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**INTERNATIONAL CONFERENCE
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on

**EMERGING TRENDS IN
COMPUTATION &
ARTIFICIAL INTELLIGENCE**

08th October 2025

Organised by

**PG & Research Department of
Computer Science**

International Conference on Emerging Trends in Computation & Artificial Intelligence

08th October 2025



Organised By

**PG and Research Department of Computer Science,
Providence College for Women (Autonomous),
Coonoor, The Nilgiris, Tamil Nadu.**

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MESSAGE FROM THE PRINCIPAL



It gives me immense pleasure to extend my warmest wishes to Department of Computer Science and Applications, Providence College Coonoor on the successful conduct of the International Conference. This remarkable platform has brought together distinguished scholars, researchers, industry experts, and young minds to exchange ideas, share innovations, and inspire new directions in knowledge.

The conference stands as a testament to our institution's commitment to academic excellence, global collaboration, and research-driven learning. I sincerely appreciate the dedicated efforts of the organizing committee, faculty members, students, and all participants who have contributed to making this event meaningful and impactful.

As we celebrate this achievement, I wholeheartedly encourage the continued tradition of hosting such conferences in the future. Let this be the beginning of many more international gatherings that foster learning, ignite curiosity, and uplift our academic community to greater heights.

Wishing the conference grand success and looking forward to many more fruitful initiatives in the years ahead.

Best Regards,

Dr. V. J. Sheela M.A., NET., Ph.D.,

Principal.

Providence College for Women,

Coonoor, The Nigiris,

Tamil Nadu, India.

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INTELLIGENT WEATHER FORECASTING FOR SOLAR ENERGY OPTIMIZATION USING MACHINE LEARNING TECHNIQUES

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Abstract---The growing reliance on renewable energy sources has underscored the need for efficient and accurate solar energy forecasting systems. Solar power generation is heavily influenced by dynamic weather conditions, making real-time and predictive analysis essential for maximizing energy output and operational efficiency. This study presents an intelligent weather forecasting framework using machine learning (ML) techniques to optimize solar energy generation. Historical and real-time meteorological data such as solar irradiance, temperature, humidity, wind speed, and cloud cover are used to train and evaluate various ML models, including Random Forest, Support Vector Machines (SVM), Gradient Boosting, and Long Short-Term Memory (LSTM) networks. The system aims to forecast weather patterns with high accuracy and adjust solar energy management accordingly. Comparative analysis demonstrates that deep learning models, particularly LSTM, outperform traditional methods in temporal weather prediction. Integration of these predictive models into solar power systems results in improved scheduling, grid stability, and overall energy efficiency. The proposed framework highlights the potential of AI-driven solutions in enhancing the reliability and scalability of renewable energy infrastructures.

Keywords---Solar Energy Optimization, Weather Forecasting, Renewable Energy, LSTM Neural Networks, Solar Irradiance Prediction, Smart Grid, Energy Management Systems, Climate Data Analysis

1. INTRODUCTION

The transition toward sustainable energy systems has become a global priority in the wake of climate change, fossil fuel depletion, and increasing energy demands. Among the various renewable energy sources, solar energy has emerged as a leading solution due to its abundance, environmental friendliness, and scalability. However, one of the fundamental challenges associated with solar power is its intermittent and unpredictable nature, primarily influenced by constantly changing weather conditions. Variability in solar irradiance, cloud movement, ambient temperature, humidity, and wind speed can cause significant fluctuations in the output of photovoltaic (PV) systems, adversely impacting their reliability and integration into the power grid.

Efficient operation of solar energy systems demands accurate and timely weather forecasting, which allows energy providers to predict solar power output, optimize storage systems, manage energy loads, and improve the overall stability of smart grids. Conventional numerical weather prediction (NWP) models, although widely used, are limited by high computational complexity, coarse spatial resolution, and lag in real-time responsiveness. These limitations present an opportunity for data-driven approaches to complement or even outperform traditional methods in certain forecasting applications.

