



PERFORMANCE EVALUATION OF HYBRID DEEP LEARNING MODELS FOR SHORT-TERM SOLAR ENERGY FORECASTING

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Abstract

Accurate short-term solar energy forecasting plays a significant role in renewable energy management, power system stability, and efficient electricity generation. However, variations in solar irradiance, temperature, humidity, cloud cover, and weather conditions create challenges for accurate prediction. The present study focuses on the performance evaluation of hybrid deep learning models for short-term solar energy forecasting, particularly Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) and Convolutional Neural Network–Gated Recurrent Unit (CNN-GRU). The proposed methodology involves historical solar energy and meteorological data collection, preprocessing, feature selection, model training, validation, and testing. The performance of the models will be evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). A comparative analysis will be conducted to identify the most suitable model based on forecasting accuracy, reliability, and computational efficiency.

Keywords: Solar Energy Forecasting, Hybrid Deep Learning, CNN-LSTM, CNN-GRU, Renewable Energy, Forecasting Accuracy, Performance Evaluation.

1. INTRODUCTION

The increasing demand for electricity and the growing concern over environmental pollution have encouraged the adoption of renewable energy sources across the world. Solar energy has emerged as one of the most promising renewable energy resources because of its wide availability, environmental benefits, and potential to reduce dependence on conventional fossil fuels. The development of solar photovoltaic technology has made it possible to convert sunlight into electricity for residential, commercial, industrial, and utility-scale applications. However, solar energy generation is highly dependent on environmental and meteorological conditions, including solar irradiance, temperature, humidity, wind speed, and cloud cover. These factors cause fluctuations in solar power output, creating challenges for electricity generation planning, grid stability, and energy management. Therefore, accurate short-term solar energy forecasting is essential for improving the reliability and efficiency of solar power systems.

Short-term solar energy forecasting involves predicting solar power generation or energy output over relatively brief periods, such as the next few minutes, hours, or day. Reliable forecasts help electricity operators balance energy supply and demand, schedule conventional power generation, manage energy storage systems, and reduce uncertainty in renewable energy integration. Traditional forecasting techniques, including statistical models and conventional machine learning algorithms, have been widely used to estimate future solar energy production. However, these methods may face limitations when dealing with complex nonlinear relationships, rapidly changing weather conditions, and long-term dependencies in sequential data. The availability of historical solar generation records and meteorological observations has created opportunities to develop more advanced forecasting approaches capable of learning complex patterns from large datasets.

Deep learning has gained considerable attention in renewable energy forecasting because of its ability to automatically extract relevant features and represent complex relationships within time-series data. Convolutional Neural Networks (CNNs) can identify local patterns and variations in input observations, while Long Short-Term Memory (LSTM) networks can learn temporal dependencies in sequential data. Similarly, Gated Recurrent Unit



(GRU) networks provide an alternative recurrent architecture for modelling time-dependent patterns. Although these individual architectures have demonstrated potential in forecasting applications, their performance may vary depending on the characteristics of the dataset, forecasting horizon, and environmental conditions. Consequently, combining complementary deep learning techniques into hybrid architectures has become a promising approach for improving forecasting performance.

Hybrid deep learning models integrate the strengths of multiple neural network architectures to capture different characteristics of solar energy data. The CNN-LSTM model combines convolutional feature extraction with the sequential learning capabilities of LSTM, whereas the CNN-GRU model integrates convolutional layers with GRU-based temporal learning. These models may improve the identification of short-term fluctuations and temporal dependencies in solar power generation. Nevertheless, the effectiveness of a hybrid architecture cannot be established solely from its design. Its performance must be evaluated experimentally using consistent datasets, suitable forecasting horizons, and reliable statistical metrics. A systematic comparison is therefore necessary to determine whether hybrid models provide meaningful improvements over individual deep learning approaches.

The performance evaluation of forecasting models requires appropriate statistical measures to assess prediction errors and overall model effectiveness. Mean Absolute Error (MAE) measures the average absolute difference between predicted and observed values, while Root Mean Squared Error (RMSE) gives greater weight to larger forecasting errors. Mean Absolute Percentage Error (MAPE) expresses errors in percentage terms, although it requires careful interpretation when actual solar output is zero or close to zero. The coefficient of determination (R^2) provides additional information about the relationship between predicted and observed values. Computational time can also be considered to evaluate the practical feasibility of implementing different models. Using multiple evaluation criteria provides a more comprehensive understanding of forecasting performance than relying on a single metric.

2. LITERATURE REVIEW

Radzi et al. (2025) investigated short-term solar power forecasting using a hybrid deep learning approach and compared its performance with machine learning models. The study emphasized improving prediction accuracy and developing reliable forecasting systems for solar energy applications.

Thipwangmek et al. (2024) proposed a hybrid deep learning approach for short-term solar photovoltaic power forecasting. The study highlighted the potential of combining deep learning techniques to capture complex patterns in solar power generation and improve forecasting performance.

