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Jurnal Nasional Teknologi dan Sistem Informasi

| ISSN (Print) 2460-3465 | ISSN (Online) 2476-8812 |



Research Article

Development of a Real-time Solar Panel Power Prediction Model Using the Long Short-term Memory

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INFORMASI ARTIKEL

Sejarah Artikel:

Diterima Redaksi: 02 Juli 2026

Revisi Akhir: 20 Agustus 2026

Diterbitkan Online: 03 September 2026

KATA KUNCI

Long Short-Term Memory,
Solar power prediction,
Microgrid,
Time-series forecasting,
Renewable energy

KORESPONDENSI

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ABSTRACT

Indonesia's remote islands face significant challenges in electricity access due to the high cost and logistical difficulties of extending the national grid, leading many communities to rely on expensive and polluting diesel generators. Solar-based microgrids offer a sustainable alternative, yet the intermittent nature of solar energy, driven by fluctuating weather conditions, poses major obstacles to a reliable power supply and efficient system sizing. This study addresses these issues by developing a real-time solar panel power prediction model using Long Short-Term Memory (LSTM) networks. A 50 Wp solar panel system equipped with an INA260 current sensor, a voltage sensor, a DHT-22 temperature sensor, and an ESP32 microcontroller was constructed to collect real-time voltage, current, and temperature data at 10-second intervals. The collected data underwent preprocessing, feature engineering, and transformation into supervised learning sequences for training. Three temporal resolutions of the LSTM model were systematically evaluated: 3-minute, 2-minute, and 1-minute, all with 30 output timesteps. Performance was assessed using rolling-window predictions on the held-out test set with metrics including RMSE, MAPE, and R^2 . Results demonstrated that finer temporal resolution significantly improves forecasting accuracy. The 1-minute variation achieved the best performance with the lowest RMSE and highest R^2 , effectively capturing both diurnal patterns and short-term fluctuations in solar power output. The developed LSTM model enables accurate short-term predictions (30–90 minutes ahead), supporting proactive energy management, including optimized battery charging, load scheduling, and reduced grid dependency. Future work will incorporate additional meteorological variables and seasonal data to improve model robustness further.

1. INTRODUCTION

Indonesia, an archipelago comprising over 17,000 islands, has many small, remote islands that are not yet covered by the national electricity grid. The logistical challenges and high costs of building conventional grid infrastructure across oceans often force remote communities to rely on expensive, environmentally unfriendly diesel-fueled power plants [1]. Solar-based microgrids offer an ideal solution for providing reliable, affordable, and sustainable electricity to these small islands, leveraging the abundant local natural resource of sunlight [2], [3].

However, the highly intermittent nature of solar energy, influenced by weather variations (solar radiation intensity, temperature, and cloudiness), makes electricity supply management challenging [4], [5]. This uncertainty in energy production creates the risk of power shortages and reduces the overall reliability of the microgrid system [6]. Furthermore, without optimal planning, microgrid development can lead to high investment costs due to component oversizing or high operational costs due to overreliance on the main PLN grid [7], [8].

To address these challenges, an approach that accurately predicts solar energy production and adapts to complex temporal patterns

is needed. Long Short-Term Memory (LSTM), a variant of Recurrent Neural Networks (RNNs), offers significant advantages in modeling time-series data with long-term dependencies [9], [10]. Unlike conventional prediction models or traditional Artificial Neural Networks (ANNs), LSTMs can selectively retain information from previous periods via gating mechanisms (forget, input, and output gates), making them more accurate at predicting fluctuations in solar panel production influenced by daily and seasonal weather patterns [11].

This research aims to develop a solar panel power prediction model using LSTMs to predict energy output accurately. These predictions can be used to optimize energy management, reduce dependence on the main grid, and improve system reliability. Furthermore, this approach is expected to reduce microgrid construction and operational costs through more efficient configurations based on LSTM predictions.

Although numerous studies have examined solar energy-based microgrids, the application of LSTMs to predict solar energy production at a laboratory scale in Indonesia remains limited. Most previous studies still use conventional statistical prediction models or ANNs, which are less effective at capturing long-term temporal patterns [12]. Therefore, this research is crucial to support the clean energy transition in remote areas of Indonesia through a more accurate and adaptive approach.

