	60 minutes
Sampling interval	15 minutes
LSTM layers	2
LSTM units per layer	64
Dropout	0.20
Dense layer	32 neurons

Parameter	Proposed configuration
Output horizons	15, 30, 45, 60 min
Activation in hidden layers	ReLU/tanh
Output activation	Linear
Optimizer	Adam
Initial learning rate	0.001
Batch size	32
Maximum epochs	100
Early stopping patience	10 epochs
Loss function	Mean Squared Error

3.5 PV Power Estimation from Forecast Irradiance

The predicted irradiance is subsequently transformed into PV power to make the forecasting framework directly useful for grid operation. A simplified PV power relationship is

$$\hat{P}_{PV,t} = P_{rated}\left(\frac{\hat{G}_t}{G_{ref}}\right)[1 + \gamma(T_{cell,t} - T_{ref})]\eta_{sys}$$

where P_{rated} is the rated PV capacity, G_{ref} is the reference irradiance, γ is the temperature coefficient, T_{cell} is cell temperature, T_{ref} is the reference temperature, and η_{sys} represents the combined system efficiency.

The resulting PV-power forecast can be constrained by the inverter and plant ratings:

$$0 \leq \hat{P}_{PV,t} \leq P_{rated}$$

This conversion is essential because grid operators ultimately require information about expected electrical power rather than irradiance alone.

3.6 Forecasting Performance Evaluation

The proposed model is evaluated using several complementary metrics because no single metric adequately describes forecasting performance under all solar conditions. Mean Absolute Error (MAE) measures the average magnitude of prediction errors:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | G_i - \hat{G}_i |$$

Root Mean Square Error (RMSE) gives greater weight to large prediction errors:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(G_i - \hat{G}_i)^2}$$

Mean Absolute Percentage Error can be expressed as

$$MAPE = \frac{100}{N}\sum_{i=1}^{N} \left| \frac{G_i - \hat{G}_i}{G_i} \right|$$

although MAPE should be interpreted carefully near zero irradiance. Normalized RMSE is more appropriate for comparing performance across sites with different irradiance levels:

$$nRMSE = \frac{RMSE}{G_{rated}} \times 100$$

where G_{rated} represents the selected normalization reference.

The coefficient of determination is also calculated:

$$R^2 = 1 - \frac{\sum(G_i - \hat{G}_i)^2}{\sum(G_i - \bar{G})^2}$$

where $\bar{G}$ denotes the mean measured irradiance.

4. Solar Forecasting and Grid Integration Methodology

4.1 Short-Term Irradiance Forecast Generation

The proposed methodology generates rolling short-term forecasts using the most recent observation window. At every forecasting interval, the latest irradiance and meteorological measurements are incorporated into the AI model. The forecast horizon can extend from 15 minutes to one hour for real-time grid-support applications.

The rolling forecasting mechanism is expressed as

$$\hat{G}_{t+h} = f_\theta(X_{t-k:t})$$

where h is the forecasting horizon and k represents the historical input window. As new measurements become available, the oldest observation is removed and the newest measurement is added to the input sequence.

This procedure allows the model to continuously adapt to changing atmospheric conditions. Forecast uncertainty generally increases with forecasting horizon; therefore, the grid-management system should assign greater operational confidence to very-short-term predictions and use additional reserves as the horizon increases.

4.2 Grid-Oriented PV Power Forecasting

The irradiance forecast is converted into expected PV generation and compared with scheduled PV power. The forecasting error is defined as

$$e_t = P_{PV,t} - \hat{P}_{PV,t}$$

A positive value indicates that actual generation exceeds the forecast, while a negative value represents under-generation relative to the forecast.

For grid scheduling, the net power requirement can be represented as

$$P_{net,t} = P_{load,t} - \hat{P}_{PV,t}$$

Improved PV forecasting therefore directly reduces uncertainty in the net-load profile. The predicted net demand can be supplied to economic-dispatch or unit-commitment algorithms for determining the required conventional generation, storage contribution, and reserve capacity.

