INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol.17 No. 6 (2025) 268-279
https://publisher.uthm.edu.my/ojs/index.php/ijie

Solar Power Forecasting of 8 MWp Solar Farm Malacca Using LSTM-based Model with Weather Forecast Data: A Case Study of Malaysia

Muhamad Guntor Mansor Tobeng[1,2], Mohd Zainizan Sahdan[1]*, Abdul Rasid Abdul Razzaq[1], Mohd Razali Tomari[3], Feri Adriyanto[4], Siti Ashraf Abdullah[5]

[1] *Faculty of Technical and Vocational Education (FPTV), Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat Johor, MALAYSIA*
[2] *Gading Kencana Sdn Bhd, Blok 2, Presint Alami, Persiaran Akuatik, Seksyen 13, 40100 Shah Alam Selangor, MALAYSIA*
[3] *Faculty of Electrical and Electronic Engineering (FKEE), Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat Johor, MALAYSIA*
[4] *Department of Electrical Engineering, Sebelas Maret University, Surakarta 57126, INDONESIA*
[5] *Microelectronic and Nanotechnology-Shamsuddin Reasearch Centre (MiNT-SRC), Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat Johor, MALAYSIA*

*Corresponding Author: zainizan@uthm.edu.my
DOI: https://doi.org/10.30880/ijie.2025.17.06.022

Article Info

Received: 30 May 2025
Accepted: 13 September 2025
Available online: 30 December 2025

Keywords

solar power forecasting, long short-term memory, univariate, multivariate

Abstract

Malaysia's tropical climate offers vast potential for photovoltaic (PV) energy due to high solar irradiance, but frequent weather fluctuations pose challenges to forecasting accuracy and energy reliability. This study compares the performance of four LSTM-based models, Univariate LSTM, Multivariate LSTM with weather sensor data, Multivariate LSTM with both weather sensor and meteorological (MET Malaysia) data, and Bidirectional LSTM (Bi-LSTM) using real data from an 8 MWp solar farm in Ayer Keroh, Malacca. The Univariate LSTM model achieved the best performance, with the lowest error metrics (MAE: 0.0275 kW, MSE: 0.0037 kW, RMSE: 0.0611 kW) and the highest coefficient of determination (R^2 = 0.94), indicating strong predictive accuracy for both short- and long-term horizons. Although the Univariate LSTM model achieved the highest forecasting accuracy in this study, the Multivariate LSTM model that integrates both weather sensor and meteorological (MET) data proved to be the most practical and applicable for real-world use. With performance metrics of MAE: 0.0375 kW, MSE: 0.0044 kW, RMSE: 0.0664 kW, and R^2 = 0.92, this model demonstrates strong predictive capability while accounting for external weather influences. In energy sector applications where weather variability significantly impacts solar energy production, incorporating such additional input features enables better generalization and robustness. Therefore, despite slightly lower accuracy compared to the Univariate model, the Multivariate LSTM offers a more reliable and scalable solution for deployment in Malaysia's solar forecasting applications.

1. Introduction

Malaysia offers a great potential for photovoltaic (PV) system installations, thanks to its tropical climate. The country's annual temperature ranges from 24.9°C in January to 25.9°C in May, showcasing minimal seasonal variation. Daily solar irradiation intensity spans between 4.7 and 6.5 kWh/m^2, with peninsular Malaysia receiving up to 1800 kWh/m^2 annually and East Malaysia slightly higher at 1900 kWh/m^2, creating a strong opportunity to expand PV installation systems [1]. Tenaga Nasional Berhad (TNB), Malaysia's primary energy supplier, and the Malaysian Energy Commission (EC) introduced the LSS (Large Scale Solar) initiative, enabling LSS system developers to generate electricity through solar PV systems and supply it to the grid [2]. This initiative has driven many solar companies to establish solar farms, feeding the energy generated into the TNB grid. However, integrating solar PV into TNB's power grids presents significant technical challenges. Solar energy generation is inherently weather-dependent, with unpredictable climate variations leading to system instability [3]. These challenges include frequent reverse power flow, overvoltage issues, inefficient utility planning, and subsequent financial losses. To mitigate these risks and ensure reliable energy delivery while reducing financial losses, LSS developers must implement accurate solar PV generation forecasting models for the grid system. This ensures better system planning, stability, and optimized integration of renewable energy sources.

In recent years, Long Short-Term Memory (LSTM) networks have emerged as prominent deep learning (DL) architecture for solar power forecasting, garnering substantial interest from researchers and practitioners in the renewable energy domain. Hochreiter and Schmidhuber [4] proposed LSTM networks consist of an improved version of Recurrent Neural Networks (RNNs), its designed especially to tackle issues such as the vanishing gradient problem, which frequently limits the learning capabilities of traditional RNNs. In time-series forecasting applications, where it is crucial to capture long-term relationships in sequential data, these difficulties are especially significant. Solar power generation is inherently intermittent and influenced by dynamic meteorological conditions such as solar irradiance, temperature, wind speed, and cloud cover. Due to the complex and nonlinear nature of solar power data, traditional statistical models like Autoregressive Integrated Moving Average (ARIMA) have demonstrated little efficacy in effectively estimation [5].

As a result, there has been an increasing focus on DL-based approaches. DL offers significant advantages for solar power forecasting by effectively capturing complex, nonlinear relationships in multivariate and time-series data. Models like LSTM, GRU, and CNN can automatically learn from past patterns, reducing the need for manual feature engineering and improving forecast accuracy. LSTMs use gating mechanisms such as input, forget, and output gates, which control the information flow inside the network. LSTMs are especially useful for time-series forecasting in renewable energy applications because of these features, which enable them to selectively preserve key long-term information while eliminating unnecessary elements. Their adaptability to various time intervals and scalability across locations make them highly suitable for real-world solar energy applications, ultimately supporting more reliable and efficient energy management [6].

Several studies have validated the superior performance of LSTM networks in solar power forecasting. For example, Janice et al. [7], reported that DL model such as LSTM significantly outperformed traditional statistical methods in predicting short-term solar power outputs by effectively learning and integrating exogenous features such as temperature, humidity, and wind speed. Similarly, Mandal et al. in 2021 [8], compared univariate and multivariate LSTM models for very short-term GHI forecasting. The findings revealed that LSTMs excelled in addressing the complexities of time-series problems, particularly in capturing long-term dependencies. While univariate models offered simplicity and computational efficiency, multivariate models provided enhanced accuracy by incorporating exogenous variables. The trade-off between these approaches highlighted the importance of model selection based on the specific requirements of forecasting scenarios.