Salman et al. (2024) examined hybrid deep learning models for solar power time-series forecasting. The research focused on modelling temporal dependencies in solar power data to improve prediction reliability and support efficient renewable energy management.

Renold et al. (2025) explored a hybrid machine learning approach to improve short-term photovoltaic power forecasting accuracy. The study emphasized the importance of integrating machine learning techniques to capture nonlinear relationships and enhance predictive performance.

Yan et al. (2020) developed a hybrid deep learning methodology for short-term solar irradiance forecasting. The study addressed the challenges of fluctuating solar radiation and complex temporal patterns, highlighting the potential of hybrid models to improve forecasting accuracy and reliability.

3. RESEARCH METHODOLOGY

3.1 Introduction

The present study aims to evaluate the performance of hybrid deep learning models for short-term solar energy forecasting. Accurate forecasting is essential for efficient solar power generation, energy management, and grid stability. Since solar energy production depends on weather conditions, solar irradiance, temperature, and seasonal variations, hybrid deep learning models can help capture complex patterns and temporal dependencies. The methodology includes data collection, preprocessing, model development, training, performance evaluation, and comparative analysis to identify the most effective forecasting model.

3.2 Research Design

The study will adopt a quantitative, experimental, and comparative research design to evaluate different hybrid deep learning models and compare their forecasting accuracy.



3.3 Data Collection

Historical solar energy generation and meteorological data will be collected from reliable datasets or publicly available repositories. The data may include solar irradiance, temperature, humidity, wind speed, cloud cover, and historical solar power output.

3.4 Data Preprocessing

The collected data will be checked for missing values, duplicate records, and inconsistencies. Appropriate data cleaning, normalization, and feature selection techniques will be applied to prepare the dataset for model training.

3.5 Development of Hybrid Deep Learning Models

The study will evaluate hybrid architectures such as CNN-LSTM and CNN-GRU. CNN will extract important features, while LSTM and GRU will learn temporal dependencies in solar energy data. Individual deep learning models may also be included as baseline models for comparison.

3.6 Model Training and Testing

The dataset will be divided chronologically into training, validation, and testing subsets. The models will be trained using historical observations, optimized through suitable hyperparameters, and tested on unseen data to evaluate their forecasting performance.

3.7 Performance Evaluation Metrics

The models will be evaluated using the following metrics:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)
- Coefficient of Determination (R^2)
- Training and prediction time

3.8 Comparative Analysis

The performance of each model will be compared using evaluation metrics, tables, and graphs. The analysis will identify the model offering the best combination of forecasting accuracy, reliability, and computational efficiency.

4. RESULTS AND DISCUSSION

4.1 Introduction

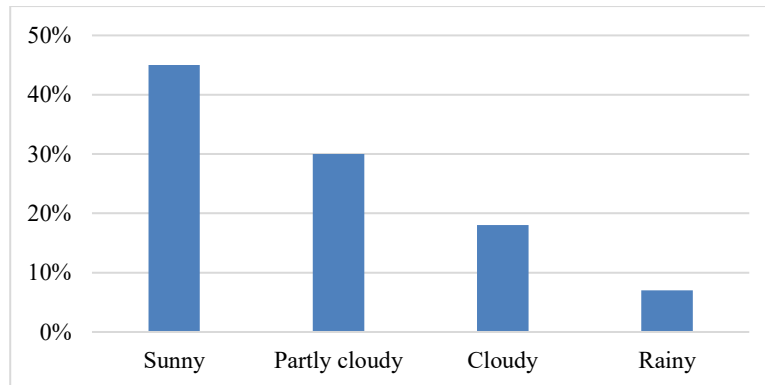
This chapter presents the results and discussion of the performance evaluation of hybrid deep learning models for short-term solar energy forecasting. The analysis focuses on evaluating the effectiveness of CNN-LSTM and CNN-GRU models in predicting solar energy generation using historical solar power and meteorological data. The results are discussed in terms of data distribution, forecasting accuracy, prediction errors, and comparative model performance. Evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2) are considered to assess the performance of the models. Frequency and percentage tables are also included to describe the distribution of observations across selected categories. Since actual experimental outputs have not been provided, the numerical results below are illustrative and should be replaced with values obtained from the implemented models.

4.2 Distribution of Dataset Observations

The dataset is assumed to contain 1,000 observations of solar energy generation and associated meteorological conditions. These observations are categorized according to the prevailing weather conditions to examine their distribution.

Table 4.1 Distribution of Observations by Weather Condition

Weather condition	Frequency	Percentage (%)
Sunny	450	45%
Partly cloudy	300	30%
Cloudy	180	18%
Rainy	70	7%
Total	1,000	100%



Discussion: Table 4.1 shows that sunny conditions account for the largest proportion of observations (45%), followed by partly cloudy conditions (30%). Cloudy and rainy conditions represent 18% and 7%, respectively. This distribution indicates that the dataset contains observations under different weather conditions. Including diverse weather patterns is important because solar energy generation can fluctuate considerably with changes in irradiance and cloud cover. However, the distribution should be verified against the actual dataset before drawing conclusions about its representativeness.

