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LSTM-based Prediction of Photovoltaic Voltage with Lightweight Load Scenarios

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ABSTRACT

Accurate prediction of photovoltaic (PV) output is critical for enhancing the efficiency, reliability, and management of renewable energy systems, especially in small-scale, off-grid applications. Despite advances in data-driven modeling, capturing the complex temporal dynamics of PV voltage output under varying environmental conditions remains a challenge. The novelty of this study lies in applying an LSTM-based approach specifically to predict the DC voltage of low-load PV systems with minute-level granularity, which has received limited attention in existing works that primarily focus on power prediction or high-load PV systems. The dataset, collected over a one-year period from a real-world PV installation, was preprocessed through one-minute interval resampling and Min-Max normalization to ensure input stability and improve model convergence. The LSTM architecture comprised three stacked layers with dropout regularization to prevent overfitting and was trained using the Adam optimizer with mean squared error (MSE) as the loss function. Model performance was assessed using MSE, mean absolute error (MAE), and mean absolute percentage error (MAPE). The LSTM model demonstrated strong predictive capability, capturing both short-term fluctuations and long-term trends, with an MSE of 0.02, MAE of 0.03, and MAPE of 0.17%. A comparative analysis with a Gated Recurrent Unit (GRU) model revealed that while GRU offered computational efficiency, the LSTM model delivered superior accuracy.

1. INTRODUCTION

The transition toward green energy has become a global agenda to address the climate crisis and reduce dependence on fossil fuels. Green energy refers to environmentally friendly and renewable energy sources that do not produce carbon emissions during their generation process [1]. Member countries of the European Union have committed to increasing the share of green energy as a renewable source by 55% by the year 2030 [2]. One of the most widely developed forms of green energy today is solar energy, which is derived from solar radiation and can be converted into electricity using photovoltaic technology [3]. In Indonesia, a notable example is the Cirata Dam, where a floating solar panel installation with a capacity of 145 MWac has been constructed [4]. The use of green energy, such as solar panels, not only supports environmental sustainability but also serves as a solution for sustainable energy needs, especially in remote areas that are difficult to reach by conventional electricity grids, such as in Guajira, Colombia [5].

Solar panels, or photovoltaic (PV) systems, are devices that convert direct sunlight into electrical energy using the photovoltaic effect [6]. These panels are increasingly utilized in residential, industrial, and agricultural power systems due to their low operational costs and long service life [7][8]. Optimal use of PV systems is a universal goal; hybrid MPPT (Maximum Power Point Tracking) methods, which combine the strengths of both conventional and modern approaches, have emerged as promising solutions to enhance scalability, minimize oscillations, and improve the accuracy of maximum power point tracking [9]. In Europe, PV energy is generated by approximately 17,000 power plants, with rooftop solar contributing less than 5% [10]. In the industrial sector in Italy, for example, a company that installed a PV system reported a monthly energy production of around 900 kWh, leading to an 84% reduction in energy consumption and a 57% decrease in costs [11]. However, one of the major challenges in utilizing solar panels is the fluctuating nature of their output, which depends on weather conditions, time of day, and panel orientation [12]. Therefore, it is essential to have accurate prediction methods to estimate output parameters such as voltage and current, in order to improve the efficiency of solar power usage and energy management.

In the context of modern technology, artificial intelligence (AI) has played a significant role in pattern recognition for modeling complex and nonlinear systems, such as accurately classifying potato leaf diseases [13]. In the healthcare domain, AI has been utilized to predict regional sanitation conditions using Support Vector Machine (SVM) algorithms [14]. AI is also applied in the design and planning of rooftop PV systems with terracotta tiles [15]. Furthermore, AI contributes to enhancing PV generation under various climatic conditions, as conventional controllers often fall short in optimizing PV output [16]. By leveraging historical data, AI algorithms can identify hidden patterns and generate accurate predictions, even under uncertain conditions [17]. This presents a major opportunity to improve the real-time estimation accuracy of solar panel output, enabling energy management systems to operate more adaptively and efficiently.