Recently, Time series forecasting has recently seen a major increase in interest in the investigation of sophisticated Long Short-Term Memory (LSTM) variations, such as bidirectional LSTM (Bi-LSTM) [9-10]. One of the unique benefits of Bi-LSTMs is that they can analyze input sequences both forward and backward, giving a thorough grasp of temporal relationships. Bi-LSTMs offer distinct advantages, namely process input sequences in both forward and backward directions, providing a comprehensive understanding of temporal dependencies. This bidirectional architecture has demonstrated its effectiveness in reducing forecasting errors over longer horizons compared to benchmark model, as highlighted by Nadimi *et al.* [12]. However, the suitability of these architectures depends on the nature and structure of the dataset. This study aims to systematically evaluate the performance of univariate, multivariate, and bidirectional LSTM (Bi-LSTM) models for solar power forecasting. The dataset utilized in this work comprises solar power generation data, weather sensor readings, and meteorological features to assess the forecasting trends between actual and predicted values. Both univariate and multivariate LSTM models are explored to evaluate their respective performances across different forecasting horizons. Our findings will help identify the most suitable LSTM variant for solar power forecasting, balancing the need for computational efficiency and predictive accuracy, thus advancing the field's understanding of deep learning applications in renewable energy forecasting.

2. Methodology

2.1 Data Collection and Data Pre-Processing

The data is categorized into three primary types. The first category comprises an 8 MWp solar energy dataset and weather sensor data, including temperature and irradiance measurements obtained from Thermopile Pyranometers. These data were collected from a solar farm owned by Gading Kencana Sdn Bhd, located in Ayer Keroh, Malacca, at geographic coordinates 2.29301°N and 102.34285°E as shown in Fig. 1. The second category consists of weather data sourced from the Malaysian Meteorological Department (MET Malaysia), specifically from the Ayer Keroh station situated at geographic coordinates 2.25459°N and 102.24326°E, approximately 16.7 km from the Gading Kencana solar farm. The dataset was collected from the solar farm over the entire year of 2022, comprising daily records from January to December for power output, temperature, and irradiance dataset as shown in table 1. Notably, the raw measurements were initially recorded at a high sampling rate of 0.05 seconds, and pre-processing data has been done for daily intervals to align with other input data. In contrast, the weather data from MET Malaysia is provided at a daily resolution (sampling interval of 24 hours), which provides additional environmental parameters include temperature, wind speed, humidity, global radiation, and cloud cover (see table 1).

Fig. 1 *8 MWp Gading Kencana Ayer Keroh solar farm overview* [12]

Fig. 2 shows the heatmap of Pearson correlation coefficient matrix, the heatmap provides insights into the relationships between various environmental factors and solar power generation. Strong positive correlations are observed between daily total solar power and both irradiance (0.84) and global radiation (0.84), highlighting the direct impact of sunlight on solar energy production. Temperature has a moderate negative correlation (-0.42), suggesting that higher temperatures may slightly reduce solar power output. Similarly, cloud cover shows a moderate negative correlation (-0.33), indicating that increased cloudiness reduces solar energy availability. Humidity and wind speed also show minor negative correlations (-0.18 and -0.45, respectively), signifying their lesser but still noticeable influence on solar power generation. These relationships provide valuable insights for optimizing solar power forecasting and system management, emphasizing the importance of environmental factors in solar energy production. This input selection, consisting of weather sensor data (wsensor) collected from solar farm Malacca and both weather sensor (wsensor) and meteorological (met) data, will be used in the Multivariate LSTM model to evaluate the model's accuracy. By incorporating these diverse datasets, the study aims to assess the predictive performance of the Multivariate LSTM model, examining how different combinations of input variables impact the accuracy of solar power forecasting.

Table 1 *Input data from solar farm Malacca and MET Malaysia*

Input Data	Solar Farm Malacca	MET Malaysia
Power from solar farm	✓	
mean temperature	✓	✓
Irradiance	✓	
Global Radiation		✓
Mean Surface Wind Speed		✓
Mean Relative Humidity		✓
Cloud Cover		✓

In this study, the univariate LSTM model utilized historical solar power generation (MW) data from 2022, the data interval was set to 10 minutes between each data. A time step of 144 was set to capture daily cycles, and the data was scaled using MinMaxScaler for normalization. The architecture consisted of a single LSTM layer with 64 hidden units, followed by a dense output layer. The model was trained for a maximum of 200 epochs using the Adam optimizer with an initial learning rate of 0.001 and Mean Squared Error (MSE) as the loss function. To prevent overfitting, an EarlyStopping mechanism was applied, monitoring the validation loss with a patience of 10 epochs. Additionally, a horizon LSTM model was developed to predict solar power at multiple short-term intervals (10 minutes to 5 hours ahead). The architecture was optimized similarly to the univariate LSTM model for short-term forecasts.