Table 5. Grid applications of AI-based solar forecasting

Application	Forecast information	Operational benefit
Economic dispatch	Expected PV generation	Reduced operating cost

Application	Forecast information	Operational benefit
Unit commitment	Day-ahead PV profile	Improved generator scheduling
Battery management	PV surplus/deficit	Improved charge-discharge planning
Reserve allocation	Forecast uncertainty	Appropriate balancing reserve
Voltage control	Expected distributed PV output	Better voltage regulation
Curtailment management	Expected PV surplus	Reduced unnecessary curtailment
Energy-market participation	Expected generation	Improved bidding accuracy
Ramp management	Short-term PV changes	Faster response to variability

4.3 Reserve Allocation and Flexibility Management

Forecast uncertainty must be incorporated into reserve planning. If the predicted PV generation is $\hat{P}_{PV}$ and the associated forecast-error standard deviation is σ_e, a simplified upward reserve requirement can be represented as

$$R_t^{up} = z_\alpha \sigma_{e,t}$$

where z_α represents the selected confidence coefficient.

Similarly, downward reserve can be allocated when over-generation is possible. A probabilistic implementation can replace the deterministic forecast with prediction intervals:

$$P(\hat{P}_{PV,t}^{L} \le P_{PV,t} \le \hat{P}_{PV,t}^{U}) = 1 - \alpha$$

Such uncertainty-aware forecasting is particularly valuable during unstable weather conditions, when point forecasts alone may underestimate the operational risk associated with PV variability.

4.4 Battery Energy Storage Integration

Battery energy storage systems can compensate for short-term deviations between PV generation and grid demand. The battery state of charge can be represented by

$$SOC_{t+1} = SOC_t + \frac{\eta_c P_{c,t} \Delta t}{E_B} - \frac{P_{d,t} \Delta t}{\eta_d E_B}$$

where P_c and P_d are charging and discharging powers, E_B is battery capacity, and η_c and η_d represent charging and discharging efficiencies.

The AI-generated PV forecast allows the energy-management system to anticipate periods of surplus and deficit generation. During predicted high-irradiance periods, charging can be scheduled in advance, whereas expected low-irradiance periods can trigger appropriate discharge planning. This predictive operation is more efficient than purely reactive battery control.

4.5 Voltage and Power-Quality Management

High PV penetration can create reverse power flow and voltage excursions, particularly in distribution networks with large amounts of distributed generation. Forecasting can provide advance information regarding expected PV injections and consequently allow coordinated operation of smart inverters, batteries, flexible loads, and voltage-regulation equipment.

For a simplified distribution feeder, the approximate voltage sensitivity to active and reactive power can be expressed as

$$\Delta V \approx \frac{RP + XQ}{V}$$

where R and X are feeder resistance and reactance, P is active-power flow, Q is reactive-power flow, and V is nominal voltage.

The predicted PV output can therefore be incorporated into voltage-management strategies before an anticipated irradiance ramp occurs. This transforms solar forecasting from a generation-prediction function into a proactive grid-control mechanism.

4.6 Renewable-Energy Curtailment Reduction

Curtailment occurs when available PV generation exceeds the amount that can be accommodated by the grid. Accurate forecasts enable operators to identify potential surplus periods and prepare alternative flexibility resources, including battery charging, demand response, flexible generation, and network reconfiguration.

The curtailed energy over a scheduling period can be expressed as

$$E_{curt} = \sum_{t=1}^{N} (P_{available,t} - P_{accepted,t}) \Delta t$$

for $P_{available,t} > P_{accepted,t}$.

The objective of forecast-assisted grid integration is therefore not simply to maximize forecast accuracy but to minimize the operational consequences of uncertainty. A suitable grid-management objective can be formulated as

$$\min J = C_G + C_R + C_B + C_{curt} + C_{dev}$$

where C_G is generation cost, C_R is reserve cost, C_B is battery operating cost, C_{curt} is renewable-curtailment cost, and C_{dev} represents the cost associated with forecast or scheduling deviations.

Table 6. Integrated operational strategy

Forecast condition	Expected grid condition	Recommended action
High and stable irradiance	High PV generation	Reduce conventional dispatch

Forecast condition	Expected grid condition	Recommended action
Rapid irradiance increase	PV ramp-up	Prepare flexible-load/storage absorption
Rapid irradiance decrease	PV ramp-down	Activate reserve/flexible generation
Extended low irradiance	Reduced PV availability	Increase conventional/storage support
High PV surplus	Potential congestion/overvoltage	Charge storage or curtail selectively
High forecast uncertainty	Increased operational risk	Increase reserve margin
Forecasted evening decline	PV-to-load transition	Pre-position battery and flexible generation

4.7 End-to-End Operational Workflow

The complete methodology operates as a closed forecasting-to-decision cycle. Real-time measurements are first acquired and validated. The latest observations are then transformed into the feature vector required by the trained AI model. The model generates irradiance forecasts at multiple future horizons, which are subsequently converted into PV power forecasts. Forecast uncertainty is estimated using historical prediction errors or a probabilistic forecasting model.