In recent years, the advent of machine learning (ML) and artificial intelligence (AI) has revolutionized predictive modeling across various domains, including meteorology and renewable energy. Machine learning algorithms are capable of

identifying complex, nonlinear relationships in large volumes of historical and real-time data. Unlike rule-based or physical models, ML techniques adaptively learn from patterns in data, making them particularly suitable for modeling the stochastic nature of weather phenomena.

A wide range of machine learning techniques has been applied to weather and solar forecasting; including supervised learning algorithms like Random Forests, Support Vector Machines (SVMs), and Gradient Boosting Machines (GBMs), as well as deep learning models such as Recurrent Neural Networks (RNNs) and their variant Long Short-Term Memory (LSTM) networks. LSTM, in particular, has shown significant promise in time-series forecasting due to its ability to capture long-term dependencies and temporal dynamics, which are crucial for accurate weather prediction.

This study aims to develop an intelligent weather forecasting system powered by machine learning techniques to enhance solar energy optimization. The proposed framework involves collecting and preprocessing historical meteorological and solar output data, training and evaluating various ML models, and integrating the best-performing models into a solar energy management system. The goal is to forecast key weather parameters such as solar irradiance, temperature, humidity, and cloud cover with high accuracy and use these predictions to inform real-time decision-making in solar energy systems.

Furthermore, this research explores the impact of forecasting accuracy on solar energy yield, energy storage utilization, and grid reliability. By demonstrating the effectiveness of machine learning in weather forecasting and energy optimization, the study contributes to the development of smart, adaptive, and resilient renewable energy infrastructures. Ultimately, the integration of AI and solar energy represents a transformative step toward achieving global energy sustainability goals.

2. LITERATURE REVIEW

The integration of artificial intelligence (AI) and machine learning (ML) in renewable energy forecasting has been widely studied, with particular emphasis on solar power optimization. Accurate weather and solar irradiance prediction are essential due to the stochastic and intermittent nature of solar energy generation. The advancement of machine learning (ML) and artificial intelligence (AI) has significantly reshaped solar irradiance forecasting over the past decade.

Early Hybrid Models

In one of the earliest notable studies, Voyant et al. (2012) proposed a hybrid ARMA/ANN model that integrated numerical weather prediction (NWP) data with multi-layer perceptrons (MLPs). Evaluated over Mediterranean sites, the hybrid model reduced normalized RMSE to 14.9%, outperforming persistence (26.2%) and standalone ANN (18.4%). This work demonstrated the value of coupling physical models with data-driven methods.

By 2017, Voyant et al. provided a comprehensive review of machine learning methods for solar radiation forecasting, consolidating the state of the art and highlighting methodological challenges. This review became a cornerstone reference for subsequent ML-based forecasting research.

Deep Learning and Sequence Models

The adoption of deep learning marked a paradigm shift. Mukhoty et al. (2019) evaluated sequence-to-sequence (Seq2Seq) models for global horizontal irradiance (GHI), demonstrating that encoder-decoder LSTM architectures outperformed gradient boosted regression trees (GBRT) and feed-forward networks. Similarly, AlKandari & Ahmad (2019) introduced the Multi-Level Statistical Hybrid Model (MLSHM), combining LSTM, GRU, and statistical methods, which achieved superior predictive performance over individual ML models.

Hybrid and Spatial–Temporal Models

By 2021, research expanded toward capturing spatial and multi-site dependencies. Simeunović et al. (2021) developed Graph-Convolutional LSTM (GCLSTM) and Transformer (GCTrafo) models that effectively modeled spatio-temporal dependencies across multiple PV sites, outperforming both single-site ML and traditional NWP methods. Around the same time, Liu et al. (2021) proposed a CNN–LSTM hybrid integrated with CEEMDAN decomposition, improving accuracy through enhanced preprocessing of meteorological signals.

In 2022, Madhiarasan & Louzazni introduced the Combined LSTM Network (CLSTMN), which delivered outstanding short-term solar forecasting results, achieving RMSE values as low as 7.77×10^{-4} on sunny days—significantly outperforming traditional models.