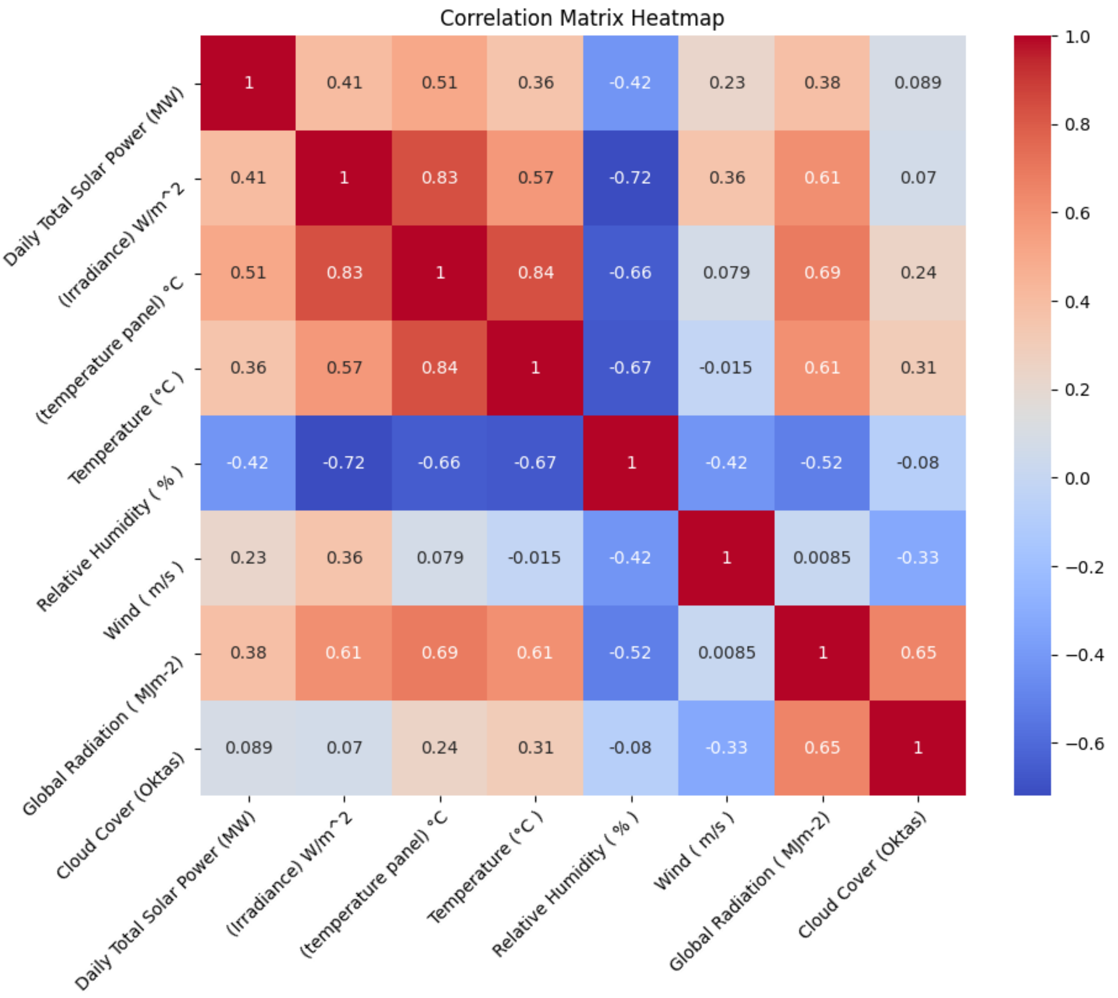


Fig. 2 *Heatmap of Pearson correlation coefficient matrix*

For developing the multivariate LSTM-based solar power forecasting model involved selecting relevant meteorological and sensor data variables, including solar power output, irradiance, panel temperature, ambient temperature, relative humidity, wind speed, global radiation, and cloud cover. Data cleaning, linear interpolation and normalization was used as data pre-processing in this experiment. Linear interpolation is applied to all numeric columns in the dataset to fill any missing values. Normalization to a [0, 1] range has been set using MinMaxScaler to improve model convergence [14]. The dataset was split into training (70%) and testing (30%) subsets, and a sliding window technique with a time_steps value of 144 captured temporal dependencies over 10-minute intervals. The architecture of LSTM model consists of several layers, including an initial LSTM layer with 64 units returning sequences, a dropout layer with a 20% rate to prevent overfitting, 32 units of second LSTM layer and a single unit of dense output layer for predictions. Using the Adam optimizer (learning rate: 0.002), the model stopped early and would cease training after 10 epochs if validation loss did not improve while maintaining the optimal weights. With a 10% validation split and a batch size of 32, the model was trained across 200 epochs.

Then, all models were evaluated based on standard performance metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2) [15]. Visual comparisons of predicted versus actual solar power values were presented using line plots and scatter plots to assess the models' accuracy. This is the test environment: The Intel(R) Core(TM) i7-

Int. Journal of Integrated Engineering Vol. 17 No. 6 (2025) p. 268-279

6820HQ CPU runs at 2.70 and 2.71 GHz and has 32.0 GB of RAM (31.9 GB of usable RAM). The operating system is Windows 11 Pro. Keras, a deep learning framework built on top of Python 3.7, is used for all model development and performance assessments.

2.2 Long Short-Term Memory (LSTM)

An LSTM network is composed of multiple memory blocks, commonly referred to as cells. Fig. 3 shows schematic and topological representation of LSTM and Bi-LSTM model. The schematic of the LSTM unit (a) highlights its key components, including the forget gate (f_t), input gate (i_t), candidate cell state ($\tilde{C}_t$), cell state (C_t), and output gate (o_t). These gates work together to regulate the flow of information, enabling the LSTM to retain or forget information as needed, addressing the vanishing gradient problem often encountered in traditional recurrent neural networks. The forget gate decides what information to discard from the cell state, while the input gate determines what new information to store. The cell state (C_t) is updated by combining retained information with new candidate states, and the output gate controls what part of the cell state is passed as the hidden state (h_t).

The following formulas define an LSTM's gating mechanism [6];

$$i^t = \sigma(W^i x_t + U^i h_{t-1} + b^i) \tag{1}$$

$$f_t = \sigma(W^f x_t + U^f h_{t-1} + b^f) \tag{2}$$

$$o_t = \sigma(W^o x_t + U^o h_{t-1} + b^o) \tag{3}$$

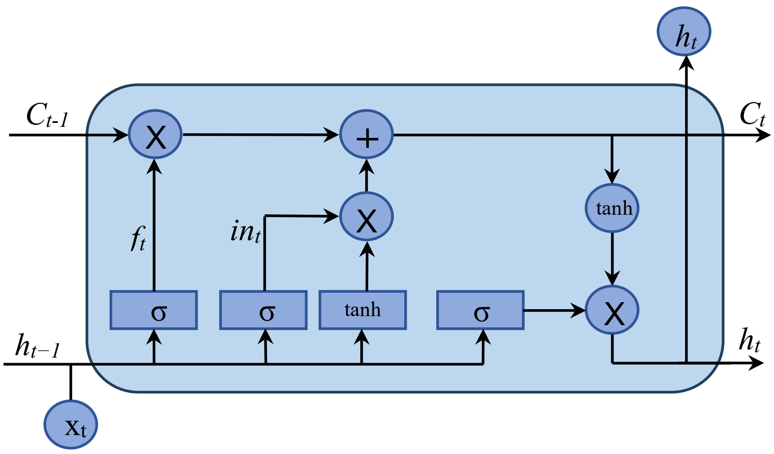
$$\tilde{C}_t = tanh(W^g x_t + U^g h_{t-1} + b^g \tag{4}$$

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \tilde{C}_t \tag{5}$$

$$h_t = o_t \otimes tanh(c_t) \tag{6}$$

where:

i_t : The input gate
f_t : The forget gate
o_t : The output gate at time step t
$\tilde{C}_t$: The new memory cell vector
h_t : The hidden state
σ : The sigmoid function
W, U : Parameter matrices
$\otimes$: The Kronecker product (entry-wise product).