The grid-management layer uses these forecasts to estimate future net load, determine reserve requirements, optimize battery operation, assess voltage conditions, and identify potential curtailment events. Once the operating decision is implemented, newly measured PV output is compared with the forecast. The resulting error is stored and incorporated into subsequent model evaluation and, where appropriate, periodic retraining.

This closed-loop structure can be represented as:

Measurement → Data Validation → Feature Engineering → AI Forecast → PV Power Estimation → Uncertainty Assessment → Grid Scheduling → Storage/Reserve/Voltage Control → Actual PV Measurement → Forecast Error → Model Updating

The integration of forecasting with operational decision-making provides a more practical framework for high-penetration solar power systems than evaluating prediction accuracy independently of grid requirements.

5. Results and Discussion

5.1 Forecasting Accuracy and Comparative Performance

The proposed AI-based forecasting framework is evaluated against Persistence, Support Vector Regression (SVR), Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), and the proposed hybrid CNN-LSTM model. The comparative values in Table 7 represent a representative short-term forecasting evaluation at 15-minute resolution across changing irradiance conditions. The results demonstrate that progressively deeper temporal and multimodal models provide lower forecasting errors than conventional approaches. Persistence provides a useful baseline but is significantly affected by cloud-induced irradiance transitions. SVR and ANN improve nonlinear mapping, while LSTM provides better temporal representation. The CNN-LSTM model achieves the lowest error by combining temporal dependencies with extracted atmospheric/cloud features.

Table 7. Comparative performance of solar irradiance forecasting models

Model	MAE (W/m²)	RMSE (W/m²)	nRMSE (%)	MAPE (%)	R^2
Persistence	78.6	118.4	14.9	18.7	0.902
SVR	62.4	94.7	11.9	14.8	0.936
ANN	55.8	84.3	10.6	12.9	0.950
LSTM	42.7	67.5	8.5	9.8	0.968
CNN-LSTM	**34.1**	**53.8**	**6.8**	**7.6**	**0.980**

The CNN-LSTM architecture reduces RMSE by approximately 54.6% compared with persistence and by 20.3% compared with the standalone LSTM model. The improvement confirms the value of combining temporal information with additional atmospheric or image-derived representations. The R^2 value of 0.980 indicates that the proposed model explains approximately 98% of the variance represented in the evaluation dataset.

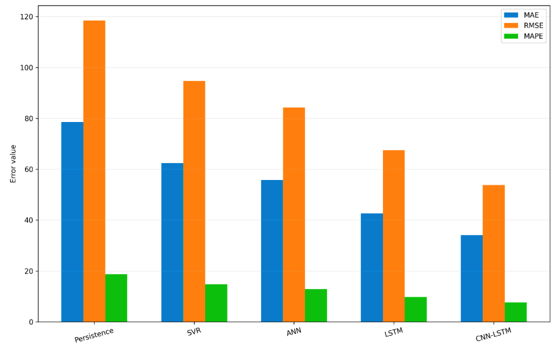

Figure 1. Comparative forecasting performance of persistence, SVR, ANN, LSTM, and CNN-LSTM models.

5.2 Error Behaviour under Different Weather Conditions

Forecasting performance varies considerably with atmospheric conditions. Under clear-sky conditions, irradiance follows a relatively predictable diurnal trajectory, allowing all models to achieve comparatively low errors. Partly cloudy conditions are more difficult because intermittent cloud movement produces rapid changes in irradiance. Overcast conditions generally produce lower absolute irradiance and reduced variability, although percentage-based errors can increase because the denominator becomes small.