One of the most effective algorithms for time-based pattern recognition is Long Short-Term Memory (LSTM), a variant of the Recurrent Neural Network (RNN) [18][19]. LSTM is specifically designed to process and predict sequential data by capturing long-term dependencies [20][21]. This capability makes it particularly suitable for predicting solar panel voltage, where the output is highly dependent on time and varying environmental conditions.

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LSTM can retain important information from previous time steps while disregarding less relevant data, making it ideal for forecasting the performance of PV systems [22].

Several previous studies have applied LSTM to predict PV system outputs such as voltage, current, and power. These studies have demonstrated that LSTM can achieve higher prediction accuracy compared to feedforward neural networks, with R^2, MSE, RMSE, MAE, and MBE values of 0.93, 0.008, 0.089, 0.17, and 0.09 respectively for PV radiation prediction [23]. For example, LSTM-RNN has been used to model one-day-ahead independent PV power forecasting [24]. Another study applied LSTM to predict PV power output 1.5 hours in advance, resulting in an RMSE of 0.094 and a standard deviation of 0.016 [25]. Furthermore, LSTM has successfully predicted PV output with an error range of 3.46–13.46% based on time series data [26]. However, to date, no previous study has used the LSTM algorithm specifically to predict solar panel voltage output one hour ahead.

However, the use of LSTM for solar panel prediction also presents several challenges. One of the main issues is the need for large and representative training datasets, as well as the risk of overfitting if the model is not properly configured [27][28]. Additionally, the high complexity of the LSTM architecture can lead to prolonged training times and significant computational demands, which may pose limitations for monitoring systems based on microcontrollers or embedded systems [29].

The main contribution of this study is the application of an LSTM model to predict voltage in a small-scale solar panel system with a 5 W lamp load, which is more relevant for household use or off-grid systems. Therefore, the findings of this study are expected to serve as a reference for developing lightweight AI-based monitoring systems that can be utilized in various small-scale solar energy application scenarios.

Unlike traditional forecasting models such as ARIMA or feedforward neural networks (FFNN), the LSTM architecture is specifically designed to retain long-term sequential dependencies, making it highly effective in capturing the fluctuating nature of PV output voltage. Additionally, the proposed model is trained and evaluated under low-load PV scenarios, which is more relevant for remote and embedded system deployment.

Conventional methods such as ARIMA assume linearity and stationarity in the data, which is often violated in real PV systems due to rapid weather-induced fluctuations. Similarly, FFNNs lack memory mechanisms to capture temporal trends. These limitations motivate the use of LSTM, which is capable of learning both short-term variations and long-term temporal dependencies.

This article is organized as follows: the second section presents the research methodology used in this paper. The third section discusses the results and provides an analysis based on the experiments and comparisons with other methods. The entire article is intended to assist researchers and developers in designing more effective and innovative prediction models, as well as to promote advancements in the field of artificial intelligence.

2. METHODS

The proposed prediction method is illustrated in **Figure 1**. First, the PV output voltage dataset is collected from the database. Next, data preprocessing is performed to ensure the input format of the dataset matches the requirements of the LSTM model. The preprocessing involves addressing missing data, resampling the data at one-minute intervals, as well as

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scaling and normalizing the data. The dataset is then split, with 80% used as input for building the PV voltage prediction model, and the remaining 20% used to verify that the model can accurately predict the PV output voltage. This section provides details on the dataset used, explains the challenges encountered during the preprocessing phase, and presents the prediction method applied in this study.