Long Short-Term Memory (LSTM) offers an effective solution to address the main challenges in solar energy-based microgrid management, namely the uncertainty and intermittency of energy production due to time-series weather factors [13]. This prediction model also supports precise microgrid sizing by tailoring to energy needs.

Traditional microgrid sizing techniques, such as the peak load method, which scales generation and storage based on expected peak demand, carry the risk of oversizing and high costs [14]. The average load method is less expensive than the peak load method but can compromise reliability during peak demand [15]. The use of deterministic algorithms such as linear programming, nonlinear programming, and dynamic programming provides solutions to reliability and oversizing issues. Still, it is computationally expensive for problems with many variables and constraints [16]. Therefore, algorithms based on artificial

intelligence and machine learning, such as LSTM, which can predict consumption and generation patterns with high accuracy, are preferred [17]. However, machine learning algorithms require large amounts of data for training and validation, which can limit their application. On the other hand, metaheuristic algorithms such as genetic algorithms and ant colony optimization have proven effective for optimizing microgrid systems, as they can find optimal solutions to complex, nonlinear problems [18], [19].

The problem-solving approach in this study begins with designing a solar panel system and collecting real-time power data for use as training and test data for the LSTM algorithm. This approach is expected to significantly improve the accuracy of solar energy production predictions, thereby increasing microgrid reliability and reducing operational costs due to over-reliance on the main grid. The LSTM model is adaptive because it can be retrained periodically with new data to better capture local weather patterns [20].

2. METHOD

This research employs a systematic experimental and computational approach to develop an intelligent solar microgrid using Long Short-Term Memory (LSTM) networks for accurate solar power prediction. The methodology is structured around the defined workflow, as illustrated in Figure 1, integrating hardware development, sensor calibration, data acquisition, and iterative LSTM model optimization.

2.1. Construction of Solar Data Acquisition System

In Process 1, a solar panel system equipped with a comprehensive data acquisition system was designed and constructed as illustrated in Figure 2. The hardware configuration consists of a 50 Wp solar panel, a 60 Wh VRLA battery, a solar charge controller, an inverter, and monitoring sensors, including an INA260 for current and voltage, a voltage sensor, and a DHT-22 for air temperature, connected to an ESP32 microcontroller. This setup enables real-time data acquisition of energy generation, storage, and consumption, providing the datasets for the LSTM model.