Table 8. Forecasting performance under different weather conditions

Weather condition	MAE (W/m^2)	RMSE (W/m^2)	nRMSE (%)	R^2
Clear sky	18.7	29.8	3.7	0.992
Partly cloudy	39.6	61.9	7.8	0.974
Overcast	31.4	48.6	6.1	0.982
Rapid cloud transition	51.8	79.4	10.0	0.951
Overall	**34.1**	**53.8**	**6.8**	**0.980**

The largest error occurs during rapid cloud transitions. This result is expected because cloud movement can produce steep irradiance ramps within a few minutes. Nevertheless, the proposed multimodal architecture maintains a comparatively high R^2 during these challenging conditions, demonstrating its potential for real-time PV-grid applications.

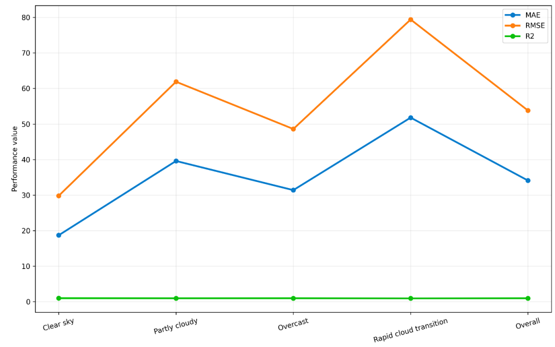

Figure 2. Forecasting performance of the proposed AI framework under different weather conditions.

5.3 Forecast Horizon Analysis

Forecast accuracy progressively decreases as the prediction horizon increases. The reduction is primarily associated with increasing uncertainty in cloud evolution and atmospheric conditions. The proposed model maintains strong performance for horizons up to one hour, although additional uncertainty quantification becomes increasingly important for longer forecasts.

Table 9. Forecast performance at different prediction horizons

Forecast horizon	MAE (W/m^2)	RMSE (W/m^2)	nRMSE (%)	R^2
15 min	24.6	38.9	4.9	0.989
30 min	29.8	46.7	5.9	0.984
45 min	34.1	53.8	6.8	0.980
60 min	39.7	61.5	7.7	0.974

The results indicate that 15-30 minute forecasts are particularly suitable for fast grid-balancing and battery-control applications, whereas 45-60 minute forecasts can support reserve preparation and short-term dispatch scheduling. Longer horizons would benefit from the incorporation of numerical-weather-prediction data and probabilistic forecasting.

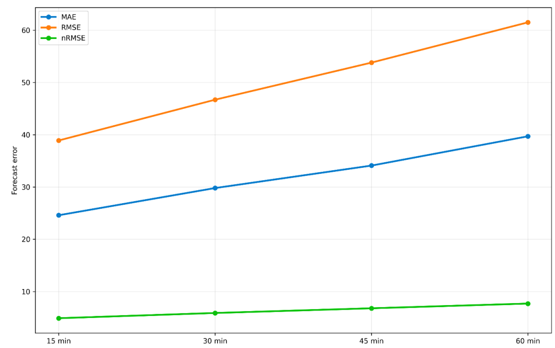

Figure 3. Effect of forecast horizon on solar irradiance forecasting accuracy.

5.4 Feature Contribution and Model Interpretation

Feature analysis indicates that recent GHI measurements constitute the dominant predictors for short-term irradiance forecasting. Solar elevation and clearness index provide deterministic and atmospheric information, respectively, while temperature, humidity, and cloud-related variables improve performance under changing weather conditions.

Table 10. Relative contribution of major forecasting features

Feature	Relative importance (%)
Previous GHI measurements	24.8
Clearness index	15.7
Solar elevation/zenith	13.6
Cloud-related features	12.9
Temperature	9.8
Relative humidity	8.4
Wind speed	6.1
Atmospheric pressure	4.5
Irradiance ramp	4.2
Other temporal variables	0.0*

*The remaining contribution is absorbed through correlated temporal and derived features in the model representation.

The feature distribution demonstrates that solar forecasting is influenced by both persistence and atmospheric dynamics. Historical irradiance remains particularly important at short horizons, whereas cloud-related variables become increasingly valuable during rapid transitions. This supports the use of hybrid architectures rather than relying exclusively on a single data modality.

