

Design and implementation of a LoRa-enabled IoT system for photovoltaic monitoring and machine learning-based power estimation

Pham Van Nam*, Tran Van Duy, Alberto Coboi, Trinh Trong Chuong,
Ninh Van Nam, Quach Duc Cuong, Bui Van Huy

Hanoi University of Industry, 298 Cau Dien, Tay Tuu, Hanoi, Vietnam.

*Corresponding author: nampv@hau.edu.vn

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ABSTRACT

Photovoltaic (PV) systems are increasingly deployed as a sustainable energy solution; however, because they strongly depend on environmental conditions and time-related factors, their output power varies significantly in real-world operation. This study proposes a low-cost IoT-based PV monitoring system integrated with LoRa wireless communication to estimate power and support anomaly detection. Machine learning regression models were first evaluated using a public dataset, incorporating both current environmental features and time-related features such as hour of the day and lag variables to capture the influence of previous conditions and environmental inertia on the panels. The predicted power was then compared with measured values to quantify errors and detect anomalies. The results show that Random Forest provides more stable prediction performance than Linear Regression, highlighting the importance of nonlinear models in capturing complex environmental relationships. Based on these findings, the models are considered references for future power prediction using data collected from the proposed standalone PV monitoring system, in which an STM32F103C8T6 microcontroller is used at the LoRa sensor node to acquire measurements from the environmental and electrical sensors, while an ESP32 microcontroller acts as the LoRa gateway to forward the data to a cloud platform. These results support the feasibility of applying machine learning-based power prediction to the proposed IoT-Based intelligent PV monitoring system.

Keywords: Photovoltaic (PV) systems; Machine learning; IoT; LoRa; Power estimation.

1. INTRODUCTION

Because of its sustainability, environmental advantages, and scalability from tiny residential installations to large-scale solar farms, solar energy is widely acknowledged as one of the most promising renewable energy sources. Approximately 730 million people globally still lack adequate access to electricity despite the quick global deployment of photovoltaic (PV) systems, underscoring the significance of distributed and decentralized renewable energy solutions in contemporary energy infrastructures [1]. The growth of PV installations, both rooftop systems and independent micro-generation units, has increased in tropical nations like Vietnam due to an abundance of solar radiation.

Even though solar energy has many benefits, operational and environmental factors have a big impact on how well PV systems operate. The available input energy for power conversion is determined by solar irradiation, and electrical efficiency is directly impacted by module and ambient temperatures. Dust buildup, partial shade, abrupt weather changes, and long-term material deterioration are other factors that complicate system behavior and lower energy yield [2–5]. Abdessadak et al. [3] showed how dust deposition affects outdoor PV performance, whereas Lillo-Sánchez et al. [5] examined PV degradation mechanisms. These results demonstrate the need for consistent and trustworthy performance monitoring in practical settings.

PV systems are impacted by solar energy's intrinsic intermittency in addition to long-term performance degradation. Power output can fluctuate quickly over brief periods of time due to

changes in cloud cover and meteorological conditions. Particularly in weak grids or distributed generation systems where power stability is more sensitive, these abrupt fluctuations may provide operational difficulties. As a result, monitoring in conjunction with power estimation is crucial for preserving system dependability, promoting operational optimization, and facilitating the early identification of anomalous system behavior.

The Internet of Things (IoT) explosive growth in recent years has opened up new possibilities for the construction of scalable and affordable PV monitoring systems. Continuous data collection, remote monitoring, and cloud-based data analysis are made possible by IoT-based solutions that combine electrical and environmental sensors with embedded controllers [6, 17]. Because of its long communication range, low power consumption, and dependable performance in outdoor situations, LoRa has garnered a lot of interest among the wireless communication technologies used in IoT systems. The viability of LoRa-based PV monitoring platforms for distributed solar systems has been shown in a number of recent studies [7, 8], underscoring the possibility of implementing scalable, economical, and energy-efficient monitoring solutions.

PV power forecasting has been the subject of extensive research in tandem with hardware developments. Early techniques mostly relied on statistical time-series techniques like ARIMA and linear regression as well as physical models [9]. By assuming a linear relationship between input factors and power output, linear regression describes the general trend. Nevertheless, it is not very good at capturing the strong daily cycles and nonlinear behavior seen in solar power generation. Due to the intrinsic fluctuation of solar irradiance, it is frequently challenging to achieve stationary data, which is necessary for ARIMA models to capture temporal patterns and trends in time-series data [10]. These drawbacks may make it difficult for conventional statistical techniques to capture the intricate connections between environmental variables and PV power output. Deep learning (DL) and machine learning (ML) approaches have been used more and more to solve this issue in recent years [18, 19]. In solar power forecasting, models like Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting, Long Short-Term Memory (LSTM), and ensemble approaches have shown encouraging performance in identifying nonlinear patterns and increasing prediction accuracy [11–15].