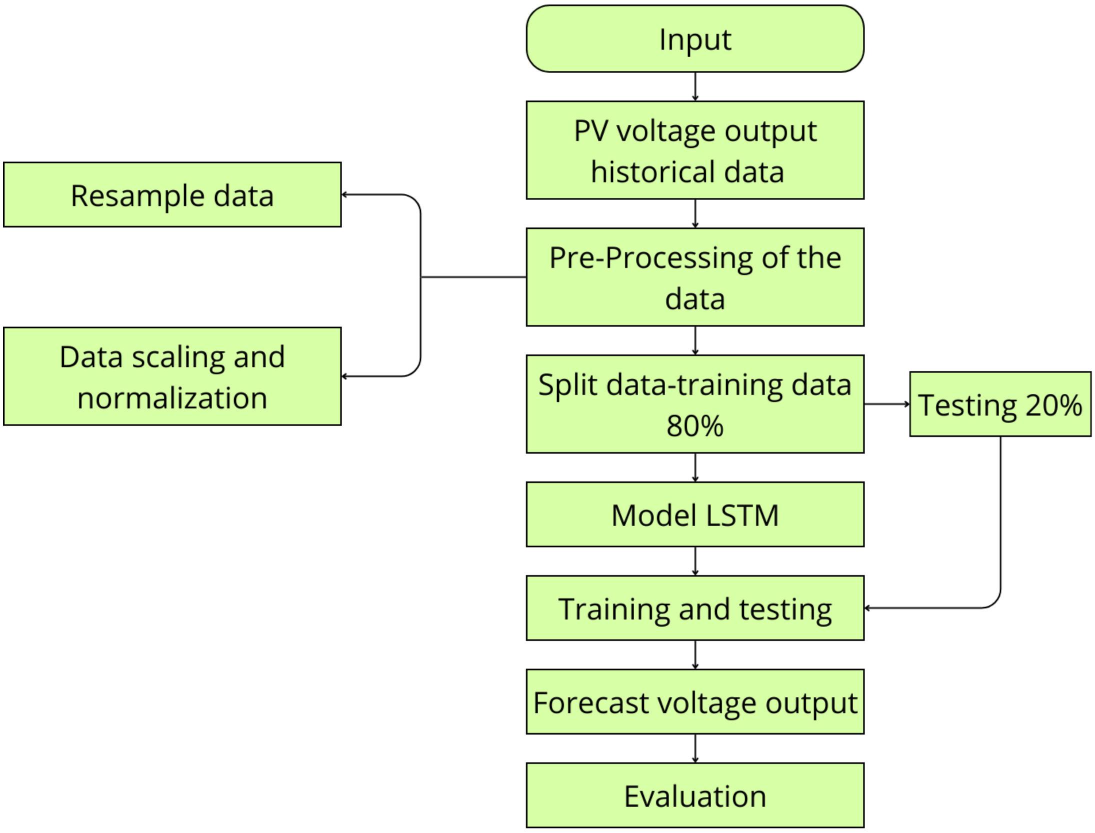

Figure 1. Flowchart of the PV voltage prediction method

2.1. Dataset

In this study, data were collected using ThingSpeak, a web-based Internet of Things (IoT) platform that enables the collection, visualization, and analysis of data from IoT devices such as sensors. The dataset used in this study is available at: https://thingspeak.mathworks.com/channels/2423989. It consists of voltage data recorded at one-minute intervals from a PV system installed at UNESA Ketintang Campus. The data cover the period from March 19, 2024, to March 29, 2025, with a total of 627 observations. For this study, additional data such as inverter voltage and current, as well as other variables like solar irradiance and temperature, were not considered.

2.2. Preprocessing data

Sudden spikes and non-stationary components in the input data can lead to inaccurate predictions in solar panel voltage forecasting models. This indicates that the model has not been trained optimally. This issue is common due to the nature of PV system output data, including voltage, which is strongly influenced by external factors such as solar irradiance, temperature, and unpredictable environmental conditions. Therefore, initial data preprocessing becomes a crucial step to enhance the quality of model training. In this study, the voltage data from the solar panel used to power a 5-watt lamp underwent a resampling process to one-minute intervals to stabilize the observation frequency, as well as normalization using the Min-Max Scaling method to ensure all values fall within a uniform range. This preprocessing

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technique not only accelerates convergence during LSTM model training but also improves overall prediction accuracy and reduces computational costs.

2.3. Normalization

Normalization, as applied in this study, is one of the data preprocessing techniques aimed at reducing the dispersion or spread of values within the dataset. This step is crucial in neural network-based modeling such as LSTM, since data with excessively large or inconsistent scales can slow down the training process and cause the model to fail to converge optimally. Essentially, the normalization process transforms all data values into a specific range, typically between 0 and 1. The dataset was normalized by calculating:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Where x is the observed voltage value of the solar panel, and x′ is the normalized value. This process is crucial, as literature indicates that normalization has a significant impact on the performance and output of any predictive model, including LSTM models [25]. The primary objective of normalization is to ensure that the data have a consistent quality and scale before being fed into the model. By eliminating scale irregularities among the data, normalization helps enhance training stability, accelerate model convergence, and ultimately produce more accurate and consistent voltage predictions particularly under load conditions such as the 5-watt lamp used in this study.