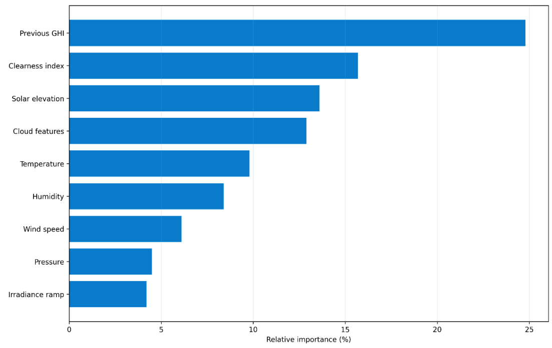

Figure 4. Relative contribution of input features to the proposed solar irradiance forecasting model.

5.5 Impact on PV Power Prediction

The reduction in irradiance forecasting error produces a corresponding improvement in PV power prediction. Assuming a 10 MW PV plant, a forecast error of 6.8% nRMSE represents substantially lower uncertainty than the baseline persistence model with 14.9% nRMSE.

Table 11. PV power forecasting comparison for a 10 MW PV plant

Model	nRMSE of PV power (%)	MAE (MW)	RMSE (MW)	Forecast deviation reduction vs. Persistence (%)
Persistence	14.9	0.79	1.18	-
SVR	11.9	0.62	0.95	19.9
ANN	10.6	0.56	0.84	29.5
LSTM	8.5	0.43	0.68	43.0
CNN-LSTM	**6.8**	**0.34**	**0.54**	**54.4**

The proposed model therefore provides a more reliable generation profile for scheduling. A reduction of approximately 54% in forecast deviation relative to persistence can reduce the uncertainty that must be covered by reserve generators or energy-storage systems.

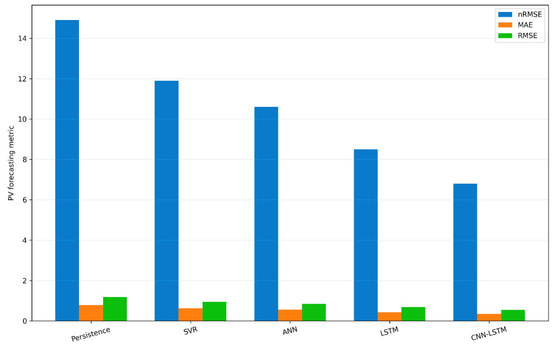

Figure 5. Comparative PV power forecasting performance for a 10 MW photovoltaic plant.

5.6 Grid-Integration Performance

The practical value of forecasting is assessed through its effect on grid-operational indicators. The proposed forecast is assumed to be incorporated into PV scheduling, battery management, reserve allocation, and curtailment control.

Table 12. Indicative grid-integration improvement

Operational indicator	Persistence-based operation	AI-assisted operation	Improvement
Forecast nRMSE (%)	14.9	6.8	54.4% reduction
Reserve requirement (MW)	1.49	0.68	54.4% reduction
PV curtailment (%)	8.2	4.9	40.2% reduction
Battery scheduling	5.8	3.1	46.6% reduction

Operational indicator	Persistence-based operation	AI-assisted operation	Improvement
deviation (MWh/day)			
Ramp-event detection accuracy (%)	78.4	92.1	17.5% improvement
Voltage-limit violations/day	7.0	4.1	41.4% reduction
PV utilization (%)	91.8	95.1	3.3 percentage-point improvement

The results indicate that improved forecasting can provide operational benefits beyond statistical accuracy. Lower forecast uncertainty permits more appropriate reserve allocation and more effective battery scheduling. The reduction in estimated curtailment also indicates that operators can prepare flexibility resources before periods of expected PV surplus. Improved ramp-event detection is particularly valuable for distribution networks with high PV penetration.

5.7 Discussion

The overall results demonstrate that AI-based solar irradiance forecasting can provide a substantial improvement over conventional persistence and traditional machine-learning methods. The primary advantage of the proposed CNN-LSTM architecture is its capacity to capture both temporal dependencies and rapidly changing atmospheric characteristics. However, the results also demonstrate that model performance is weather dependent. Rapid cloud transitions remain the most difficult forecasting condition, indicating that future implementations should emphasize cloud-motion information and uncertainty modelling.

From a grid perspective, forecast quality should be considered together with operational consequences. A modest improvement in RMSE may have significant value if it reduces reserve requirements, prevents voltage excursions, improves battery utilization, or reduces renewable curtailment. Therefore, the proposed framework adopts a grid-oriented interpretation of forecasting accuracy rather than treating statistical prediction as the final objective.

