Comparative Performance Analysis of LSTM and Bidirectional LSTM for Short-Term Solar Power Generation Forecasting Using Limited Time-Series Data

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Abstract : Short-term forecasting of solar power generation plays a critical role in enhancing the reliability and efficiency of renewable energy integration into modern power systems. However, the inherent intermittency and variability of photovoltaic (PV) output present significant challenges, particularly under limited data conditions and in the absence of exogenous variables. This study aims to analyze and compare the performance of Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) models for short-term forecasting using a limited time-series dataset obtained from a residential PV system with a capacity of 2 × 500 Wp over a 15-day period. Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The results demonstrate that both models are capable of effectively capturing temporal dynamics, as indicated by R^2 values exceeding 0.81. Quantitatively, the LSTM model achieves an MAE of 50.11 W and an RMSE of 83.70 W, while the BiLSTM model shows slightly improved performance with an MAE of 48.12 W and an RMSE of 83.14 W. Nevertheless, the high MAPE values—187.33% for LSTM and 103.59% for BiLSTM—highlight the limitations of this metric when applied to data with near-zero actual values. Overall, BiLSTM provides a marginal performance improvement over LSTM; however, both models exhibit limitations in accurately predicting extreme values.

Keywords: Bidirectional Long Short-Term Memory (BiLSTM), Long Short-Term Memory (LSTM), Photovoltaic, Renewable energy, Short-term forecasting

1. INTRODUCTION

The increasing global demand for energy has accelerated the adoption of renewable energy sources, particularly solar energy through photovoltaic (PV) systems. Solar energy is widely recognized as a clean, abundant, and environmentally friendly energy source. However, the integration of PV systems into modern power grids faces

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significant challenges due to the inherent intermittency and variability of solar power generation, which is highly influenced by environmental conditions such as solar irradiance and weather [1]. This variability can lead to instability in power systems, thereby complicating energy management, generation scheduling, and overall system operation [2].

One of the key approaches to addressing these challenges is through short-term forecasting of PV-based power generation, which plays a crucial role in improving the reliability and efficiency of power systems. Accurate forecasting enables optimal energy dispatch, effective energy storage management, and supports the integration of renewable energy into smart grid systems [3]. However, this task remains challenging due to the nonlinear characteristics and complex temporal patterns inherent in PV output data.

In recent years, research on forecasting systems based on Artificial Intelligence (AI), particularly deep learning techniques, has demonstrated superior performance in modeling time-series data. Among these methods, Long Short-Term Memory (LSTM) has been widely adopted as an extension of Recurrent Neural Networks (RNN), capable of addressing the vanishing gradient problem while capturing long-term dependencies in sequential data [4]. LSTM has been extensively applied in solar energy forecasting and has shown improved accuracy compared to conventional methods [5].

Furthermore, Bidirectional Long Short-Term Memory (BiLSTM) has been developed to enhance the model's capability in learning temporal patterns by processing data sequences in both forward and backward directions [6]. This approach enables the model to capture more comprehensive temporal information, thereby potentially improving prediction accuracy [7]. Several studies have reported that BiLSTM outperforms conventional LSTM in various energy forecasting applications [8].

Despite these advancements, most existing studies rely on large-scale datasets and incorporate exogenous variables such as temperature, humidity, and solar irradiance to improve model performance [9]. While this approach enhances prediction accuracy, it also increases model complexity and limits practical implementation, particularly in small-scale systems or data-constrained environments [10].

Based on these challenges, there is a need to investigate the fundamental capability of deep learning models, specifically LSTM and BiLSTM, in learning temporal patterns solely from historical power generation data without the inclusion of external variables. Additionally, evaluating model performance under limited time-series data conditions is essential to assess their robustness and generalization capability in real-world scenarios.

Therefore, this study aims to conduct a comparative analysis of LSTM and BiLSTM models for short-term solar power generation forecasting using a limited time-series dataset. The findings are expected to provide fundamental insights into the effectiveness of both models and serve as a foundation for the development of more advanced forecasting models in future research.

2. METHODOLOGY

This study employs a time-series forecasting approach to compare the performance of Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory

(BiLSTM) models in predicting power generation from a photovoltaic (PV) system. The dataset was collected from a residential solar panel system with a capacity of 2 × 500 Wp installed in Palembang, Indonesia, over a 15-day observation period. The data consist solely of historical power output without incorporating any exogenous variables, allowing the study to focus on the intrinsic capability of the models in capturing temporal patterns, as in figure 1.