2.4. Split Data

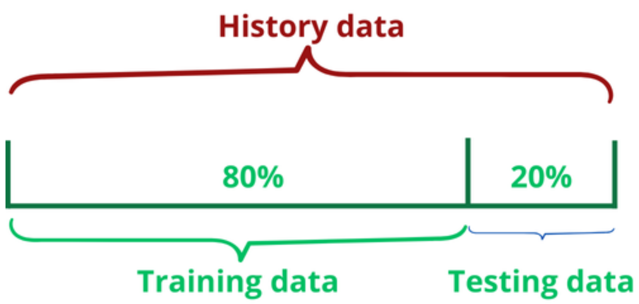

Figure 2. Specific division of historical data

The preprocessed dataset was divided into two parts: training data (80%) and testing data (20%). The input data were also reshaped into three dimensions samples, time steps, and features in accordance with the input format required by the LSTM model. This restructuring is crucial to enable the model to learn sequential patterns from the historical data.

The dataset comprised 627 observations of DC voltage recorded between March 19 and March 29, 2024. The first 80% (502 data points) were used as the training set, while the remaining 20% (125 data points) were reserved for testing. Importantly, since this is a time-series problem, the dataset was split sequentially not randomly to preserve the temporal structure. This ensures that the model is trained on past data and tested on future data, mimicking real-world forecasting scenarios. Figure 2 illustrates the time-based division.

2.5. LSTM Model

The model employed in this study is Long Short-Term Memory (LSTM), a variant of Recurrent Neural Network (RNN) known for its effectiveness in handling time-series data. The architecture consists of three sequential LSTM layers with 256, 128, and 64 units, respectively, followed by a Dense layer with 32 units and a single output unit. To mitigate overfitting, Dropout layers with a rate of 0.2 were applied after the first two LSTM layers. The model was optimized using the Adam optimizer, with the mean squared error (MSE) as the loss function.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_1 - Y_i'| \tag{2}$$

To evaluate the accuracy of the solar panel voltage predictions generated by the developed LSTM model, three primary evaluation metrics were employed: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). These metrics were selected because they provide a comprehensive assessment of the model's performance in predicting the DC voltage output of the solar panel used to power a 5-watt lamp load.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_1 - Y_i')^2} \tag{3}$$

MAE is used to measure the average magnitude of the absolute error between the actual and predicted values, without considering the direction of the error. MSE penalizes larger prediction errors more heavily because it uses the squared differences between actual and predicted values [28]. Meanwhile, MAPE measures the error as a percentage relative to the actual value, providing a more interpretable metric in the context of general performance evaluation.

$$MAPE = (\sum_{i=0}^{n} |y(i) - \frac{\hat{y}(i)}{y(i)}|)/N \tag{4}$$

In performance evaluation, multiple statistical metrics are commonly used:

- **MSE (Mean Squared Error)**: The average of the squared differences between predicted and actual values. It penalizes larger errors more heavily.
- **RMSE (Root Mean Squared Error)**: The square root of MSE, providing an error measure in the same units as the target variable, making it easier to interpret.
- **MAE (Mean Absolute Error)**: The average of absolute differences between predicted and actual values, useful for understanding typical error magnitude.

These metrics provide a comprehensive assessment of model accuracy, robustness, and prediction bias.

2.6. Training and Testing

The test set was separated independently from the training dataset, but processed using the same algorithms and methods as the training data. Typically, datasets are split randomly. However, in the context of time series data such as solar panel voltage, random splitting can disrupt the chronological order and lead to unrepresentative training results. Therefore, in this study, the LSTM model was trained using the initial percentage of the data, while the remaining portion at the end was used as the test set. This approach preserves temporal continuity and better reflects real-world conditions in solar panel system modeling.