(a) Schematic of the LSTM units

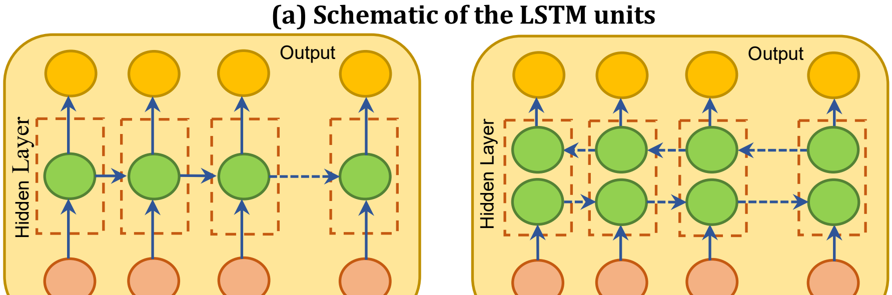


Fig. 3 *Schematic and topological representation of LSTM and Bi-LSTM model* [15]

The topological structure of the LSTM (b) shows how data flows sequentially through the network in a unidirectional manner, with inputs processed at each time step and passed forward. This structure is effective for time-series forecasting tasks, where only past data is relevant. The Bi-LSTM topology (c), on the other hand, captures dependencies from both past and future contexts by processing data both forward and backward. Combining the results from the two directions, Bi-LSTM networks excel in tasks that require understanding the entire sequence, such as text sentiment analysis or language modeling. While Bi-LSTM networks are computationally more expensive, they provide a richer understanding of sequential data compared to unidirectional LSTMs. This comprehensive visualization effectively highlights the mechanics and applications of LSTM-based architecture.

3. Results and Discussion of the Simulation

The current study evaluates the performance of several LSTM-based models for short-term solar power forecasting using both univariate and multivariate datasets. Specifically, four models were compared which are Univariate LSTM, Multivariate LSTM using only weather sensor data (Wsensor), Multivariate LSTM incorporating both weather sensor and MET Malaysia data (Wsensor+MET), and a Bidirectional LSTM (Bi-LSTM) model. As shown in Table 2, the Univariate LSTM model achieved the best overall performance, recording the lowest Mean Absolute Error (MAE) of 0.0275 kW, Mean Squared Error (MSE) of 0.0037 kW, and Root Mean Squared Error (RMSE) of 0.0611 kW. These results indicate the model's strong capability in capturing temporal dependencies using only past solar output data, without relying on additional input features.

In comparison, the Multivariate LSTM (Wsensor) model, which included weather sensor data from solar farm as additional inputs, demonstrated slightly lower performance, with MAE, MSE, and RMSE values of 0.0379, 0.0046, and 0.0680 respectively. While these metrics reflect good predictive capability, they also suggest that the added sensor data may have introduced redundancy or noise that reduced the model's forecasting precision. Nevertheless, the inclusion of contextual weather information allowed the model to generalize reasonably well to the test data.

Further experimentation using the Multivariate LSTM (Wsensor+MET) model, which is combining weather sensor and meteorological data led to marginal improvement in performance, compared to Multivariate LSTM (Wsensor) model. This model recorded an MAE of 0.0375, MSE of 0.0044, and RMSE of 0.0664. The addition of meteorological parameters such as temperature, humidity, and irradiance likely enhanced the model's ability to capture external influences on solar generation. However, the performance gain was modest, indicating that improvements may be constrained by the quality or relevance of the added variables.

The Bi-LSTM model, which was trained using the same combined input data (Wsensor+MET), performed the weakest among all four models. It registered the highest error metrics, with MAE, MSE, and RMSE values of 0.0408, 0.0052, and 0.0720 respectively. Although Bi-LSTM theoretically benefits from learning both forward and backward temporal dependencies, the results suggest that this added complexity may have led to overfitting or difficulty in learning from the available data. The deviation between predicted and actual values was more pronounced, indicating that the model may not have been well-suited for the characteristics of this dataset.

These findings suggest that, within the context of this study, the Univariate LSTM was the most effective model for solar power forecasting, likely due to the strong temporal correlations in the solar power output data. This supports previous research by Rahman *et al.* in 2023 [2], who found that univariate LSTM models can outperform multivariate models when additional inputs introduce noise or do not contribute meaningful variance. Similarly, Limouni *et al.* in 2022 observed that univariate models perform well in environments with stable weather conditions, where historical output alone can provide a reliable forecast [17].

Table 2 *Evaluation of error matric for Univariate, Multivariate LSTM (Weather sensor data only), Multivariate LSTM (Weather sensor data and MET daily data), and Bi-LSTM model*

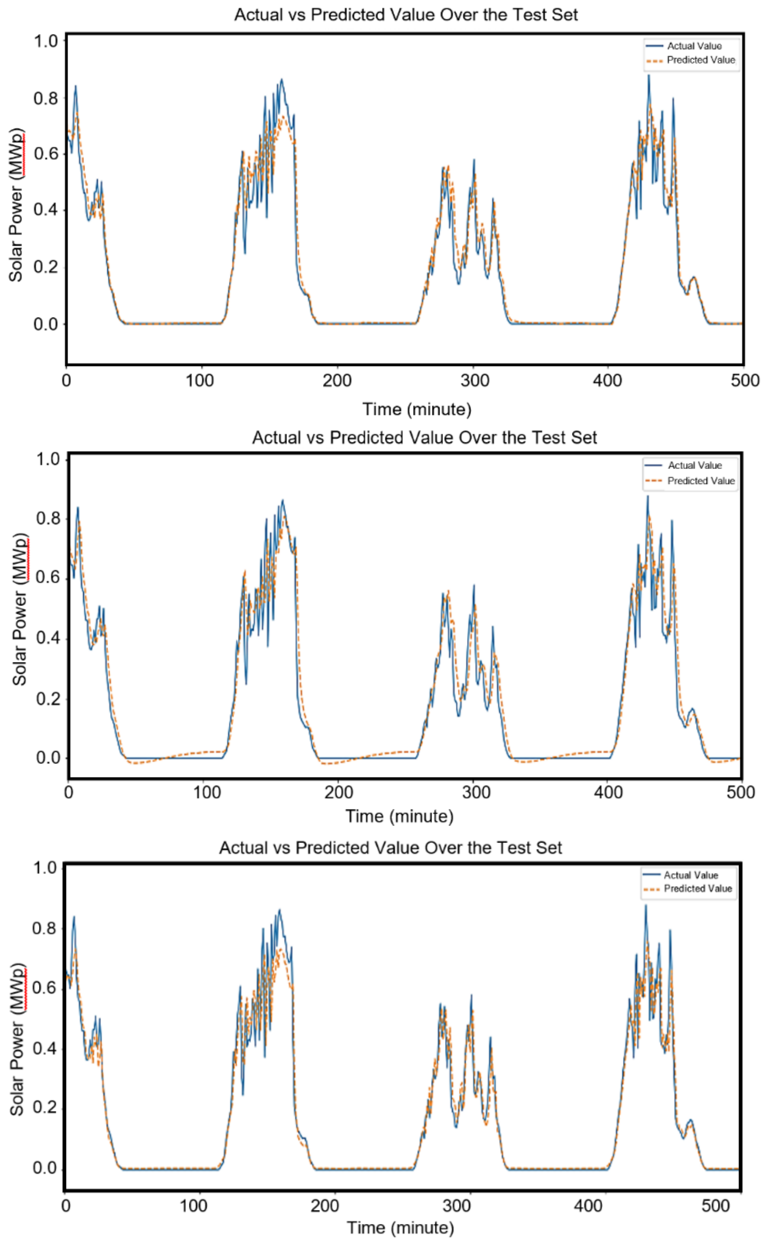
Model	MAE (kW)	MSE (kW)	RMSE (kW)
Univariate LSTM	0.0275	0.0037	0.0611
Multivariate LSTM (Wsensor)	0.0379	0.0046	0.0680
Multivariate LSTM (Wsensor+MET)	0.0375	0.0044	0.0664
Bi-LSTM	0.0408	0.0052	0.0720

