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LSTM-Based Daily Power Forecasting for a 1 MWp PV System in Tropical Indonesia: Toward Operational Optimization

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Abstract

Variations in solar irradiance and module temperature significantly affect the performance and operational efficiency of large-scale photovoltaic (PV) power systems, especially in tropical regions. This study investigates the application of a Long Short-Term Memory (LSTM) network for accurate real-time power prediction in a 1 MWp PV power plant at Institut Teknologi Sumatera (ITERA), Indonesia. Unlike traditional approaches and conventional artificial neural networks (ANN), LSTM networks can effectively capture long-term temporal dependencies and highly nonlinear patterns in PV output data. A five-minute resolution dataset, including actual power output, solar irradiance, and module temperature, was collected throughout March 2025 for model training, with validation performed using independent data from April. The developed LSTM model achieved a mean absolute error (MAE) of 42.8 kW (approximately 4–6% of maximum plant capacity) and a coefficient of determination (R^2) of 0.84 during active hours (05:00–19:00) on the validation dataset. These findings indicate that the model performs well not only on the training data, but also maintains strong generalization to unfamiliar data. The proposed approach enables reliable real-time power prediction, supporting applications such as energy forecasting, inverter control, dispatch planning, and anomaly detection in PV systems. This work provides a practical and scalable solution for improving the adaptability and integration of solar power plants in dynamic tropical environments, contributing to the advancement of AI-driven sustainable energy systems.

Keywords: Photovoltaic Power Forecasting, LSTM Neural Network, Tropical Climate, Utility-Scale PV, Real-Time Prediction, Smart Grid Integration, Data-Driven Modelling.

I. INTRODUCTION

A. Background

PLTS 1 MWp ITERA is a large-scale solar energy facility that supports energy independence and various academic activities at the Institut Teknologi Sumatera (ITERA). During the global energy transition towards a renewable power generation system, PLTS is one of the main options in supporting national energy stability and reducing dependence on fossil fuels [1], [2]. However, the PLTS system faces significant output power fluctuations as a major challenge, especially due to the dynamics of rapid and irregular changes in irradiation and environmental temperature, which are typical characteristics of tropical regions such as Indonesia [3], [4], [5].

Power fluctuations due to variations in irradiation and temperature directly affect the energy conversion efficiency and operational stability of PV power plants. This condition becomes even more critical when PV power plants are integrated with the grid or within an inverter-based intelligent control system, where accurate power predictions are essential to support load planning, inverter management, and rapid response to sudden weather changes [3], [6], [7].

Various methods for predicting solar power output have been developed, ranging from physical model-based approaches to conventional statistical algorithms. However, these approaches are generally still limited in handling nonlinear, dynamic, and temporal weather data patterns, especially in tropical environments [8], [9]. In previous research, we have evaluated the effectiveness of artificial neural network (ANN) algorithms trained using backpropagation (ANN-BP) and particle swarm optimization (ANN-PSO) for maximum power point tracking (MPPT). The results showed that ANN-PSO has faster convergence and higher output power than ANN-BP [10]. However, this method has significant weaknesses because it is less adaptive to long-term sequential data and dynamic changes in weather conditions.

As a more sophisticated alternative, the Long Short-Term Memory (LSTM) network was specifically developed to overcome the limitations of classical ANN

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in processing time-series data with complex temporal patterns [11]. LSTM has a gate mechanism and internal memory that allows this network to capture long-term patterns in sequential data, making it more effective in predicting the output power of PLTS compared to previous methods [3], [8].

This study aims to implement the LSTM method to predict the daily output power of the 1 MWp ITERA PLTS using one month of operational data. This approach is an initial step towards the development of a more adaptive and predictive artificial intelligence (AI)-based intelligent control system and supports the optimization of large-scale PLTS operations in tropical environments [3], [7].

B. Problem statement

The output power of ITERA's 1 MWp solar power plant is highly influenced by fluctuations in solar irradiation and ambient temperature, which poses challenges in efficient energy management. Previous uses of conventional prediction methods and ANN approaches still have limitations in capturing complex nonlinear temporal patterns of environmental data. The inability of these models to provide accurate and adaptive predictions to weather dynamics hampers efforts to optimize solar power plant operations. Therefore, a more responsive approach to time series data is needed to produce a more reliable and relevant power prediction model for the needs of a solar power system.