3. RESULTS AND DISCUSSION

As previously explained, the predictive model was developed and trained in stages to obtain the most accurate results. In this section, the collected output voltage data from the solar panel is used to evaluate the performance of the proposed model. The primary focus of this evaluation is to assess the extent to which the LSTM model can accurately predict the solar panel voltage under real-world conditions, particularly in a PV system loaded with a 5 W lamp. Accordingly, the model's effectiveness in representing the behavior of solar panel output voltage can be comprehensively analyzed based on the available test data.

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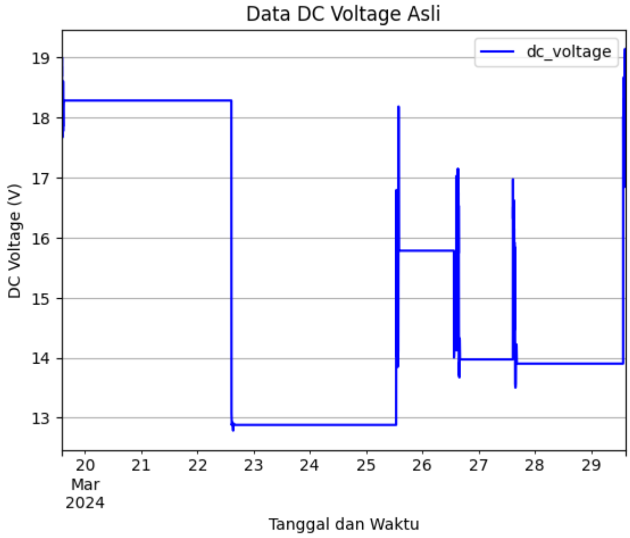

Figure 3. Actual data

Figure 3 above shows the graph of the actual DC voltage (volts) generated by the solar panel during the observation period in March 2024. It can be seen that the voltage values experienced significant fluctuations from March 20 to March 29. The highest voltage recorded was close to 19 V, while the lowest value dropped to around 12.8 V. The drastic voltage decrease, particularly between March 23 and 25, was likely caused by cloudy weather conditions or obstruction of sunlight reaching the solar panel. After March 25, although the voltage increased, the fluctuation pattern remained with several irregular peaks and valleys. This pattern indicates that the PV system is strongly influenced by external factors such as sunlight intensity and load variability. These data serve as the basis for the training and testing process of the prediction model using the proposed Long Short-Term Memory (LSTM) method in this study.

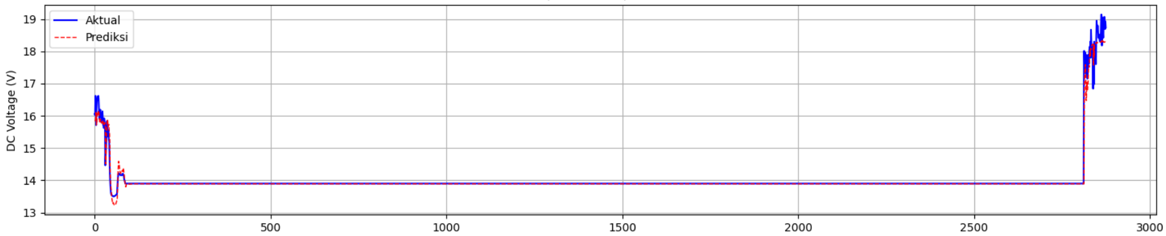

Figure 4. Prediction vs actual

Figure 4 above presents a comparison between the actual DC voltage and the predicted results using the LSTM model. The actual data shown are the resampled raw data with a one-minute interval, providing a more stable and structured data representation for model training. The top graph illustrates the overall prediction results against the actual data, with low error values: an MSE of 0.02, MAE of 0.03, and MAPE of 0.17%, indicating excellent prediction performance. It is evident that the prediction closely follows the general fluctuation pattern of the actual voltage, including periods of sudden voltage changes.