Nevertheless, although the multivariate LSTM models were inferior to the Univariate LSTM in terms of forecasting accuracy in this study, they remain the preferred choice in many industrial applications. This preference is largely due to their ability to incorporate dynamic weather-related variables such as solar irradiance, temperature, wind speed, and humidity, which are essential for forecasting under real-world conditions with high variability. These inputs help enhance model adaptability and robustness in operational settings, especially where solar output is heavily influenced by changing environmental factors.

(a)

(b)

(c)



(d)

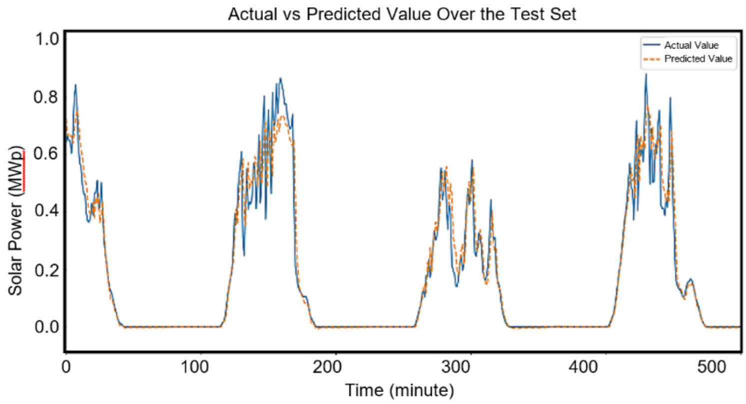
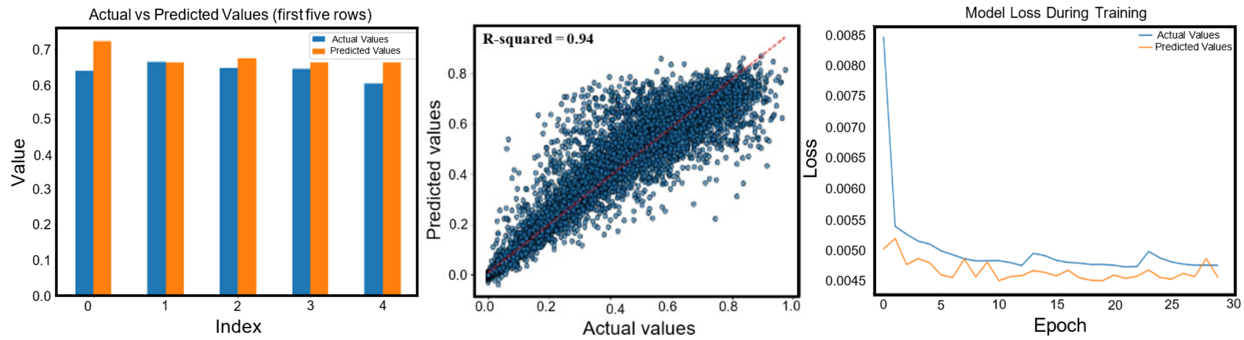
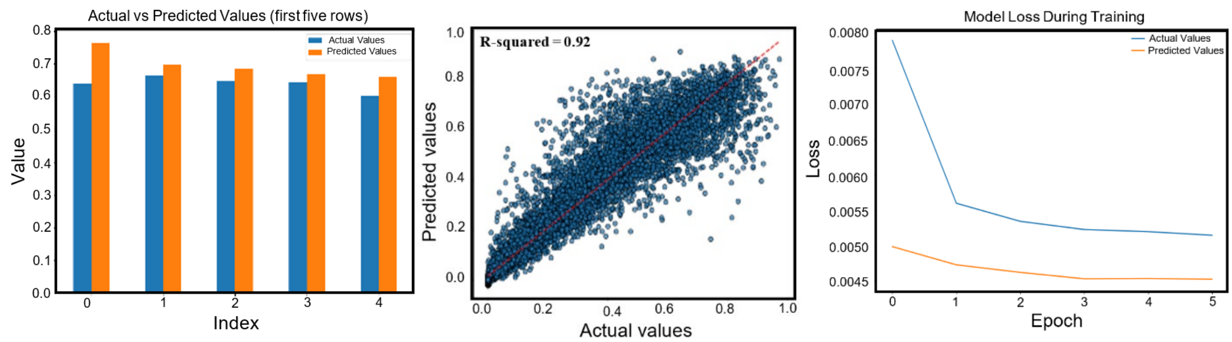


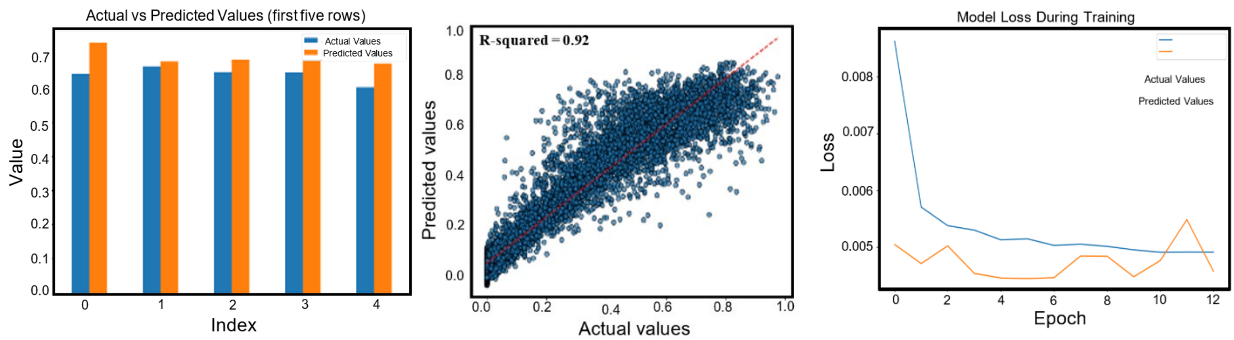
Fig. 4 *Actual Vs predicted graph for (a) Univariate LSTM; (b) Multivariate LSTM (Wsensor); (c) Multivariate LSTM (Wsensor+MET); (d) Bi-LSTM*