The preprocessing stage includes data cleaning to remove invalid values and normalization using the Min-Max Scaling method. Subsequently, the time-series data are transformed into a supervised learning format using the sliding window technique. The LSTM and BiLSTM models are then developed with comparable configurations and trained using the Adam optimizer and Mean Squared Error (MSE) as the loss function. The dataset is divided into 80% for training and 20% for testing. Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Finally, the results of both models are compared to determine the best-performing model under limited data conditions.

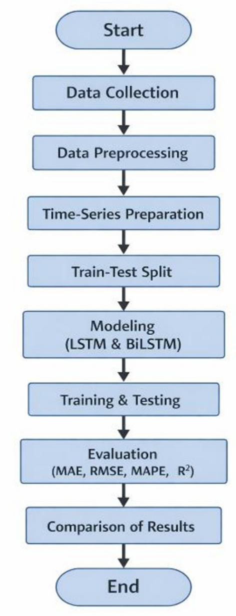


Figure 1. Flowchart

3. DISCUSSION

The solar power generation system used in this study consists of two monocrystalline photovoltaic panels, each with a capacity of 550 Wp, which convert solar irradiance into direct current (DC) electrical energy. The generated energy is managed by a Maximum Power Point Tracking (MPPT) solar charge controller rated at 24 VDC 60 A, which optimizes the operating point of the PV panels to ensure maximum power output while regulating the charging process to the energy storage system. The electrical energy is subsequently stored in batteries with a total capacity of 2 × 200 Ah at 24 VDC, serving as the primary energy storage to maintain the continuity of power supply to the load. The solar power production data used in this study were collected over a 15-day period through an installed energy monitoring system.

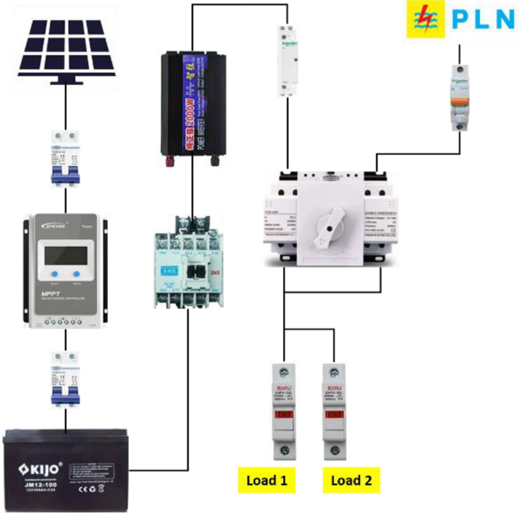


Figure 2. Block diagram PV production

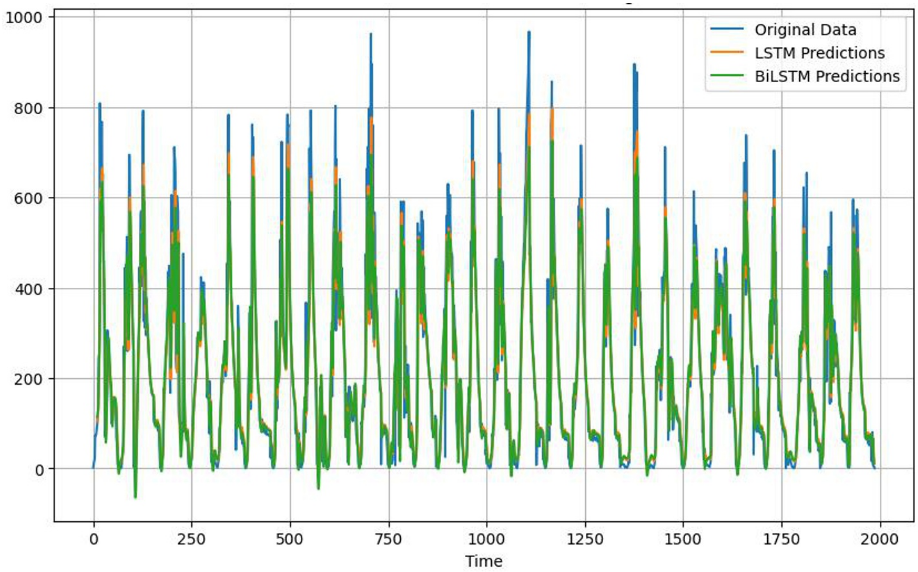
The results indicate that both Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) models demonstrate strong capability in capturing the temporal dynamics of solar power generation data. Both models are able to follow daily fluctuation patterns, including peak and off-peak periods, suggesting that recurrent neural network-based architectures are effective in modeling temporal dependencies in time-series data, as in figure 2.