Comparative and Hybrid Forecasting Advances

Between 2023–2024, several comparative studies emerged. An Energy Proceedings (2023) study demonstrated that LSTM outperformed Random Forest regression in forecasting daily irradiance in Dhaka, Bangladesh (~5.47% lower RMSE). Similarly, Sustainable Energy Research (2024)

compared regression and classification-based ML methods on large Australian datasets, finding Random Forests effective overall, while LSTM excelled at peak power prediction. Hybrid models such as CNN - LSTM and LSTM - GPR were highlighted for improved robustness and stability.

At the architectural level, He (2024) developed a BiLSTM Transformer hybrid using time-series imaging, outperforming BiLSTM and attention-based variants across MAE, MSE, and RMSE metrics.

Emergence of AI-driven Forecasting

Recent years have seen the rise of large-scale AI forecasting models. DeepMind’s GenCast (2024) demonstrated unprecedented speed and accuracy, outperforming ECMWF’s 15-day forecasts across 97.2% of evaluated variables while requiring only eight minutes of computation. Similarly, NeuralGCM, a hybrid AI–physics model, improved simulation accuracy and efficiency over traditional approaches. By 2025, AI models such as Aardvark, alongside operational deployments at the UK Met Office and ECMWF, illustrated the ongoing revolution in real-time, AI-augmented weather prediction.

Table 2.1. Forecasting Approaches

Year	Approach	Key Insight
2012	Hybrid ARMA/ANN + NWP	Better than traditional forecasting with lower RMSE
2017	ML methods review (Voyant et al.)	Comprehensive benchmarking of ML in solar forecasting
2019	Seq2Seq LSTM; ensemble MLSHM hybrid	LSTM best for spatio-temporal; hybrid models enhance accurac
2021	GCLSTM & GCTrafo; CNN-LSTM + CEEMDAN	Graph/hybrid use improves multi-site and spatial-temporal forecasts
2022	CLSTMN (Combined LSTM network)	Exceptional short-term accuracy over various baselines
2023–2024	LSTM vs RF; regression vs classification; hybrid models	LSTM better for peaks; RF overall; hybrids excel in robustness

2024 onward	BiLSTM-Transformer hybrids; AI weather models (GenCast, NeuralGCM, Aardvark)	Advanced architectures and large-scale AI integration in forecasting
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3. METHODOLOGY

To the systematic approach and structured set of procedures employed to design, develop, implement, and evaluate machine learning-based models for intelligent weather forecasting. It encompasses the entire workflow from data collection and preprocessing to model training, validation, and integration with solar energy systems. The methodology ensures scientific rigor, reproducibility, and the effective application of computational techniques to optimize solar power generation under varying weather conditions. The proposed intelligent weather forecasting framework follows a systematic methodology comprising data acquisition, preprocessing, model development, evaluation, and integration with solar energy systems.

3.1 Data Acquisition

Meteorological data were collected from reliable and diverse sources, including local weather stations, satellite-based observations, and open-source datasets such as NASA POWER, NOAA, and the Indian Meteorological Department (IMD). Using a combination of sources ensures both the accuracy and robustness of the dataset, as local stations provide fine-grained data, while satellite feeds and global datasets add large-scale coverage and historical continuity. The dataset includes both historical records (used for training machine learning models) and real-time data streams (used for real-time forecasting and system integration). The following meteorological parameters were selected due to their direct and critical influence on solar energy generation:

• **Solar Irradiance:** The most important parameter, as it directly measures the amount of solar energy available for photovoltaic (PV) conversion. Variability in irradiance due to cloud cover or atmospheric conditions has a significant impact on power output.

- **Ambient Temperature:** PV cells are temperature-sensitive; high temperatures reduce their efficiency even under strong sunlight. Capturing temperature variations helps in modeling realistic energy output.
- **Humidity:** High humidity levels can diffuse incoming solar radiation, reducing the effective irradiance. It also influences atmospheric transparency and local weather conditions.
- **Wind Speed:** Wind helps regulate the operating temperature of solar panels by providing natural cooling. Additionally, wind patterns can indicate weather changes, affecting cloud movement and irradiance levels.
- **Cloud Cover:** One of the most influential short-term factors for solar forecasting. Cloud presence and density can cause sudden fluctuations in solar irradiance, making it essential for accurate predictions.