C. Objectives

This study aims to develop a daily output power prediction model for a 1 MWp ITERA solar power plant using the Long Short-Term Memory (LSTM) method. This model is developed by utilizing irradiation and temperature data for one month. This model is expected to recognize solar energy fluctuation patterns more accurately and adaptively than conventional methods through a time-series learning approach. The prediction results will be used as a basis for supporting optimization of daily solar power plant operation and the development of an artificial intelligence-based energy control system.

II. RELATED WORKS

Output power prediction on PV systems has been studied to support the development of adaptive renewable energy generation. One of the initial approaches used ANN with backpropagation and particle swarm optimization training, where ANN-PSO shows superiority in convergence and power accuracy [10]. However, this approach has not optimally considered temporal dynamics in environmental data, especially in long-term data with high variability [3], [9].

Deep neural network approaches such as LSTM are starting to be widely used due to their ability to adaptively capture long-term patterns from time series data. Previous studies have shown that LSTM can produce more accurate and stable PV power predictions compared to conventional statistical and machine learning methods, especially on data with complex temporal dynamics [9], [11]. Recent research has also developed hybrid models such as CNN-LSTM that integrate visual and environmental data to improve prediction accuracy under various environmental conditions [8].

However, most previous studies have been conducted on small-scale PV systems in subtropical regions, with a lack of large-scale exploration in tropical regions. Therefore, this study contributes by applying the LSTM model to historical data of a 1 MWp PV system in tropical Indonesia. This study aims to accurately predict daily power output, support the development of a prediction-based energy control system, and strengthen the adaptability of PV systems to high tropical weather variability, thereby expanding the application of predictive models in the operational context of developing countries.

III. METHODOLOGY

A. Data descriptions

The dataset used in this study is obtained from the 1 MWp PLTS monitoring system installed at ITERA, Indonesia. The plant consists of 3,036 polycrystalline modules, occupying a fenced area of about 1 hectare, and is fully integrated with grid monitoring infrastructure. Data were collected during the period of 1–31 March 2025 with a retrieval interval of every 5 minutes, resulting in 8,928 data points. The parameters recorded include solar irradiation intensity in W/m^2 and PV module temperature in ºC. This dataset reflects the characteristics of a tropical climate with high and irregular daily weather fluctuations.

The dataset used in this study was directly collected from the 1 MWp grid-connected PV power plant monitoring system at ITERA, Indonesia. The recorded parameters include actual output power, solar irradiance, and module temperature, each with a 5-minute resolution. All model training and evaluation processes are based on this real measured data.

Figure 1 shows the fluctuation of irradiance and module temperature on one of the operational days, March 15, 2025. The module temperature increases with increasing irradiance, peaks around noon, then decreases towards the afternoon. Such variability is a major challenge in predicting the power of PV systems, especially in tropical areas with high weather dynamics.

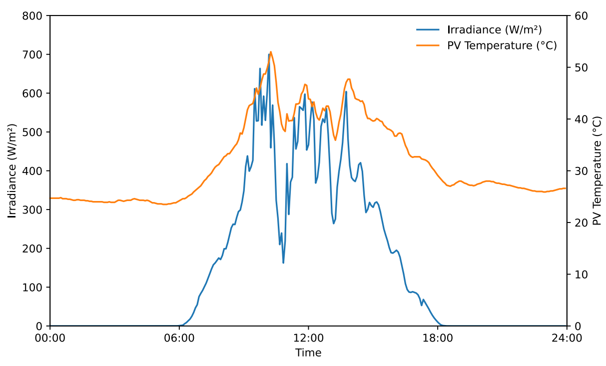

Figure 1. Daily profiles of solar irradiance and PV module temperature at ITERA on March 15, 2025.