From a comparative perspective, the BiLSTM model exhibits slightly superior performance compared to the LSTM model. This can be attributed to its bidirectional processing mechanism, which enables the model to utilize temporal information more comprehensively from both past and future sequences during training. Consequently, BiLSTM offers enhanced representation capacity in capturing complex temporal patterns, particularly in datasets characterized by dynamic fluctuations.

However, both models still exhibit limitations in accurately predicting extreme values, particularly during peak demand and near-zero output conditions. The observed deviations at these points suggest that the models are not fully capable of capturing short-term volatility or sudden fluctuations. This limitation is likely due to the relatively small dataset (15 days), which may not sufficiently represent the full range of extreme patterns during the training process.

In addition, the absence of exogenous variables such as solar irradiance, temperature, and weather conditions also affects prediction accuracy. In photovoltaic systems, these factors significantly influence power generation; therefore, relying solely on historical power data limits the model's ability to capture external drivers of variability, as in figure 3.

Figure 3. LSTM and BiLSTM prediction result graph



Quantitatively, the evaluation results show that the LSTM model achieves a Mean Absolute Error (MAE) of 50.11 W and a Root Mean Squared Error (RMSE) of 83.70 W, while the BiLSTM model yields slightly better performance with an MAE of 48.12 W and an RMSE of 83.14 W. The coefficient of determination (R^2) exceeds 0.81 for both models, indicating a strong capability in explaining the variance of the observed data. However, the Mean Absolute Percentage Error (MAPE) shows a significant disparity, with values of 187.33% for LSTM and 103.59% for BiLSTM, highlighting substantial relative errors during periods with near-zero actual values, as in table 1.

Table 1. Evaluation of prediction results

	LSTM	BiLSTM
MAE	50,114 W	48,120 W
RMSE	83,701 W	83,143 W
MAPE	187,333%	103,591% W
R^2	0,811	0,813

Mean Absolute Error (MAE) dan *Root Mean Squared Error* (RMSE), The relatively low MAE value compared to the maximum load (approximately 900 W) indicates that the average prediction error remains within an acceptable range for practical power system applications. Meanwhile, the higher RMSE value compared to

MAE confirms the presence of extreme errors at specific points, particularly during peak load conditions. From a technical standpoint, this reflects the limitation of the models in capturing short-term volatility, even though long-term temporal patterns can be effectively learned.

Mean Absolute Percentage Error (MAPE), The high MAPE values, particularly for the LSTM model, highlight the limitations of this metric when applied to datasets with near-zero values. Under such conditions, even small absolute errors can result in disproportionately large percentage errors. Therefore, MAPE is not entirely representative for evaluating performance in solar power forecasting contexts, and alternative metrics such as symmetric MAPE (sMAPE) or Mean Absolute Scaled Error (MASE) are more appropriate for providing a more robust and objective assessment.

The coefficient of determination (R^2) values of 0.8105 for LSTM and 0.8131 for BiLSTM indicate that both models are capable of explaining more than 81% of the variance in the observed data. This demonstrates a relatively high level of model fit for short-term forecasting applications in power systems. Although the performance difference between LSTM and BiLSTM is relatively small, it remains meaningful, as even marginal improvements in prediction accuracy can have significant implications for operational efficiency in power system management.

4. CONCLUSION

This study concludes that Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) architectures are effective in modeling the temporal characteristics of photovoltaic power generation in short-term forecasting scenarios under limited data conditions. Both models are capable of explaining more than 81% of the variance in the observed data ($R^2 > 0.81$), indicating sufficient temporal representation capacity despite relying solely on univariate input data. Quantitatively, BiLSTM demonstrates slightly superior performance compared to LSTM, as indicated by lower MAE and RMSE values, suggesting that the bidirectional learning mechanism provides advantages in capturing more complex temporal dependencies. However, the observed performance improvement remains marginal, implying that under data-constrained conditions, increased model complexity does not necessarily translate into substantial accuracy gains. Furthermore, both models exhibit limitations in representing extreme values, particularly during peak generation and near-zero output conditions, as reflected by higher RMSE values and significantly large MAPE due to its sensitivity to near-zero actual values. These findings highlight that purely data-driven approaches based on historical data have inherent limitations in capturing short-term variability influenced by exogenous factors. Therefore, future research should focus on incorporating external variables, extending the temporal coverage of datasets, and developing hybrid or attention-based architectures to enhance model generalization capability and robustness in renewable energy forecasting applications.

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