Although deep learning models like LSTM and RNN may capture intricate temporal correlations, they frequently need a lot of computer power and big training datasets. In a similar vein, ensemble deep learning frameworks and meta-heuristic optimization techniques have been suggested to increase forecasting accuracy; however, they may increase computing complexity and decrease interpretability. On the other hand, tree-based ensemble models, like Random Forest, are appropriate for embedded or edge-deployed systems because they offer a compromise between nonlinear modeling capacity, robustness to noise, minimal processing load, and interpretability.

Fewer studies explicitly incorporate machine learning-based power prediction into inexpensive IoT-enabled standalone PV monitoring systems, despite the wealth of literature on large-scale PV forecasting. Furthermore, in small-scale decentralized installations, the impact of temporal features, such as lagged environmental variables reflecting thermal inertia and short-term irradiance memory, remains understudied.

This work creates an IoT-based PV monitoring system that integrates LoRa connectivity for data collection in order to fill these gaps. An embedded controller is used to gather electrical and environmental data, such as voltage, current, solar radiation, temperature, and humidity. To estimate PV power output, machine learning regression models are developed using a publicly available dataset. The comparative analysis indicates that Random Forest provides more stable prediction performance than Linear Regression. Based on these findings, the Random Forest model provides a reference for future power prediction and anomaly detection using data collected from the proposed monitoring system.

2. METHODOLOGY

2.1. Dataset description

This study makes use of the publicly accessible Solar Power generating Data dataset from Kaggle [16], which includes plant-level environmental measures and inverter-level generation records gathered from two PV power plants in India over a 34-day period, recorded at 15-minute intervals. The dataset consists of two complementary parts for each plant: Weather Sensor Data and Generation Data. The Generation Data offers comprehensive inverter-level measurements from 22 different inverters, such as DC power, AC power, daily energy output, and cumulative total yield. A centrally located sensor array collects synchronized plant-level readings of solar irradiance, ambient temperature, and module temperature, which are included in the Weather Sensor Data.

2.2. Feature extraction

2.2.1. Environmental feature

Environmental sensors installed at the PV system were used to gather the input data, which included measurements of ambient temperature, module temperature, and solar irradiance. The theoretical maximum power production is directly determined by solar irradiance, which serves as the main energy input to the PV conversion process. PV cells' electrical efficiency is impacted by module temperature since higher temperatures often result in lower conversion efficiency because of greater internal resistance. Module temperature and overall system performance are indirectly influenced by ambient temperature, which is a reflection of the surrounding environmental conditions. The nonlinear link between operating circumstances and power production can be modeled using these environmental factors as basic predictors.

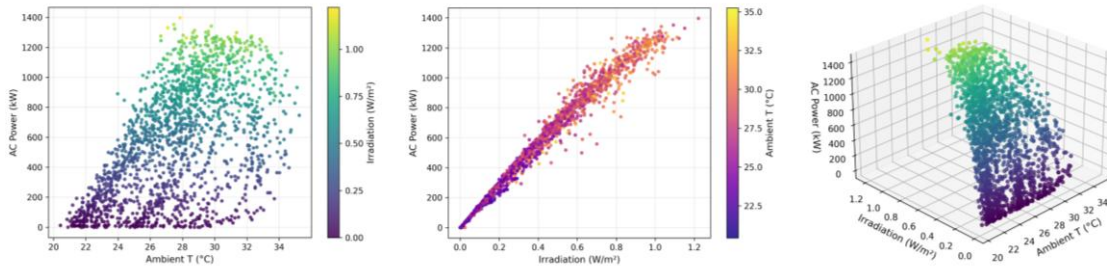


Figure 1. Relationships among AC power, solar irradiation, and ambient temperature: 2D correlations and 3D distribution.

2.2.2. Temporal feature extraction

Seasonal fluctuations and diurnal sun cycles control the considerable temporal dynamics of PV power generation. Time-related characteristics were taken from the timestamp variable t and added to the regression framework in order to represent these structured temporal patterns. Direct numerical representation may create artificial discontinuities (like the shift from 23:00 to 00:00) since variables like hour and month are intrinsically periodic. Trigonometric transformations were used to maintain cyclic continuity.

For a periodic variable x with period T , cyclical encoding is defined as:

$$x_{\sin} = \sin\left(\frac{2\pi x}{T}\right) \quad (1)$$

$$x_{\cos} = \cos\left(\frac{2\pi x}{T}\right) \quad (2)$$

2.2.3. Characteristics of lagged variables and moving averages

Short-term temporal dependencies resulting from inverter dynamic response characteristics, gradual irradiance shifts caused by cloud movement, and module thermal inertia are intrinsic to PV systems. To capture these time-dependent behaviors, lagged variables and moving average features were created independently for each inverter within each plant. Let y_t stand for an external variable at time step t , such as radiation, ambient temperature, or module temperature. Formally defined as x_{t-k} , where k represents the lag order, lag features were created to depict past system states. The chosen environmental variables in this investigation were subjected to lag orders $k \in \{1,2,3\}$. The regression model can take into account delayed system reactions to environmental changes and short-term memory effects thanks to these lagged representations.