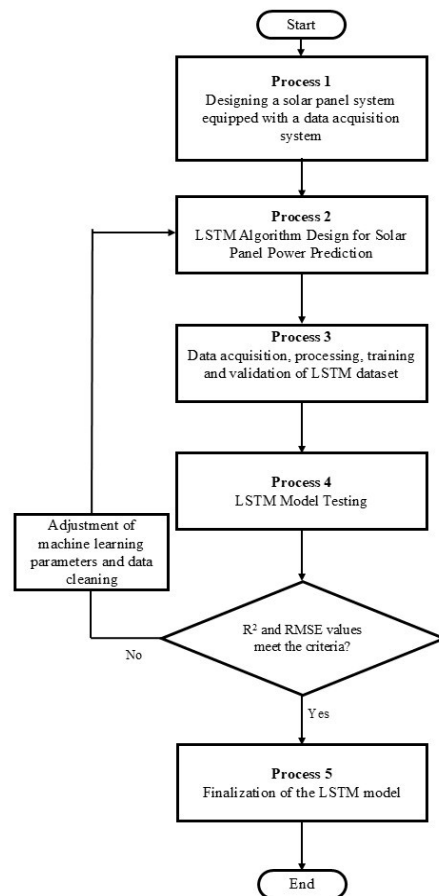


Figure1. LSTM Solar Power Prediction Research Workflow

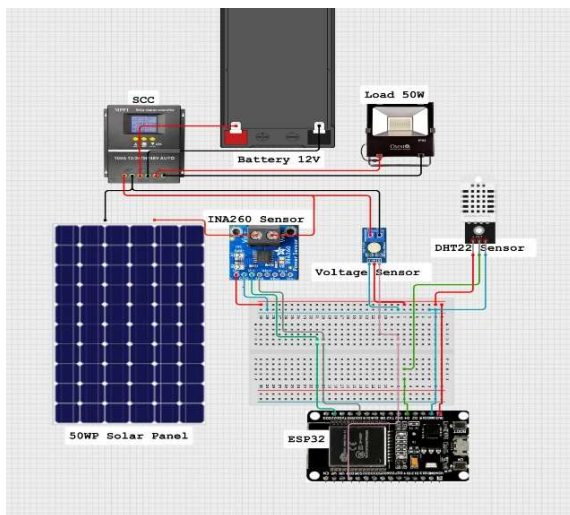


Figure2. Solar Panel Data Acquisition System

Sensor calibration was performed rigorously before full deployment. For the INA260 current sensor, calibration was performed using a precision adjustable current source ranging from 0.1 A to 1 A. Multiple readings were taken at each level, averaged, and then compared against a digital multimeter reference. Linear regression yielded the equation $y = 0.9742x + 0.0217$, with an R^2 of 0.99, indicating excellent linearity. Scale

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factor and zero-offset corrections were subsequently implemented in the microcontroller firmware.

Voltage sensor calibration was conducted using a variable power supply from 1 V to 12 V. The resulting regression equation was $y = 1.0031x - 0.5636$ with a perfect R^2 of 1, confirming outstanding linearity. The identified scale factor and offset values were applied as compensation factors in the data acquisition program to ensure high-precision readings.

The temperature sensor (DHT22) calibration was performed by comparing its readings against a precise reference calibrator across a temperature range of approximately 25°C to 42°C. Multiple measurements were taken and averaged at each calibration point to minimize noise. The data pairs were then analyzed using linear regression, producing the equation $y = 1.0388x - 0.9081$ with an excellent coefficient of determination R^2 of 0.99. The derived regression equation will be integrated into the microcontroller firmware as a correction formula, ensuring that raw DHT22 readings are accurately compensated before being fed into the data acquisition system and LSTM model for reliable solar power prediction in the microgrid.

2.2. Design of LSTM Model

Process 2 involved designing the LSTM algorithm for solar panel power prediction. The model was developed in Python using

TensorFlow/Keras with multiple LSTM layers followed by dense output layers to capture long-term temporal dependencies. Global parameters such as input steps, output steps, epochs, and batch size were tuned across different temporal resolutions.

In Process 3, data acquisition, processing, training, and validation were executed. Air Temperature and solar power, derived from the product of voltage and current, were collected from on-site measurements at 10-second resolution. Data underwent cleaning, Min-Max normalization, and sliding-window transformation into supervised sequences with variations of 60, 90, and 180 input steps (3 hours backward) and 30 output steps each (30, 60, and 90 minutes forward).

The LSTM data preprocessing begins with loading the raw CSV dataset containing the timestamp, power output, and temperature. Numeric cleaning is performed by converting string values to numeric types, followed by dropping rows with missing values in key columns. The timestamp is converted to a datetime format and set as the index for time-series handling. The data then undergoes resampling to 1-, 2-, and 3-minute intervals using mean aggregation, linear interpolation for short gaps, and smoothing with a moving average to reduce noise. Additional features are engineered, including first-order differences and cyclical time encodings using sine and cosine transformations of the hour and minute to capture daily periodicity. Min-Max scaling is applied separately to features and the target, and is fitted only on the training set (80% chronological split) to prevent data leakage.

After preprocessing, the normalized data is converted into supervised sequences using a sliding-window approach. With the variation of 60, 90, 180 input steps (3 hours backward) and 30 output steps each (30, 60, and 90 minutes forward), the `generate_sequences` function creates input-output pairs. For each valid time point, the model receives a window of past features, including weather variables, deltas, and cyclical encodings, to predict future power output values. This creates 3D input tensors suitable for LSTM.

The LSTM model is built using TensorFlow/Keras as a Sequential stack consisting of an LSTM layer (128 units), a RepeatVector for output steps, another LSTM layer (64 units with `return_sequences`), Dropout layers for regularization, and a final Dense layer. The model is compiled with the Adam optimizer (learning rate 0.001) and the Huber loss function. Training incorporates early stopping (`patience=10`) and learning rate reduction on plateau to prevent overfitting. Sample weighting is applied to emphasize higher power values. After training, the model, feature scaler, and target scaler are saved for later use in real-time prediction. A separate simulation script loads the saved model and runs rolling predictions across a full day by continuously updating the input window with new data up to the current timestamp. This pipeline ensures the LSTM effectively learns temporal dependencies in solar power generation while maintaining data integrity and temporal order.