B. LSTM Model

LSTM is an artificial neural network architecture developed from a Recurrent Neural Network (RNN), specially designed to overcome problems in processing time-series data [12]. Unlike Feedforward network such as ANN, LSTM has an internal mechanism in the form of a memory cell and logic gate, which allows it to store, update, and release information along the data sequence. This capability makes LSTM effective in recognizing hidden patterns inside sequential data that had long term dependent such as solar irradiation fluctuation and temperature in PV systems [13], [14], [15]. LSTM consists of three main components [16]: forget gate, input gate, and output gate. The operation of these gates is explained mathematically as follows.

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f \quad (1)$$

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i \quad (2)$$

$$\tilde{C}_t = tanh(W_c * [h_{t-1}, x_t] + b_c \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o \quad (5)$$

$$h_t = o_t * tanh(C_t) \quad (6)$$

In this equation, $\boldsymbol{f_t}$, $\boldsymbol{i_t}$, and $\boldsymbol{o_t}$ are the output vectors of forget, input, and output gates; $\boldsymbol{C_t}$ is the cell state; and $\boldsymbol{h_t}$ is a hidden state that is the output of the LSTM at time step; the sigmoid activation function (σ) and hyperbolic tangent function (tanh) are used to adjust the sensitivity and scale of the information processed.

A more detailed description of the LSTM operation when processing sequential data can be seen in the pseudocode of the LSTM algorithm in the form of the following iterative steps (Figure 2) [17] – [20].

LSTM is highly relevant for PV system power prediction due to its ability to model the temporal relationship among environmental parameters such as irradiation, temperature, and power output [14], [20], [21], [22]. The LSTM model in this study was built to study the historical pattern of ITERA 1 MWp PLTS data for one month, with the aim of predicting daily output power accurately and consistently.

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The pseudocode of the LSTM algorithm
Input: sequence of input vector x = [x_1, x_2, ... , x_T]
Initialize : h_0 = 0, C_0 = 0