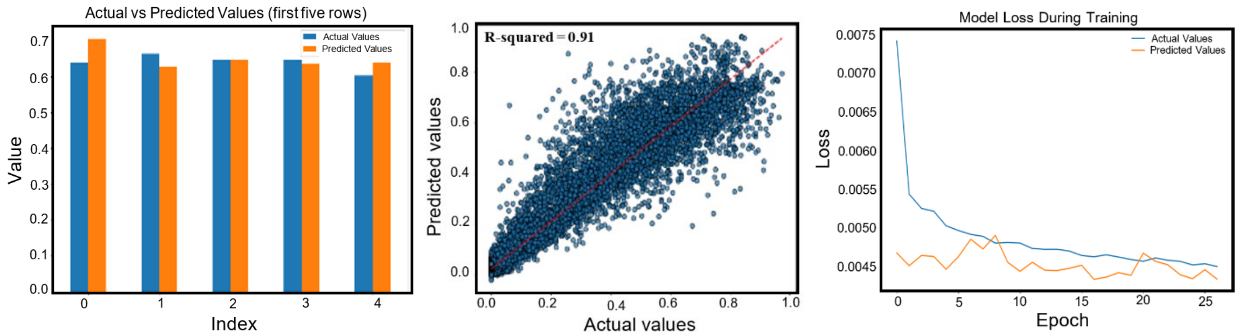
(a)



(b)



(c)



(d)

Fig. 5 Histogram, scattered graph and epoch graph for *(a) Univariate LSTM; (b) Multivariate LSTM (Wsensor); (c) Multivariate LSTM (Wsensor+MET); (d) Bi-LSTM*

Based on the visual observations from Fig. 4, several insights can be drawn that support the quantitative findings previously discussed. The figure presents the actual versus predicted solar power output for four models which are Univariate LSTM, Multivariate LSTM using weather sensor data (Wsensor), Multivariate LSTM with both weather sensor and MET Malaysia data (Wsensor+MET), and Bi-LSTM. Among these, the Univariate LSTM model (Fig. 4a) shows the closest match between the predicted and actual values, with minimal deviation throughout the test period. The predicted curve closely follows the actual solar output, particularly during high generation periods, confirming the model's low error values (MAE = 0.0275, MSE = 0.0037, RMSE = 0.0611). This visual alignment further supports its superior performance in capturing temporal patterns using only past solar output data.

In contrast, the Multivariate LSTM (Wsensor) model (Fig. 4b) also follows the general trend of the actual output but with slightly more deviation, especially during sharp rises and peaks. The predicted line appears smoother, which may indicate that the additional sensor data introduced some redundancy or noise. This aligns with the slightly higher error metrics (MAE = 0.0379, RMSE = 0.0680) compared to the univariate model. Fig. 4c, which illustrates the Multivariate LSTM (Wsensor+MET), shows a marginal improvement in tracking the actual values compared to the sensor-only model. The inclusion of meteorological data, such as temperature and humidity, likely contributed to a better understanding of external influencing factors, which is consistent with its improved MAE (0.0375) and RMSE (0.0664).

Lastly, the Bi-LSTM model (Fig. 4d) demonstrates the weakest performance among all models. The predicted values show noticeable deviations from the actual output, particularly during peak solar periods, suggesting that the model struggled to generalize well. This is in line with its highest error metrics (MAE = 0.0408, RMSE = 0.0720). Although Bi-LSTM is designed to capture both past and future dependencies in sequence data, its added complexity may have led to overfitting or poor adaptation to the dataset's characteristics. Overall, the graphical results in Fig. 4 visually reinforce the numerical findings, the Univariate LSTM outperforms the others in accuracy, while the multivariate models, despite being slightly less accurate, its remain relevant for real-world applications due to their ability to handle varying weather conditions.

Fig. 5 shows scattered plot, epoch-loss curve and histogram graph for actual versus predicted value. Starting with the scattered plots, the Univariate LSTM model (Fig. 5a) shows the strongest correlation between actual and predicted values, with an R^2 value of 0.94, indicating that 94% of the variance in solar power output is well captured by the model. This high R^2 value reflects the superior performance observed earlier in Fig. 4, where the Univariate LSTM closely tracked the actual solar power trend. In comparison, both the Multivariate LSTM models (Wsensor and Wsensor+MET) show slightly lower R^2 values of 0.92 (Fig. 5b and 5c), while the Bi-LSTM model (Fig. 5d) has the lowest R^2 value of 0.91. These findings align with the prior error metrics (MAE, RMSE) discussed, reinforcing that the Univariate model remains the most accurate for this dataset.

An R^2 value indicates how well a model's predicted values match the actual observed values. In regression models such as LSTM used for solar power forecasting, an R^2 of 0.80 or higher is generally accepted as a benchmark for good performance, as it means that at least 80% of the variance in the output is explained by the input features. In this study, all models achieved R^2 values above 0.90, demonstrating very strong predictive performance. This finding aligns with recent literature, which considers R^2 values exceeding 0.80 as reliable for accurate forecasting in solar energy applications [18].

Moving to the epoch-loss graphs, the Univariate LSTM again demonstrates stable and low training loss across 30 epochs, indicating good convergence and minimal overfitting. The Multivariate LSTM (Wsensor) converged quickly within the first five epochs but displayed higher and less stable loss compared to the univariate model.

The addition of MET data (Fig. 5c) appears to slightly improve loss stabilization over more epochs. Meanwhile, the Bi-LSTM model shows relatively higher loss values during training and slower convergence, consistent with its inferior prediction accuracy observed in both the scattered plot and Fig. 4. This highlights that added model complexity like bidirectionality may not always yield better results in time-series solar data with clear unidirectional trends.

Finally, the histograms comparing the first five rows of actual and predicted values confirm the overall performance trends observed in the other two graphs. The Univariate LSTM (Fig. 5a) again shows minimal deviation between actual and predicted bars, while the multivariate and Bi-LSTM models display slightly more mismatch, especially for row indices 2 and 3. Although this histogram only samples a small portion of the dataset, it reinforces the general trend, thus simpler architectures like univariate LSTM can be highly effective when historical solar output dominates the forecast influence.