In Process 4, the trained LSTM models underwent systematic testing and performance evaluation using the held-out test dataset (the remaining 20% of the chronological data split). The testing procedure involved rolling-window predictions to simulate real-

time operation, in which the model continuously received updated input sequences and generated multi-step forecasts of future solar power output. Three model variations were evaluated, each configured with 30 output steps but differing in input steps and temporal resolution: 60 steps (3-minute resolution), 90 steps (2-minute resolution), and 180 steps (1-minute resolution). This allowed assessment of how different lengths of historical context and data granularity affect predictive performance.

The evaluation framework employed standard time-series regression metrics to quantify prediction accuracy, including Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Visual validation was conducted using comparison charts that plotted actual versus predicted power values over the test period. Additionally, the models were tested under rolling prediction scenarios that mimic live deployment by progressively updating the input window with new sensor data up to the current timestamp.

Following the comprehensive testing of all variations, the optimal LSTM configuration was selected based on overall predictive accuracy, generalization capability, and suitability for real-time microgrid applications. The finalized model architecture, including the trained weights, Min-Max scalers for the feature and target variables, and associated preprocessing parameters, was saved as a TensorFlow/Keras model for subsequent deployment.

3. RESULTS

Figure 3 illustrates the performance of the LSTM model for 3-minute temporal variation across both the training and testing datasets. The graph compares the actual solar panel power output (blue solid line) with the model's predicted values (red dashed line) over approximately 300 data points. This variation processes historical data at 3-minute intervals, allowing the model to learn broader temporal patterns while predicting 30 steps, equivalent to 90 minutes. As shown, the LSTM model captures the overall diurnal trend of solar power generation; however, it exhibits limited responsiveness to the rapid and sharp fluctuations characteristic of the actual power curve.

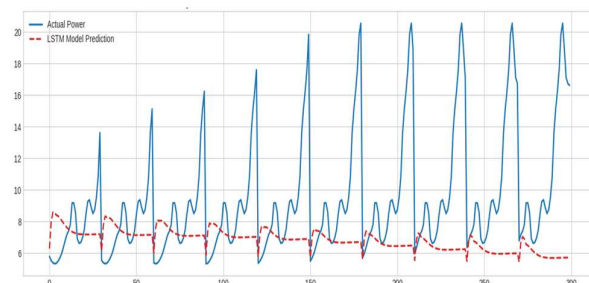


Figure 3. LSTM Performance at 3-minute temporal variation

A detailed examination reveals that the model tends to produce smoother predictions and to underestimate peak power magnitudes, particularly during midday when solar irradiance is highest. Thus, the RMSE value for this model is 9.39 W, and the R^2 value is 0.75. This behavior is typical in LSTM forecasting of highly intermittent renewable energy sources, where the model

prioritizes general patterns over abrupt changes due to factors such as passing clouds or sudden irradiance variations. With 300 data points used primarily for training in this configuration, the results indicate that while the 3-minute resolution provides adequate long-term context, it lacks the granularity needed to model short-term dynamics fully. Consequently, the model shows moderate pattern alignment but struggles to track rapid transients precisely, highlighting the need for finer temporal resolution in subsequent variations to improve forecasting fidelity for real-time microgrid applications.

Figure 4 illustrates the performance of the LSTM model for the 2-minute temporal variation on both training and testing datasets. This configuration utilizes historical data at 2-minute intervals, providing an intermediate level of temporal granularity between the coarser 3-minute and finer 1-minute resolutions. The model was trained on approximately 300 data points to learn the underlying patterns at this resolution while forecasting 30 steps, equivalent to 60 minutes into the future.