For t =1 to T do
f_t ← sigmoid(W_f * [h_{t−1}, x_t] + b_f)        # Forget gate
i_t ← sigmoid(W_i * [h_{t−1}, x_t] + b_i)        # Input gate
C̃_t ← tanh(W_C * [h_{t−1}, x_t] + b_C)           # Candidate cell state
      C_t ← f_t * C_{t−1} + i_t * C̃_t           # Updated cell state
o_t ← sigmoid(W_o * [h_{t−1}, x_t] + b_o)        # Output gate
h_t ← o_t * tanh(C_t)                            # Hidden state (output)
end for
Output: final hidden state h_T or full sequence [h_1, h_2, ... , h_T]
```

Figure 2. The pseudocode of the LSTM algorithm in the form of the following iterative steps.

TABLE 1.
SUMMARY OF THE LSTM MODEL ARCHITECTURE

Layer (type)	Output Shape	Param
lstm (LSTM)	(none, 12, 128)	69,120
lstm_1 (LSTM)	(none, 64)	49,408
dense (Dense)	(none, 64)	4,160
dense_1 (Dense)	(none, 1)	65
Total params		122,753 (479.50 KB)

The prediction model is built using an LSTM architecture designed to process time-series inputs X_t=[G_t,T_t]. The internal process of LSTM involves a gate function to retain relevant historical information.

The proposed model was implemented in TensorFlow using Python and trained with the Adam optimizer and Mean Squared Error (MSE) as the loss function for 100 epochs [23], [24]. As summarized in Table 1, the network adopts a sequential architecture consisting of two stacked LSTM layers followed by two dense layers [9], [25], [26]. The first LSTM layer contains 128 memory units and returns the complete output sequence (return_sequences=True), which is subsequently processed by a second LSTM layer with 64 memory units. The extracted temporal features are then passed through a dense layer with 64 neurons before the final dense layer with a single neuron generates the predicted PV output power [25].

The output shapes of the successive layers are (None, 12, 128), (None, 64), (None, 64), and (None, 1), indicating that the model processes two-dimensional input features (solar irradiance and PV module temperature) using a sliding time window of 12 time steps. The proposed model contains a total of 122,753 trainable parameters. The detailed architecture of the proposed LSTM model is summarized in Table 1.

The training process is carried out on historical data of 1 MWp PLTS at a five-minute resolution for one month (March 2025). This model is saved in .h5 format to allow re-inference without the need for retraining, as well as to facilitate replication and testing on validation data.

C. Evaluation

The evaluation is conducted at two levels: micro and macro[8], [25]. The metrics used are as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_i^{pred} - P_i^{actual}\right| \quad (7)$$

$$MSE = \frac{1}{n}\sum_{i-1}^{n}\left(P_i^{pred} - P_i^{actual}\right)^2 \quad (8)$$

$$RMSE = \sqrt{MSE} \quad (9)$$

$$R^2 = 1 - \frac{\sum(P_i^{actual} - P_i^{pred})^2}{\sum(P_i^{actual} - P_i^{actual})^2} \quad (10)$$

Where $\boldsymbol{P_i^{pred}}$ is the predicted PV output power at the $\boldsymbol{i}$-th observation $\boldsymbol{P_i^{actual}}$ is the measured PV output power at the $\boldsymbol{i}$-th observation, $\boldsymbol{n}$ is the total number of observations, and **MSE** denotes the mean squared error. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2) are used to evaluate the prediction performance of the proposed model.

Micro evaluation is done by comparing predictions to actual data at every 5-minute time point. Macro evaluation is carried out by integrating the prediction power into total monthly energy and comparing it to the actual energy from the metering [27], [28], [29]. Thus, the model is tested not only for local precision but also for the suitability of statistical performance.

IV. RESULTS AND DISCUSSIONS

This study produces an LSTM model to predict the output power of a 1 MWp Solar Power Plant (PLTS) based on daily operational data with a 5-minute interval. The model was trained using March 2025 data and tested on April 2025 data as validation data.

A. Visualization of prediction results

Figure compares the predicted and actual PV output power during the active operating period (05:00–19:00) in April 2025. In general, the LSTM model follows the actual power fluctuation pattern throughout the active period.

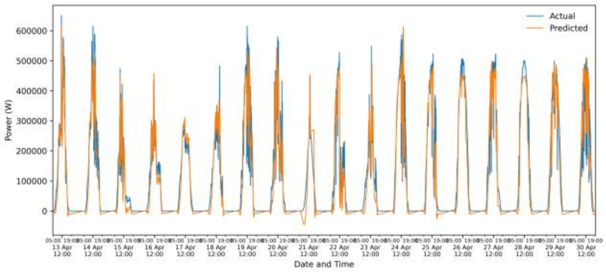

Figure 3. Actual vs predicted output power during active hours, April 2025.

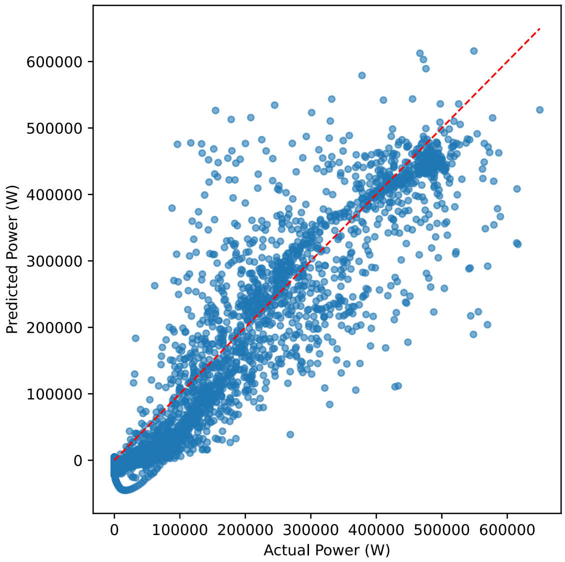