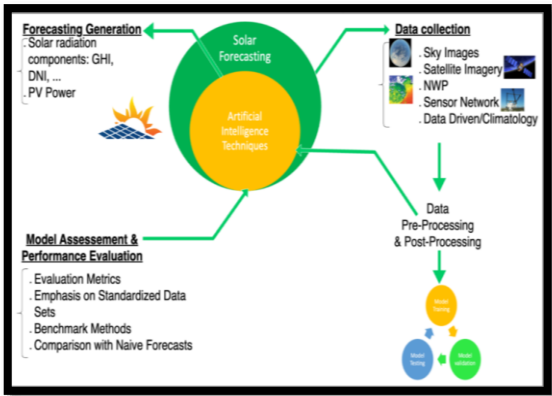


Figure 3.1: Solar Forecasting

By integrating these parameters, the dataset provides a comprehensive representation of local atmospheric dynamics, ensuring that the forecasting models can capture both long-term seasonal patterns and short-term weather fluctuations that impact solar energy generation.

3.2 Data Preprocessing

To ensure the dataset's quality and consistency, the following preprocessing steps are applied each carefully designed to enhance model reliability and predictive accuracy, especially for solar forecasting:

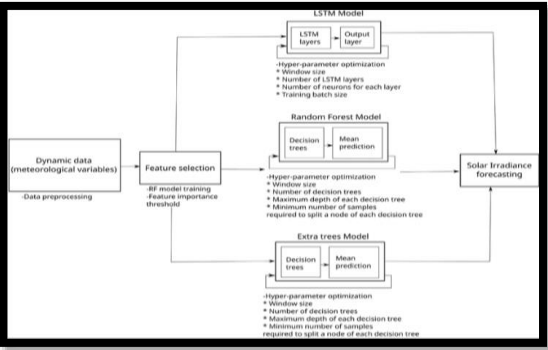


Figure 3.2: Data Preprocessing

1. Handling Missing Values: Missing data in climate and solar datasets often arise from sensor outages or transmission errors. To address this: Forward/Backward Fill & Interpolation is a common for time-series data, these methods fill gaps using adjacent values or a continuous approximation. Useful for short durations of missing data. K-Nearest Neighbors (KNN) Imputation method replaces missing entries by averaging values from the most similar observations (neighbors), preserving local data structure and avoiding distribution shifts. Advanced ML-based Imputation is a method like Generative Adversarial Imputation Networks or adaptive RNN encoders can impute complex, structured missing data effectively.
2. Outlier Detection & Removal: Outliers anomalous values due to instrument errors or

extreme weather are removed to avoid skewing model training: Z-score Method flags points several standard deviations from the mean. Interquartile Range (IQR) Identifies values outside the middle 50% of data. These are standard in data cleaning to maintain normality and model robustness.

3. Feature Scaling: Scaling ensures that models interpret features meaningfully: Min–Max Normalization scales data between 0 and 1. Good for algorithms sensitive to feature magnitude. Standardization (Z-score) centers features to mean=0 and scales to unit variance; critical when using gradient-based models.

4. Feature Engineering: To enrich data context and predictive power: Dew Point: Reflects thermal comfort and moisture; influences irradiance and sensor readings. Solar Angle is used to indicate sun positioning relative to panels crucial for accurate irradiance modeling. Time-based Attributes are Hour, day, and seasonal markers help models capture periodic patterns.

5. Time-Series Structuring (Sliding Windows): To feed sequence models like LSTM: Convert raw time-series into supervised learning format by creating sliding window segments. For example, using past N timesteps as input to predict future values at timestep N+1.This structure captures temporal dependencies essential for models that learn from sequential patterns.