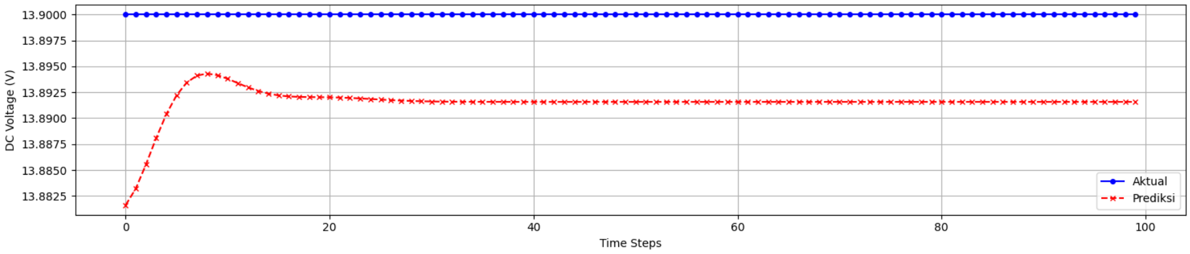

Figure 5. Prediction details

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Meanwhile, the subsequent graph provides a zoomed-in view of a small segment of the data to examine prediction accuracy in greater detail. It is observed that the predicted values tend to be slightly lower than the actual measurements, yet they remain within a very close range. This smooth and consistent prediction pattern relative to the actual data indicates that the LSTM model effectively learned the characteristics of the solar panel voltage, despite the presence of noise and minor fluctuations in the data.

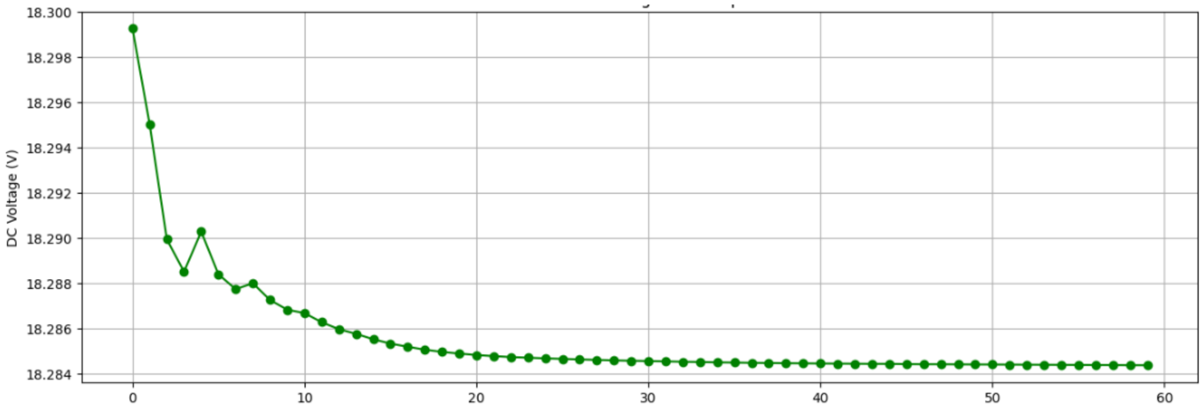

Figure 6. Prediction for the next 60 minutes

Figure 6 shows the multistep prediction results up to 60 steps ahead for the DC voltage of the solar panel using the LSTM model. Each step represents a one-minute interval, so this graph depicts the voltage prediction for the next hour. It can be seen that the initial predicted voltage value is around 18.299 V, which then gradually decreases to a relatively stable value close to 18.284 V. This pattern reflects the system's tendency toward a steady-state condition within a short time frame. The smooth and consistent prediction curve indicates that the LSTM model is not only capable of forecasting short-term trends but also provides reasonably accurate estimates for future time steps. These results are significant in the context of PV system monitoring, especially for load planning or decision-making based on predicted available energy.