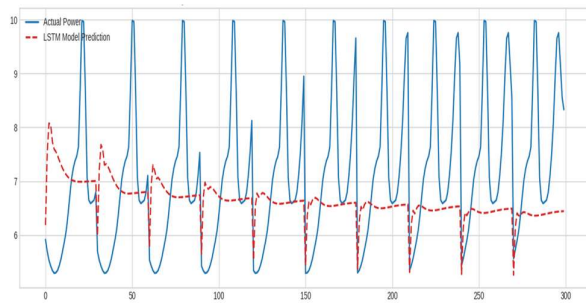


Figure 4. LSTM Performance at 2-minute temporal variation

A closer analysis of the comparison chart reveals that the LSTM model effectively captures the overall diurnal profile and major fluctuations in solar power generation. However, it still exhibits moderate smoothing of sharp peaks and underestimates certain high-irradiance transients. With an RMSE of 8.40 W and an R^2 value of 0.80, the model demonstrates improved pattern alignment compared to the 3-minute variation, indicating better learning of short-term dependencies due to the increased input sequence length. Nevertheless, deviations remain noticeable during low-power periods and sudden changes, which is attributable to the intermittent nature of solar irradiance. These results suggest that while the 2-minute resolution enhances forecasting fidelity over coarser settings, further refinement in temporal granularity is beneficial for achieving higher precision in real-time solar power prediction for microgrid applications.

Figure 5 illustrates the performance of the LSTM model for the 1-minute temporal variation on both training and testing datasets. This configuration employs the finest temporal resolution among the tested variants, using 180 input steps, corresponding to approximately 3 hours of historical data at 1-minute intervals. The model was trained to capture detailed short-term patterns while forecasting 30 steps (approximately 30 minutes), using around 300 data points for training in this high-resolution setup.

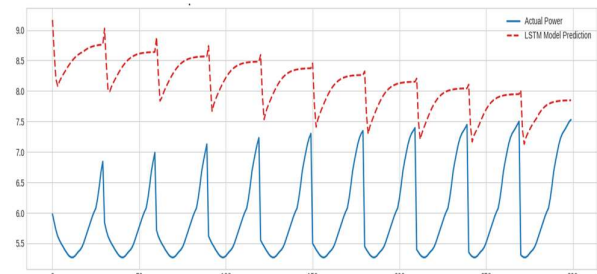


Figure 5. LSTM Performance at 1-minute temporal variation

A detailed examination of the comparison charts shows that the LSTM model demonstrates the strongest alignment with the actual solar power profile among all variations. It effectively captures both the overall diurnal cycle and many of the sharp fluctuations and peak outputs during periods of high solar irradiance. With an RMSE of 7.91 W and the highest R^2 value of 0.82, this variant achieves superior predictive accuracy and pattern matching. Although some smoothing of extremely rapid transients and minor deviations during very low-power periods is still observed, the 1-minute resolution significantly reduces prediction errors. It improves responsiveness compared to the coarser 3-minute and 2-minute configurations. These results confirm that longer input sequences with finer temporal granularity enable the LSTM network to better model the complex, intermittent dynamics of solar power generation, making it the most suitable for real-time microgrid energy management applications.

Figures 6, 7, and 8 present the comparative performance of the LSTM model across the three temporal variations on the test dataset. These graphs show the actual solar panel power output versus LSTM predictions over 30 time steps, providing visual insight into the model's behavior at different resolutions. Collectively, the figures demonstrate the impact of temporal granularity on prediction quality, with all models trained using the sliding-window approach and evaluated via rolling multi-step forecasting.

The 3-minute temporal variation exhibits the lowest performance among the three configurations. As shown in the graph, the model struggles to capture rapid fluctuations and sharp transitions in actual power output, resulting in significant smoothing and notable deviations, particularly during periods of declining irradiance. This configuration yields an RMSE of 24.19 W and a MAPE of 71.60%, indicating limited ability to model short-term dynamics despite successfully following the broader diurnal trend. The coarser resolution appears insufficient for handling the intermittent nature of solar generation.

In contrast, the 2-minute temporal variation shows moderate improvement. The LSTM predictions align more closely with actual values during stable periods, though noticeable lag and underestimation persist during steep changes. With an RMSE of 16.53 W and an MAPE of 47.70%, this variant offers better responsiveness than the 3-minute model, benefiting from increased historical context. However, it still fails to fully replicate high-frequency variations, highlighting the trade-off between computational efficiency and forecasting precision.