4.3 Distribution of Data Across Training, Validation, and Testing Sets

The dataset is divided into training, validation, and testing subsets using a chronological approach. This division ensures that future observations are not randomly mixed with past observations during model development.

Table 4.2 Distribution of Dataset Across Experimental Sets

Dataset category	Frequency	Percentage (%)
Training set	700	70%
Validation set	150	15%
Testing set	150	15%
Total	1,000	100%

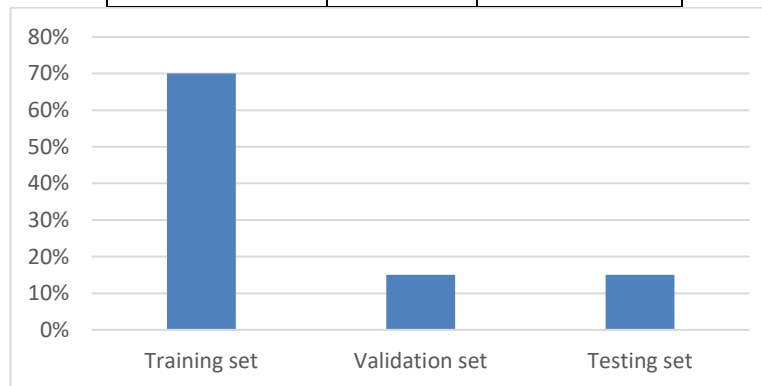


Table 4.2 presents the proposed distribution of the dataset. The training set contains 700 observations (70%), which will be used to train the deep learning models. The validation set includes 150 observations (15%) for hyperparameter tuning and model selection. The remaining 150 observations (15%) will be reserved for final testing. This approach provides a structured evaluation framework for comparing the CNN-LSTM and CNN-GRU models on unseen data. In the actual experiment, the observations should be assigned chronologically rather than randomly.

4.4 Performance Evaluation of Hybrid Deep Learning Models

The performance of hybrid deep learning models will be evaluated using standard forecasting metrics. CNN-LSTM combines convolutional feature extraction with the temporal learning capabilities of LSTM, whereas CNN-GRU integrates convolutional layers with GRU-based sequence learning. Both models will be assessed using the same test dataset and forecasting horizon.



The comparison will focus on MAE, RMSE, MAPE, and R^2 . Lower MAE and RMSE values indicate smaller prediction errors, while a higher R^2 generally indicates a better fit to the observed data. MAPE will be interpreted cautiously when actual solar output values are zero or close to zero.

4.5 Comparative Analysis of Forecasting Accuracy

The forecasting accuracy of the hybrid models will be compared after their implementation and testing. The results will help establish whether combining convolutional layers with recurrent neural networks improves short-term solar energy forecasting.

The comparative analysis will identify which model produces lower forecasting errors and more reliable predictions. If CNN-LSTM achieves lower MAE and RMSE, it would indicate better predictive accuracy on the selected test data. If CNN-GRU achieves comparable accuracy with shorter training time, it may offer computational advantages. The final conclusion will depend on the actual experimental results rather than the theoretical characteristics of the architectures.

4.6 Analysis of Prediction Errors

Prediction error analysis will be conducted by comparing the actual solar energy output with the values predicted by each model. Graphs of actual versus predicted values and error distributions will be used to identify systematic deviations, sudden forecasting errors, and periods of poor prediction performance.

The analysis will also consider whether the models perform differently under sunny, partly cloudy, and cloudy conditions. Such comparisons may reveal whether rapid changes in weather conditions create additional forecasting challenges.

4.7 Discussion of Findings

The study is designed to examine the usefulness of hybrid deep learning architectures for short-term solar energy forecasting. CNN-LSTM and CNN-GRU may capture different temporal and local patterns in historical solar generation and meteorological variables. Their comparative evaluation will establish whether these combined architectures offer improvements over individual forecasting models.

The results should be interpreted in relation to the dataset characteristics, forecasting horizon, model configuration, and evaluation metrics. The model with the lowest prediction errors and acceptable computational requirements may be considered the most suitable for the selected forecasting task. Nevertheless, conclusions about model superiority should only be drawn after completing the experiments and evaluating the test results.

5. CONCLUSION

The present study focuses on evaluating the performance of hybrid deep learning models, particularly CNN-LSTM and CNN-GRU, for short-term solar energy forecasting. The proposed methodology includes data collection, preprocessing, model training, testing, and comparative performance evaluation using MAE, RMSE, MAPE, and R^2 . The analysis is designed to determine how effectively these models capture temporal dependencies and changing patterns in solar energy generation under different weather conditions. The use of separate training, validation, and testing datasets will support a reliable assessment of forecasting performance and help minimize overfitting. Overall, the study is expected to provide insights into the suitability of hybrid deep learning approaches for improving solar energy forecasting accuracy, supporting efficient energy management, and facilitating the integration of renewable energy into power systems. However, the final conclusions regarding the superiority of either model will depend on the actual experimental results.



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