Then, the performance of the Univariate LSTM, Multivariate LSTM (Weather sensor), and Multivariate LSTM (Weather sensor + MET) models was assessed across multiple forecasting horizons ranging from 10 minutes to 5 hours. The models were evaluated based on MAE, MSE, normalized RMSE (nRMSE), and R^2, providing insights into their forecasting accuracy over time. Table 3 shows the error metrics analysis of the models across different horizons, its reveals distinct performance characteristics for the Univariate LSTM, Multivariate LSTM (Weather Sensor), and Multivariate LSTM (Weather Sensor and MET Data). The Univariate LSTM model demonstrated consistent performance across all forecasting horizons, which is better compared to previous reported [2]. The MAE remained stable at 0.0297, and the MSE slightly decreased from 0.0039 at 10 minutes to 0.0036 at 5 hours. The nRMSE showed a small improvement over longer horizons, reducing from 0.0626 to 0.0599. Additionally, the R^2 metric increased slightly from 0.93 at shorter horizons to 0.94 at longer horizons, indicating strong predictive accuracy over extended time periods. The stable performance across horizons suggests that the Univariate LSTM model effectively captures the temporal patterns in the data, maintaining accuracy even for long-term forecasts.

The Multivariate LSTM (Weather sensor) model exhibited better performance than the Univariate LSTM for shorter horizons, with an MAE of 0.0282 at 10 minutes compared to 0.0297 for the Univariate LSTM. The MSE and nRMSE also improved slightly, with the MSE decreasing from 0.0038 at 10 minutes to 0.0034 at 5 hours. The R^2 metric remained consistently high, increasing from 0.93 to 0.94 as the forecast horizon extended. This model's performance suggests that incorporating weather sensor data improves short-term forecasts and provides competitive accuracy for long-term horizons. Its slight advantage over the Univariate LSTM in short horizons highlights the value of sensor data for capturing fine-grained variability in solar power output. The Multivariate LSTM (Weather sensor + MET) model showed mixed performance across horizons. For shorter horizons, it exhibited competitive accuracy, with an MAE of 0.0327 and an MSE of 0.0045 at 10 minutes.

Table 3 *Evaluation matrix of univariate and Multivariate LSTM model's error for multi-time horizons*

Univariate LSTM										
Horizon	10 min	20 min	30 min	40 min	50 min	1 hour	2 hour	3 hour	4 hour	5 hour
MAE (kW)	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297
MSE (kW)	0.0039	0.0038	0.0038	0.0037	0.0037	0.0037	0.0037	0.0036	0.0036	0.0036
nRMSE (kW)	0.0626	0.0619	0.0616	0.0611	0.0612	0.0610	0.0610	0.0597	0.0600	0.0599
R^2	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.94	0.94	0.94
Multivariate LSTM (Weather sensor)										
Horizon	10 min	20 min	30 min	40 min	50 min	1 hour	2 hour	3 hour	4 hour	5 hour
MAE (kW)	0.0282	0.0272	0.0267	0.0273	0.0275	0.0262	0.0268	0.0264	0.0266	0.0266
MSE (kW)	0.0038	0.0038	0.0037	0.0037	0.0036	0.0036	0.0036	0.0036	0.0034	0.0034
nRMSE (kW)	0.0620	0.0612	0.0609	0.0608	0.0604	0.0602	0.0602	0.0596	0.0587	0.0584
R^2	0.93	0.93	0.93	0.93	0.93	0.94	0.94	0.94	0.94	0.94
Multivariate LSTM (Weather sensor and MET data)										
Horizon	10 min	20 min	30 min	40 min	50 min	1 hour	2 hour	3 hour	4 hour	5 hour
MAE (kW)	0.0327	0.0376	0.1040	0.0337	0.0436	0.0542	0.0331	0.0522	0.0515	0.0561
MSE (kW)	0.0045	0.0043	0.0223	0.0040	0.0053	0.0080	0.0040	0.0074	0.0062	0.0070
nRMSE (kW)	0.0668	0.0658	0.1495	0.0631	0.0725	0.0895	0.0634	0.0862	0.0789	0.0840
R^2	0.92	0.92	0.60	0.93	0.91	0.86	0.93	0.87	0.89	0.87

However, performance deteriorated significantly for intermediate horizons, such as at 30 minutes, where the MAE increased to 0.1040 and the R^2 dropped sharply to 0.60. For longer horizons (e.g., 2 hours), the model regained some of its predictive power, achieving an R^2 of 0.93 and a relatively low MAE of 0.0331. This variability indicates that while the inclusion of meteorological data enhances the model's ability to capture external factors, it may introduce complexity or noise that affects performance at certain horizons. The inconsistent results highlight the importance of optimizing input feature selection and addressing overfitting or data quality issues for robust performance across all forecast horizons. The Univariate LSTM demonstrated the most stable performance across all forecast horizons, making it a reliable choice for consistent predictions. The Multivariate LSTM (Weather sensor) provided slightly better accuracy for shorter horizons, leveraging sensor data to capture finer temporal details. However, the Multivariate LSTM (Weather sensor + MET) exhibited inconsistent performance, with significant degradation at intermediate horizons, likely due to the added complexity of meteorological inputs. This highlights the trade-off between incorporating additional features and maintaining model accuracy. For scenarios requiring stable and accurate predictions across both short and long horizons, the Univariate LSTM is the most reliable choice. However, for applications prioritizing short-term accuracy, the Multivariate LSTM (Weather sensor) is a better alternative. While the Multivariate LSTM (Weather sensor + MET) shows promise, its application would benefit from further refinement in feature engineering and model tuning to address performance variability.

4. Conclusion

This study comprehensively evaluated the performance of LSTM-based models for solar power forecasting using both univariate and multivariate datasets across varying forecasting horizons. Among the models, the Univariate LSTM demonstrated superior and consistent performance across all horizons, achieving the lowest error metrics and the highest R^2 value (0.94). Its simplicity and ability to effectively capture temporal patterns without the need for additional input variables make it a reliable choice for scenarios requiring stable and accurate predictions across short and long-term horizons. The Multivariate LSTM models, incorporating weather sensor data (Wsensor) and meteorological data (Wsensor + MET), offered valuable insights into the role of additional input variables. The Multivariate LSTM (Wsensor) showed slightly better accuracy for short-term forecasts by leveraging sensor data to capture fine-grained variability, while the Multivariate LSTM (Wsensor + MET) exhibited marginal improvements over its Wsensor counterpart. However, the added complexity of meteorological inputs introduced variability in performance, particularly at intermediate horizons, underscoring the need for careful feature selection and model tuning to optimize predictive accuracy.