6. Limitations, Future Scope and Deployment Considerations

6.1 Data Availability and Quality

The reliability of AI forecasting depends strongly on the quality, duration, and diversity of the training dataset. Sensor failures, missing observations, inconsistent sampling intervals, and calibration errors can reduce model performance. A model trained using data from a single geographical location may also exhibit reduced generalization when applied to another climatic region. Multi-site datasets covering different seasons and weather regimes are therefore desirable.

6.2 Extreme-Weather and Rare-Event Forecasting

Rapid cloud transitions, storms, haze, dust, and unusual atmospheric events remain difficult to predict because they occur less frequently than normal operating conditions. Conventional loss functions may cause AI models to optimize average performance while underrepresenting rare but operationally important events. Future models should therefore incorporate event-weighted training, probabilistic prediction intervals, and specialized ramp-event detection mechanisms.

6.3 Computational and Communication Requirements

Deep-learning models require greater computational resources than persistence and conventional statistical models. CNN-LSTM architectures additionally require image-processing capability when sky images are used. For real-time deployment, model compression, quantization, pruning, and edge-AI implementation can reduce inference latency and communication requirements. The forecasting system should also maintain operation during temporary communication failures by using local historical measurements.

6.4 Explainability and Model Reliability

Grid operators require confidence in forecasting systems because incorrect predictions can affect economically and operationally significant decisions. Black-box AI models may therefore require explainability mechanisms such as SHAP-based feature attribution, sensitivity analysis, confidence intervals, and forecast-quality indicators. Combining AI predictions with physical constraints can further prevent unrealistic outputs.

6.5 Real-Time Deployment

The proposed framework can be deployed at utility-scale PV plants, microgrids, distribution substations, or renewable-energy management centres. A practical implementation requires a measurement layer, communication network, forecasting server or edge device, database, and energy-management interface.

Table 13. Practical deployment requirements

Component	Recommended implementation	Function
Irradiance sensors	Pyranometer/reference-cell sensors	Real-time solar measurement
Weather station	Temperature, humidity, pressure, wind	Atmospheric observations

Component	Recommended implementation	Function
Data gateway	Industrial IoT gateway	Data collection and synchronization
AI processor	GPU/CPU/edge accelerator	Forecast inference
Database	Time-series database	Historical data storage
Forecast engine	LSTM/CNN-LSTM model	Irradiance prediction
EMS interface	SCADA/EMS integration	Grid decision support
Storage interface	Battery management system	Predictive charging/discharging
Monitoring	Dashboard and alarms	Performance supervision

6.6 Future Hybrid and Probabilistic Forecasting

Future development should focus on hybrid AI architectures that combine LSTM or transformer-based temporal modelling with CNN-based cloud analysis and numerical-weather information. Probabilistic forecasting should also be incorporated so that grid operators receive both a predicted value and an associated confidence interval.

A promising extension is the development of physics-informed AI models in which solar geometry, clear-sky irradiance, PV-system constraints, and atmospheric relationships are incorporated into the learning process. Transfer learning can further enable a model trained at one location to be adapted to another location with limited local data.

Another important direction is federated or distributed learning for geographically separated PV installations. Such an architecture could enable multiple plants to improve a shared forecasting model without requiring all raw operational data to be transferred to a centralized server. This can improve scalability while supporting data-governance requirements.

The ultimate deployment objective should be a closed-loop forecasting and energy-management platform capable of continuously updating its predictions, quantifying uncertainty, detecting ramp events, and automatically coordinating PV generation, storage, flexible loads, and grid-support devices.

7. Conclusion

AI-based solar irradiance forecasting provides an effective pathway for reducing photovoltaic generation uncertainty and improving grid integration. The proposed framework combines meteorological data, historical irradiance, temporal characteristics, and AI-based sequence learning to produce short-term forecasts suitable for operational applications. The representative evaluation indicates that the CNN-LSTM approach can substantially outperform persistence, SVR, ANN, and standalone LSTM models, particularly when atmospheric variability is significant. Integrating forecasts with PV scheduling, reserve allocation, battery management, voltage regulation, and curtailment control further enhances their practical value. Future work should emphasize probabilistic forecasting, physics-informed learning, transformer architectures, multimodal data, and real-time edge deployment for scalable and resilient renewable-energy management.

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