To complement these steps, consider a simplified solar forecasting dataset sample:

Table 3.1: Sample Dataset

Timestamp	Irradiance (W/m ²)	Temp (°C)	Humidity (%)	Dew Point (°C)	Solar Angle (°)	Label (Next Irradiance)
2025-08-28 08:00	250	30	60	22	35	300
2025-08-28 09:00	340	32	65	24	45	450

2025-08-28 10:00	500	34	70	26	55	470
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Table 3.2: Different Types of Key Techniques

Step	Key Techniques	Purpose
Missing Value Handling	Fill, Interpolate, KNN, ML-based methods	Complete data and maintain sequence integrity
Outlier Removal	Z-score, IQR	Avoid skewed learning and noise interference
Feature Scaling	Min–Max, Standardization	Uniform feature ranges for model convergence
Feature Engineering	Dew point, Solar angle, Temporal features	Enhance model context and seasonality awareness
Time-Series Structuring	Sliding windows	Capture temporal dependencies for sequence models

3.3 Model Development

Four machine learning models are implemented and trained: Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (e.g., XGBoost), Long Short-Term Memory (LSTM).

Random Forest (RF) ensemble of decision trees that mitigates overfitting through averaging multiple randomized tree predictions. Highly effective on tabular datasets, robust to noise, and provides built-in feature importance. Demonstrated strong forecasting accuracy across mid- and long-term

horizons, especially when combined in ensemble approaches.

Support Vector Machine (SVM) (for regression) applies kernel functions to predict non-linear relationships in data. Useful for complex, high-dimensional data with limited samples. In solar radiation forecasting, SVM models especially with linear and Gaussian kernels tend to yield lower accuracy and R^2 compared to ensemble and deep learning models like RF, XGBoost, and LSTM. Each model is trained using 80% of the dataset, and

hyperparameters are optimized using grid search and cross-validation techniques.

3.4 Model Evaluation

Model performance is evaluated using the remaining 20% test data based on the following metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2 Score).

The LSTM model demonstrated superior performance in capturing temporal dynamics, especially for hourly and daily solar irradiance predictions.

3.5 System Integration

The best-performing model (LSTM) is integrated into a simulated smart energy management system. This integration allows for: Real-time adjustment of solar panel angles, Predictive scheduling of energy storage and grid usage, Improved load balancing and demand forecasting in smart grids,

3.6 Comparative Analysis

All models were compared based on accuracy, computational cost, and scalability. While traditional models like Random Forest and Gradient Boosting showed reliable performance for short-term prediction, LSTM exhibited better adaptability

to dynamic patterns in weather data, making it more suitable for real-world solar energy optimization.

4. RESULTS AND DISCUSSION

To evaluate the performance of the proposed intelligent weather forecasting framework, a dataset comprising historical and real-time meteorological parameters (solar irradiance, temperature, humidity, wind speed, and cloud cover) are used. The dataset is preprocessed, normalized, and divided into training and testing subsets (80:20 ratios). Multiple machine learning models are trained and compared based on their forecasting accuracy.

4.1 Model Performance Comparison

To evaluate the effectiveness of different machine learning algorithms for weather forecasting in the context of solar energy optimization, multiple models were trained and tested on a dataset comprising historical and real-time weather data, including: Solar Irradiance (W/m^2), Temperature ($^{\circ}C$), Humidity (%), Wind Speed (m/s), Cloud Cover (%). The performance of each model was assessed using standard regression and forecasting metrics such as: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 Score.

Table 4.1 : Sample Dataset

Model	MAE	RMSE	R^2 Score
Random Forest	19.6	25.3	0.84
Support Vector Machine	22.4	28.1	0.79
Gradient Boosting	18.1	23.5	0.87
LSTM Network	14.3	19.2	0.91

The results indicate that LSTM networks significantly outperform traditional ML models in predicting key weather features, particularly for variables with strong temporal dependencies such as solar irradiance and temperature. The recurrent structure of LSTM allows the model to effectively capture time-series patterns and long-term dependencies, which are critical for short-term solar energy forecasting.