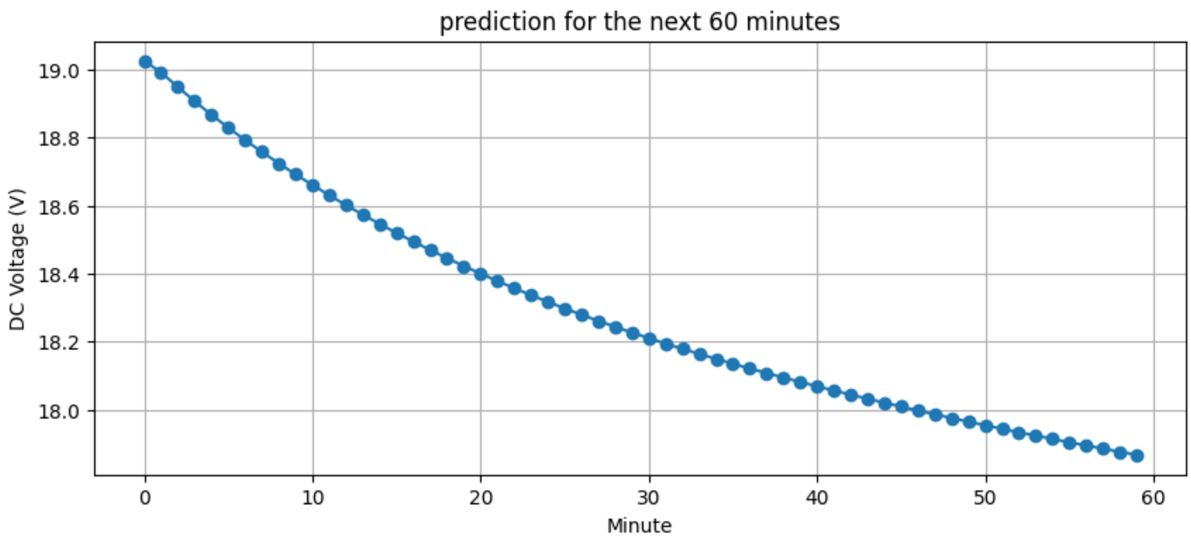

Figure 7. Prediction with GRU

In addition to using the LSTM model, the author also compared it with another model, namely the Gated Recurrent Unit (GRU). Figure 7 presents the DC voltage prediction results for the next 60 minutes using the GRU model. The horizontal axis represents time in minutes, while the vertical axis shows the DC voltage values in Volts (V). It is observed that the GRU model predicts a gradual decreasing trend in DC voltage from approximately 19.03 V to around 17.9 V. This smooth and consistent decline pattern reflects a possible condition of the photovoltaic system experiencing a slow power reduction, for example, due to changes in solar

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irradiance or panel performance degradation over time. Model performance evaluation indicates very good prediction accuracy, with an MSE of 0.0061, MAE of 0.0202, and a very low MAPE of 0.12%. These error values demonstrate that the GRU model is capable of making highly accurate predictions with minimal deviation from actual values, making it suitable for real-time IoT-based energy system monitoring and forecasting.

The significance of this research also lies in its potential integration within IoT-based PV monitoring systems. By leveraging platforms such as ThingSpeak and microcontroller-based sensors, the proposed LSTM-based voltage prediction model can be embedded into real-time, lightweight IoT systems for remote solar installations. This aligns with the growing demand for intelligent, connected energy systems that offer predictive analytics, remote diagnostics, and efficient energy management, particularly in off-grid or smart-grid scenarios.

4. CONCLUSION

This study demonstrates that the LSTM model is capable of accurately predicting DC voltage in PV systems based on historical data resampled at one-minute intervals. The performance evaluation of the LSTM model yielded a MSE of 0.02, MAE of 0.03, and MAPE of 0.17%, indicating very high prediction accuracy. Visualization of the predicted versus actual data shows strong alignment both at the overall scale and in zoomed-in detail views.

In addition to LSTM, the GRU model was also employed for comparison. The results indicate that although GRU offers slightly lighter computational performance, its prediction accuracy is somewhat lower than that of LSTM, exhibiting higher MAPE values and greater prediction deviations in certain data segments. This suggests that LSTM is superior in capturing long-term sequential patterns in DC voltage data from PV systems compared to GRU.

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

7. AUTHORS' CONTRIBUTION

Muhamad Bagus Fikril Alan: conceptualization, data collection, methodology, writing-original draft. Pradini Puspitaningayu: supervision, validation. Muhammad 'Aamir Nashrullah: formal analysis, investigation. Laras Suciningtyas: software, writing-review, editing. Md Mahbubur Rahman: resources, data curation, project administration.

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