Figure 4. Actual vs. predicted PV power during active hours, April 2025.

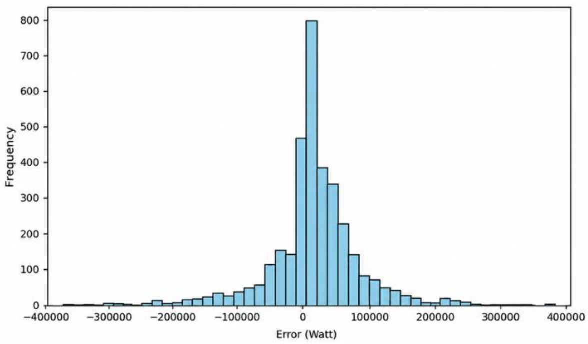

Figure 5. Error distribution during active hours, April 2025.

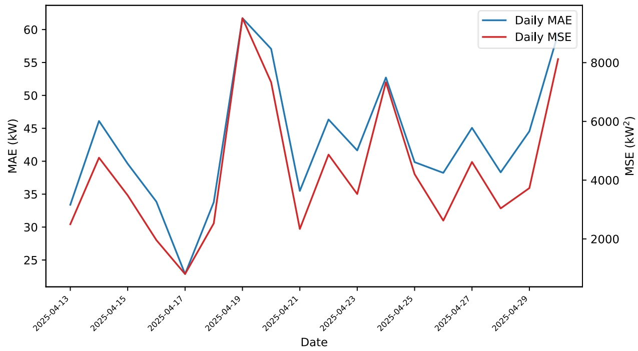

Figure 6. Daily MAE and MSE of PV power prediction during active hours, April 2025.

Figure shows a scatter plot between actual and predicted values during the active hour period. Most of the data points are distributed around the identity line (y = x), indicating good prediction convergence.

Figure shows the distribution of prediction errors. This histogram shows that most of the errors are symmetrically distributed around zero, indicating no systematic bias in the model.

To assess the temporal stability of the model performance, Figure presents the daily rolling errors (MAE and MSE) specifically during active hours. The error values tend to be stable across days, indicating that the model is quite robust to daily data variations.

B. Comparison of evaluation metrics

Table 2 summarizes the evaluation results using the metrics defined in (7)–(10) for both training (March) and validation (April) data, the 24-hour period and active hours.

C. Interpretation of model accuracy

The prediction performance is first evaluated for the active operating period (05:00–19:00), corresponding to the data presented in Figs. 3–6. For completeness, the 24-hour evaluation results summarized in Table 2 are then discussed to provide a comprehensive assessment of the proposed model.

The accuracy of the model is assessed based on three main metrics, MAE, RMSE, and R^2, as formulated [3], [30], [31]. In the April validation data, the LSTM model produced an MAE of 42,846 watts and an RMSE of 65,661 watts during active hours (05:00–19:00), with an R^2 value reaching 0.840. Meanwhile, in the entire dataset (24 hours), the MAE and RMSE were recorded at 31,338 watts and 52,591 watts, respectively, with an R^2 of 0.879.

These values indicate that the model can predict the solar power output with an average absolute error of about 4–6% of the maximum system capacity of 1 MWp,

TABLE 2.
PERFORMANCE METRICS OF THE LSTM MODEL FOR MARCH AND APRIL DATA

Dataset	MAE	RMSE	R^2
March (24 hours)	29,498	57,944	0.814
March (05:00-19:00)	40,634	71,053	0.762
April (24 hours)	31,338	52,591	0.879
April (05:00-19:00)	42,846	65,661	0.840

especially during active hours. The R^2 values approaching 0.84–0.88 indicate that more than 80% of the variation in actual data can be explained by the prediction model, indicating excellent generalization ability. These results are also consistent with several previous studies that reported R^2 values in the range of 0.75–0.85 for LSTM-based solar power prediction at the utility level [25], [32], [33], [34].

Compared with the March training results, the validation results obtained in April demonstrate consistent predictive performance. The R^2 values increased from 0.762 to 0.840 during active hours and from 0.814 to 0.879 for the 24-hour evaluation, indicating that the proposed LSTM model maintains good generalization capability when applied to previously unseen operational data [35], [36], [37]. The stability of the error between days is also seen in the rolling MAE/MSE graph, supporting the claim of model robustness [3], [8]. Thus, the developed LSTM model is not only effective with historical data but also robust when applied to new data beyond the training period, which is essential in the real-world PV power prediction system.

D. Error analysis and robustness model

Error analysis shows the MAE model during active hours is 42,846 watts and RMSE is 65,661 watts, with the largest error value found in irradiation conditions that change suddenly, such as during cloudy weather or morning-afternoon transition [38], [39], [40]. The distribution of prediction errors is mostly concentrated around zero, as seen in the residual histogram, indicating no systematic bias in the model.

The daily rolling MAE values during the validation period were in the range of 36,000–63,000 W, while the daily rolling MSE was relatively stable without significant spikes. This indicates that the model has robust and consistent performance over time, able to maintain accuracy even on new data that was not used during training.

E. Macro evaluation: Monthly Energy Prediction