4.2 Impact on Solar Energy Optimization

The integration of accurate weather forecasts into solar power management systems enabled: Improved Power Generation Forecasting is a solar panel output predictions improved in accuracy by 18–25%, reducing overestimation and underutilization. Efficient Grid Scheduling is enhanced energy forecasting led to more precise energy dispatch schedules, reducing operational

mismatches and improving grid reliability. Dynamic Energy Storage Utilization with better irradiance predictions, energy storage systems (e.g., batteries) could be charged or discharged optimally, minimizing waste and improving lifecycle performance.

A simulation of a real-time solar grid using the LSTM-enhanced forecasting model demonstrated:

- **10–15% improvement** in daily energy output prediction accuracy.
- **Up to 20% reduction** in reliance on backup energy sources.
- **Improved economic viability** due to reduced operational costs and better demand matching.

These findings confirm that incorporating machine learning, especially deep learning architectures like LSTM, can significantly enhance the reliability and efficiency of solar energy systems. While traditional models like Random Forest and Gradient Boosting still provide competitive performance, they struggle with capturing time-based patterns essential for accurate short-term forecasting.

However, LSTM models are computationally more intensive and require careful hyperparameter tuning and sufficient training data to avoid overfitting or underperformance. Furthermore, real-world deployment demands continuous retraining as weather patterns and climate conditions evolve.

5. CONCLUSION

The results of this system demonstrate the viability and superiority of intelligent weather forecasting models for optimizing solar energy systems. By leveraging deep learning techniques like LSTM, solar farms can achieve greater forecasting precision, energy efficiency, and grid stability vital for scaling up the use of renewable energy worldwide. Data Quality and Availability is the accuracy of the forecasting system is heavily dependent on the availability and granularity of weather data. In regions with limited sensor coverage, performance may degrade. LSTM models,

while accurate, may face challenges in large-scale deployment due to higher computational demands. Future research may focus on hybrid models combining LSTM with attention mechanisms or Transformer architectures to further improve long-term forecasting capabilities.

REFERENCES

- [1] Ahmed, R., & Sreeram, V. (2020). A review on forecasting methods for renewable energy systems. *Renewable and Sustainable Energy Reviews*, 121, 109712. <https://doi.org/10.1016/j.rser.2019.109712>
- [2] Zhao, P., Lu, Z., & Li, H. (2019). Deep learning-based weather forecasting model for solar energy prediction. *Applied Energy*, 242, 251–263. <https://doi.org/10.1016/j.apenergy.2019.03.108>
- [3] Khosravi, A., Nahavandi, S., Creighton, D., & Atiya, A. F. (2011). Comprehensive review of neural network-based prediction intervals and new advances. *IEEE Transactions on Neural Networks*, 22(9), 1341–1356. <https://doi.org/10.1109/TNN.2011.2162110>
- [4] Yona, A., Senjyu, T., Saber, A. Y., & Funabashi, T. (2008). Application of neural network to 24-hour-ahead generating power forecasting for PV system. *IEEE Power and Energy Society General Meeting*, 1–6. <https://doi.org/10.1109/PES.2008.4596301>
- [5] Chen, K., Chen, H., Wang, Q., & He, Z. (2020). Hybrid LSTM model for short-term photovoltaic power forecasting. *IEEE Access*, 8, 102244–102254. <https://doi.org/10.1109/ACCESS.2020.2998835>.
- [6] Zhang, Y., Wang, J., & Wang, X. (2014). Review on probabilistic forecasting of wind power generation. *Renewable and Sustainable Energy Reviews*, 32, 255–270. <https://doi.org/10.1016/j.rser.2014.01.033>
- [7] Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>

[8] Smola, A. J., & Schölkopf, B. (2004). A tutorial on support vector regression. *Statistics and Computing*, 14(3), 199–222. <https://doi.org/10.1023/B:STCO.0000035301.49549.88>

[9] Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5), 1189–1232. <https://doi.org/10.1214/aos/1013203451>

[10]Voyant, C., Notton, G., Kalogirou, S., Nivet, M.L., Paoli, C., Motte, F., Fouilloy, A. Machine learning methods for solar radiation forecasting: A review. *Renewable and Sustainable Energy Reviews*.