Moving average features were added to discrete lag terms in order to minimize high-frequency noise and capture local patterns. The rolling mean is defined as follows for a window size w :

$$MA_t^{(w)} = \frac{1}{w} \sum_{i=0}^{w-1} y_{t-i} \quad (3)$$

This is the mean of the latest w observations. For window sizes $w \in \{1,2,3\}$ for irradiation, rolling means were calculated. These windows correspond to temporal durations ranging from 15 minutes to 45 minutes, given the dataset's 15-minute sample rate. Moving averages describe current trends while lag variables store discrete historical states, improving the model's capacity to capture smooth transitions and short-term changes in PV generation.

2.3. Prediction model

2.3.1. Model selection

Two regression models with varying degrees of complexity were used to assess the efficacy of the suggested feature engineering framework: Random Forest (RF) and Linear Regression (LR).

- Due to its simplicity, interpretability, and computational efficiency, linear regression was selected as the baseline model. The anticipated output is computed as a weighted sum of the input variables because this model assumes a linear relationship between the input characteristics and the target variable. The ability to easily understand each feature's contribution through its coefficient is one of its primary benefits. It is very easy to implement and has a minimal computational cost.

- One nonlinear ensemble learning technique is Random Forest. Using random subsets of features and random samples of the data, it creates several decision trees, then averages the outcomes to combine their predictions. This approach does not require preconceived notions about the data structure in order to capture nonlinear relationships and interactions between variables.

2.3.2. Evaluation metrics

Three common regression metrics were used to assess the prediction performance of the suggested models: Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

Let y_i denote the measured AC power, $\hat{y}_i$ the predicted AC power, $\bar{y}$ the mean of the measured values, and N the total number of samples.

The RMSE is given by:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (4)$$

And penalizes larger errors more strongly, providing an intuitive measure of prediction accuracy in the same unit as AC power.

The coefficient of determination, R^2 , is computed as:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (5)$$

This metric quantifies the proportion of variance in the measured data explained by the model. In addition to these point-wise metrics, residuals defined as $e_i = \hat{y}_i - y_i$ were analyzed for selected days to assess temporal error behavior and identify potential systematic biases.

2.4. Hardware design of the data acquisition module

Five 450 W solar panels connected in series and driven by an inverter make up the PV monitoring system utilized in this investigation. Table 1 displays the PV string and PV panel specs. With an installed capacity of roughly 2.25 kWp, the PV string offers a good foundation for assessing both the suggested machine learning-based power prediction technique and the LoRa-enabled IoT monitoring system.

Table 1. Technical specifications of the PV panels used in the system.

Parameter	Value
Number of PV panels	5
Rated power per panel (Wp)	450
Total installed capacity (kWp)	2.25
Voltage at maximum power point of PV string (Vmp)	≈ 224
Current at maximum power point (A)	≈ 10.1

The data acquisition block, microcontroller block, communication block, and display block are some of the primary functional blocks that make up the monitoring module. Using the PZEM-017 power monitoring sensor, the data collection block is made to measure important solar panel operating characteristics like voltage, current, and power. The BH1750 sensor is used to measure ambient light intensity. The SHT31 sensor is used to measure environmental temperature in order to assess how environmental factors affect system performance (Figure 2). At the LoRa sensor nodes, ARM-based microcontroller modules process the data gathered from these sensors. After processing, the data is wirelessly sent via LoRa to an ESP32-based module that serves as the LoRa gateway. After that, the gateway sends the data across the Internet to the server for storage and additional processing (Figure 3).

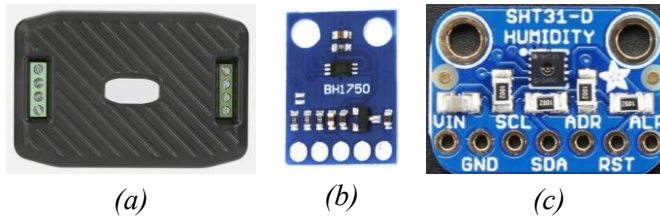


Figure 2. Sensors used in the proposed photovoltaic monitoring system: (a) PZEM-017 current and voltage sensor, (b) BH1750 light intensity sensor, (c) SHT31 temperature sensor.