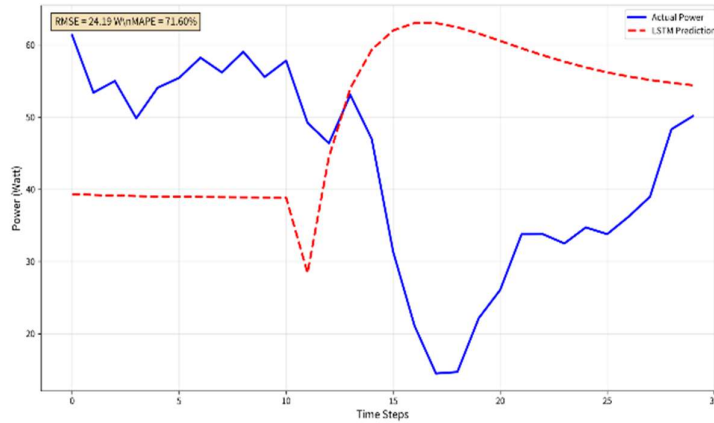


Figure 6. Actual Power vs LSTM Prediction (3-minute)

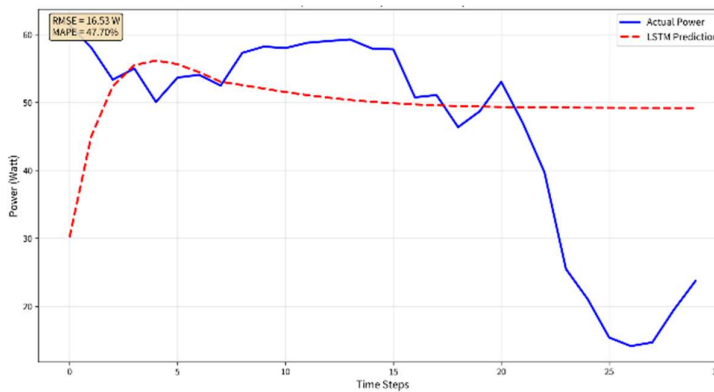


Figure 7. Actual Power vs LSTM Prediction (2-minute)

The 1-minute temporal variation delivers the most accurate predictions overall. The graph illustrates superior tracking of both peaks and troughs, with the red dashed line closely following the blue actual power curve across most time steps. This highest

resolution yields the lowest errors, confirming that longer input sequences with higher granularity enable the LSTM to learn complex temporal dependencies in solar power data more effectively.

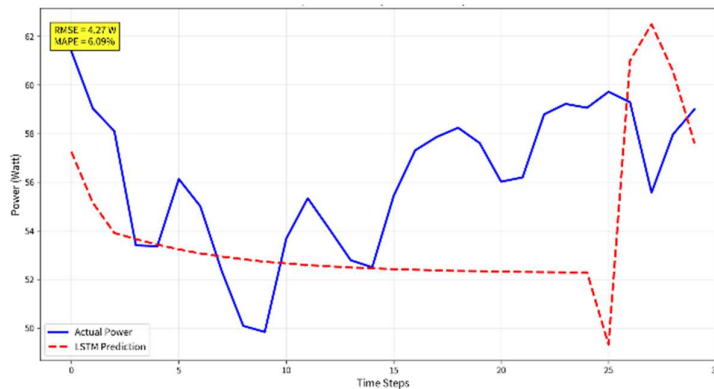


Figure 8. Actual Power vs LSTM Prediction (1-minute)

These comparative results validate the hypothesis that finer temporal resolution enhances LSTM performance for real-time solar power forecasting. The progressive improvement from 3-minute to 1-minute configurations underscores the importance of detailed historical input for microgrid applications. The 1-minute model, showing the strongest visual and quantitative agreement,

was therefore selected as the finalized configuration for deployment in the solar microgrid system.

4. DISCUSSION

The results of this study demonstrate that the LSTM-based model effectively predicts solar panel power output with notable accuracy, particularly at the 1-minute temporal resolution, achieving an RMSE of 7.91 W and R^2 of 0.82. These findings align with previous research highlighting the superiority of LSTM networks in handling time-series data with long-term dependencies compared to traditional statistical models or basic ANNs [9], [10]. For instance, studies on microgrid energy forecasting have shown that LSTM architectures outperform conventional approaches in capturing the intermittent nature of renewable sources, as their gating mechanisms enable the model to retain relevant historical patterns shaped by weather variability [11], [17]. This research extends those efforts by implementing a laboratory-scale, real-time data acquisition system tailored to the conditions of Indonesian remote islands, thereby confirming LSTM's practical applicability in resource-constrained environments.