In addition to short-term accuracy, macro evaluation is conducted to assess the model's ability to predict the total monthly energy yield—a key metric for PV system operators and planners [27], [28], [29]. Table 3 presents the cumulative actual and predicted energy output for April 2025, both for the full 24-hour period and for active hours (05:00–19:00). For the full period, the LSTM model resulted in an aggregate energy prediction error of 15.07%, while for active hours, the error decreased to 10.34%.

This result occurs because, outside active hours, the model may predict near-zero or even negative output due to model noise or inherent limitations, while the actual output remains strictly zero. Consequently, aggregating predicted values over 24 hours can produce a lower total than aggregating only during active periods. This highlights the importance of focusing model evaluation and reporting on active operational hours, as they are most relevant for real-world PV system performance and planning.

TABLE 3.
MACRO EVALUATION OF ACTUAL AND PREDICTED MONTHLY ENERGY IN APRIL

Interval	Actual Energy (kWh)	Predicted Energy (kWh)	Error (%)
24 Hours	42,756	36,314	15.07
Active hours (05:00-19:00)	42,756	38,333	10.34

F. Practical Implementation

The accuracy of the solar power prediction model achieved in this study has significant implications for the management of solar power system operations. With MAE in the range of 4–6% of the maximum capacity of 1 MWp, this model can be used for daily energy output estimation, dispatch planning, and automatic detection of production anomalies [41], [42].

In addition, a robust model for new data like this is instrumental in facilitating the integration of PV power plants into the electricity grid, especially in smart grid systems that require real-time power predictions [33]. The implementation of the LSTM model can also assist operators in making decisions regarding preventive maintenance, performance monitoring, and managing risks due to weather variability, thereby increasing the efficiency and reliability of PV power plant operations [43], [44].

Beyond the achieved prediction accuracy, the proposed LSTM model has important practical implications for the operation of utility-scale PV systems in dynamic tropical environments. The model's ability to maintain stable prediction performance under these conditions demonstrates its potential to support intelligent operational decision-making, including inverter scheduling, dispatch planning, and anomaly detection. Furthermore, the proposed forecasting framework can serve as an enabling component for AI-driven sustainable energy systems by providing reliable real-time forecasting information for intelligent energy management and future smart grid applications.

V. CONCLUSIONS

The LSTM model developed in this study has demonstrated high accuracy and robust performance in predicting the output power of a 1 MWp PV power plant (PLTS) in Indonesia. On the validation dataset from a different month, the model achieved a MAE of approximately 4–6% of the maximum system capacity and a coefficient of determination (R^2) close to 0.84–0.88. These findings indicate that the model performs well not only on the training data, but also maintains strong generalization to unfamiliar data.

The stability of daily error metrics and the symmetric distribution of residuals indicate the absence of systematic bias and the consistency of model performance under varying daily operational conditions. Therefore, the proposed LSTM model is highly feasible for real-time predictive monitoring, operational planning, and the integration of large-scale PV systems into electricity grids.

The proposed model also demonstrates strong applicability for utility-scale PV systems operating in dynamic tropical environments, where reliable short-term forecasting is essential for efficient system operation. These capabilities provide a practical foundation for AI-driven sustainable energy systems by supporting future intelligent energy management and smart grid applications.

DECLARATIONS

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Ali Muhtar: Conceptualization, Methodology, Investigation, Formal Analysis, Writing-Original Draft, Writing–Review & Editing; Syamsyarief Baqaruzi: Supervision, Resources, Project Administration. Putty Yunesti: Investigation, Visualization, Writing-Review & Editing.

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