In contrast, the Bi-LSTM model, which considers both forward and backward dependencies in sequence data, recorded the highest error metrics and the lowest R^2 value (0.91). Its complexity may have led to overfitting or an inability to generalize effectively with the given dataset, suggesting that bidirectional learning might not be beneficial for datasets of this size and nature. Overall, the results emphasize that the Univariate LSTM is the most robust and reliable model for solar power forecasting using this dataset, especially for consistent and accurate predictions. However, in industrial practice, weather plays a crucial role in capturing solar power output, making Multivariate LSTM models the most practical choice. Although Multivariate LSTM models may perform slightly worse than Univariate LSTM models, they still demonstrate great potential, especially for short-term horizons or when detailed input data is available, thus further research is needed to refine these approaches. The findings providing valuable guidance for selecting appropriate models based on specific forecasting requirements and dataset characteristics.

Acknowledgement

The authors would like to acknowledge the Universiti Tun Hussein Onn Malaysia (UTHM) Johor, Malaysia for the financial support by Industry grant (M141 and M169), and Gading Kencana Sdn Bhd for providing input data from solar farm Malacca for completing this research.

Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Muhamad Guntor Mansor Tobeng, Mohd Zainizan Sahdan, Siti Ashraf Abdullah;* ***data collection:*** *Muhamad Guntor Mansor Tobeng, Abdul Rasid Abdul Razzaq, Siti Ashraf Abdullah;* ***analysis and interpretation of results:*** *Muhamad Guntor Mansor Tobeng, Mohd Zainizan Sahdan, Mohd Razali Tomari, Siti Ashraf Abdullah;* ***draft manuscript preparation:*** *Muhamad Guntor Mansor Tobeng, Mohd Zainizan Sahdan, Abdul Rasid Abdul Razzaq, Mohd Razali Tomari, Feri Adriyanto, Siti Ashraf Abdullah. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] J. O. Petinrin and M. Shaaban, "Renewable energy for continuous energy sustainability in Malaysia," *Renew. Sustain. Energy Rev.*, vol. 50, pp. 967–981, 2015, doi: 10.1016/j.rser.2015.04.146.

[2] N. H. A. Rahman, M. Z. Hussin, S. I. Sulaiman, M. A. Hairuddin, and E. H. M. Saat, "Univariate and multivariate short-term solar power forecasting of 25MWac Pasir Gudang utility-scale photovoltaic system using LSTM approach," *Energy Reports*, vol. 9, pp. 387–393, 2023, doi: https://10.1016/j.egyr.2023.09.018.

[3] A. Islam and F. Othman, "Renewable Energy MicroGrid Power Forecasting : AI Techniques with Environmental Perspective," *Res. Sq.*, 2024, doi: https://doi.org/10.21203/rs.3.rs-4260337/v1.

[4] Sepp Hochreiter and Jurgen Schmidhuber, "Long Short Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1–32, 1997, doi: https://doi.org/10.1162/neco.1997.9.8.1735.

[5] E. Chodakowska, J. Nazarko, Ł. Nazarko, H. S. Rabayah, R. M. Abendeh, and R. Alawneh, "ARIMA Models in Solar Radiation Forecasting in Different Geographic Locations," *Energies*, vol. 16, no. 13, 2023, doi: 10.3390/en16135029.

[6] S. F. Ahmed *et al.*, *Deep learning modelling techniques : current progress, applications, advantages, and challenges*, vol. 56, no. 11. Springer Netherlands, 2023. doi: https://doi.org/10.1007/s10462-023-10466-8.

[7] J. Klaiber and C. Van Dinther, "Deep Learning for Variable Renewable Energy: A Systematic Review," *ACM Comput. Surv.*, vol. 56, no. 1, 2023, doi: 10.1145/3586006.

[8] A. K. Mandal, R. Sen, S. Goswami, and B. Chakraborty, "Comparative study of univariate and multivariate long short-term memory for very short-term forecasting of global horizontal irradiance," *Symmetry (Basel).*, vol. 13, no. 8, 2021, doi: https://doi.org/10.3390/sym13081544.

[9] P. Generation, A. C. Study, and M. Floating, "Performance of Deep Learning Techniques for Forecasting PV Power Generation: A Case Study on a 1.5 MWp Floating PV Power Plant," *Energies*, vol. 16, pp. 1–21, 2023, doi: https://doi.org/10.3390/en16052119.

[10] M. Abotaleb and P. K. Dutta, "Hybrid Information Systems," in *Non-Linear Optimization Strategies with Artificial Intelligence*, R. Bhardwaj, P. K. Dutta, P. Raj, A. Kumar, K. Saini, A. González Briones, and M. K. A. Kaabar, Eds., De Gruyter, 2024, pp. 443–458. doi: doi:10.1515/9783111331133-021.

[11] M. Dholvan, A. K. Bhuvanagiri, and S. M. Bathina, "Offensive Text Detection using Temporal Convolutional Networks Associate Professor , ECM Department , Sreenidhi Institute of Science and Junior Research Scholar , ECM Department , Sreenidhi Institute of Science and," *Int. J. Adv. Sci. Technol.*, vol. 29, no. 6, pp. 5177–5185, 2020.

[12] R. Nadimi and M. Goto, "A novel decision support system for enhancing long-term forecast accuracy in virtual power plants using bidirectional long short-term memory networks," *Appl. Energy*, vol. 382, no. January, 2025, doi: 10.1016/j.apenergy.2025.125273.

[13] Gading Kencana, "Kompleks Hijau Solar: 8MW Solar Photovoltaic Farm." Accessed: Mar. 21, 2025. [Online]. Available: https://www.gadingkencana.com.my/portfolio/kompleks-hijau-solar-8mw-solar-photovoltaic-farm/

[14] M. D. V. Prasad and S. T, "Clustering Accuracy Improvement Using Modified Min-Max Normalization Technique Min-Max Normalization Technique," pp. 0–7, 2024, doi: 10.20944/preprints202411.0486.v1.

[15] D. K. Dhaked, S. Dadhich, and D. Birla, "Power output forecasting of solar photovoltaic plant using LSTM," *Green Energy Intell. Transp.*, vol. 2, no. 5, 2023, doi: 10.1016/j.geits.2023.100113.

[16] Z. Hu, Y. Gao, S. Ji, M. Mae, and T. Imaizumi, "Improved multistep ahead photovoltaic power prediction model based on LSTM and self-attention with weather forecast data," *Appl. Energy*, vol. 359, no. June 2023, 2024, doi: https://doi.org/10.1016/j.apenergy.2024.122709.

[17] T. Limouni, R. Yaagoubi, K. Bouziane, K. Guissi, and E. H. Baali, "Univariate and Multivariate LSTM Models for One Step and Multistep PV Power Forecasting," *Int. J. Renew. Energy Dev.*, vol. 11, no. 3, pp. 815–828, 2022, doi: 10.14710/ijred.2022.43953.

[18] T. C. S. and R. S. B. Filipe D. Campos, "Short-Term Forecast of Photovoltaic Solar Energy Production Using LSTM," *Energies*, vol. 17, no. 2582, pp. 1–19, 2024.