Compared to earlier works that relied on coarser meteorological datasets or deterministic optimization techniques, the present approach benefits from high-frequency sensor data (voltage, current, and temperature) collected at 10-second intervals and resampled for model input. Traditional microgrid sizing methods, such as peak-load or average-load approaches, often lead to oversizing or reliability issues [15]. In contrast, the LSTM model's multi-step forecasting capability (up to 30–90 minutes ahead) supports more dynamic energy management strategies. This echoes findings from studies that use LSTM for load-frequency control and day-ahead forecasting in isolated microgrids, where predictive accuracy directly translates into reduced operational costs and improved integration of renewables. The progressive improvement observed across 3-minute, 2-minute, and 1-minute resolutions in this study further validates the importance of temporal granularity, an aspect less emphasized in many prior ANN or statistical models [12].

The superior performance of the finer 1-minute resolution model, particularly in capturing short-term fluctuations and diurnal patterns, addresses limitations noted in previous research on solar microgrids in developing regions [6]. While some studies have applied Prophet models or hybrid metaheuristic algorithms for microgrid optimization [18], [19], they often lack the real-time, edge-computing integration demonstrated here through the ESP32-based system. The rolling-window evaluation on the held-out test set reinforces the model's robustness for live deployment, showing reduced smoothing effects compared to coarser variants. This contributes to the growing body of evidence that AI-driven forecasting can mitigate the challenges of solar intermittency in off-grid settings, consistent with recent reviews on renewable-powered isolated microgrids.

However, certain deviations observed during rapid transients highlight ongoing challenges, as reported in the literature, including the need for additional exogenous variables such as solar irradiance or humidity [4]. The current model's reliance on a relatively limited dataset (focused on a single location and period) mirrors constraints faced in other laboratory-scale LSTM applications. Future enhancements could incorporate seasonal data and hybrid architectures, as suggested by recent

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advancements that combine LSTM with optimization algorithms such as Grey Wolf or Harris Hawk [2], [20]. These comparisons underscore that, while the current LSTM implementation achieves competitive performance, expanding the feature set and training data volume remain critical for generalizability across diverse Indonesian island climates.

Overall, this research advances the application of LSTM for solar power prediction in the Indonesian context by bridging hardware-level data collection with advanced deep learning, offering a scalable solution for remote microgrids. By achieving higher accuracy through finer temporal resolutions, it provides actionable insights for proactive energy management that surpass many conventional and early machine learning approaches documented in the literature [1]. The findings support broader clean energy transitions by enabling cost-efficient system design and operation, paving the way for more resilient and sustainable electricity access in archipelago nations. Continued integration with emerging IoT and optimization techniques will further strengthen these contributions.

5. CONCLUSION

This study successfully developed and evaluated a Long Short-Term Memory (LSTM) model for real-time solar panel power prediction in a small-scale solar microgrid system. Among the three temporal resolutions tested, the 1-minute-resolution configuration demonstrated the best performance, achieving the lowest RMSE and the highest R^2 while effectively capturing both the overall diurnal pattern and short-term fluctuations in solar power output. The results confirm that finer temporal granularity and longer historical input sequences significantly enhance the LSTM network's ability to model the intermittent nature of solar energy, validating its potential as a reliable forecasting tool for energy management applications.

The finalized LSTM model provides accurate short-term predictions that can support proactive decision-making in solar-based microgrids, including optimized battery charging/discharging strategies, load scheduling, and reduced reliance on the main grid. This approach contributes to improved system reliability and cost efficiency, particularly for remote islands in Indonesia. Future research is recommended to incorporate additional meteorological variables, extend the dataset across seasons, and explore hybrid models to further enhance prediction robustness under highly variable weather conditions.

ACKNOWLEDGMENT

The authors would like to thank the DPPM Kemdiktisaintek for funding the BOPTN Research Program for the 2025 Fiscal Year, which has supported this research.

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