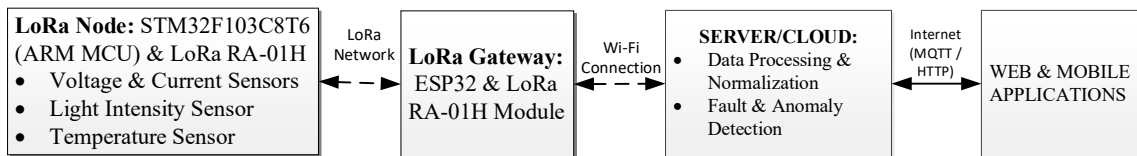


Figure 3. Architecture of the proposed LoRa-enabled IoT system for photovoltaic monitoring and machine learning-based power estimation.

3. RESULTS AND DISCUSSION

3.1. Forecasting performance

Table 2 displays the results of the two forecasting models' performance comparison. To achieve a fair comparison, the same feature set and training-testing split were used in this study's evaluation of Random Forest and Linear Regression. Random Forest is a nonlinear ensemble-based method that can describe intricate interactions, while Linear Regression is a basic model because of its ease of use and interpretability. With 5-fold cross-validation, where each fold uses 80% of the data for training and 20% for testing (train 80%, test 20%), the comparison results enable evaluation of how well linear and nonlinear regression approaches perform under identical experimental settings for PV power prediction.

Table 2. Model performance comparison.

Model	Train RMSE	Train R ²
Random Forest	30.6112 ± 1.7453	0.9939 ± 0.0008
Linear Regression	53.4892 ± 2.0134	0.9815 ± 0.0015

Following training, the models' performance under continuous time conditions was assessed using a dataset spanning five days in a row. Time-series plots and residual plots were used to compare the actual values with the projected results.

The full daily pattern of PV power generation, including the rise in the morning and the fall in the evening, is captured by the model for linear regression. This suggests that linear regression is still useful for characterizing the system's general trend (Figure 4).

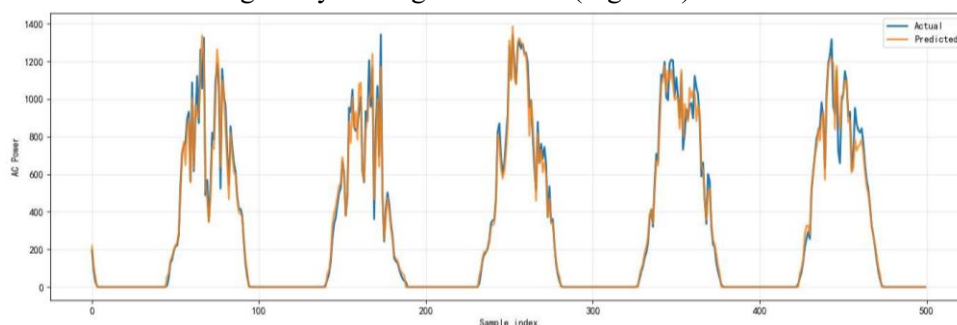


Figure 4. Comparison of actual and predicted PV power using linear regression.

The findings for Random Forest demonstrate that, in comparison to the Linear Regression model, the predicted curve more closely matches the actual data. This model not only accurately replicates the rising and falling trends of PV power generation throughout the day, but it also fairly successfully simulates short-term fluctuations, such as times when the power output changes suddenly (Figure 5).

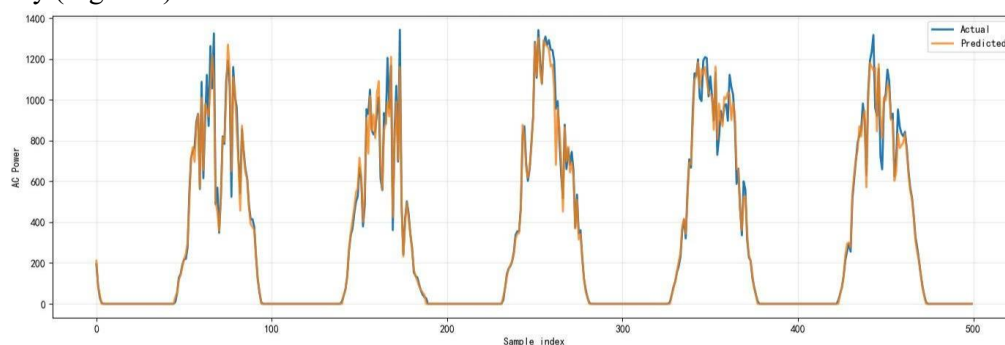


Figure 5. Comparison of actual and predicted PV power using random forest.

It is evident from the Linear Regression model's residual plot that there are multiple significant error peaks in the residuals, particularly at times when the PV power production fluctuates quickly, like at sunrise and sunset. This suggests that the linear model still leaves systematic information in the mistakes and does not adequately reflect the general structure of the data. The actual values are shown by the blue line, and the moving average of the three closest residual values is shown by the orange line (Figure 6).

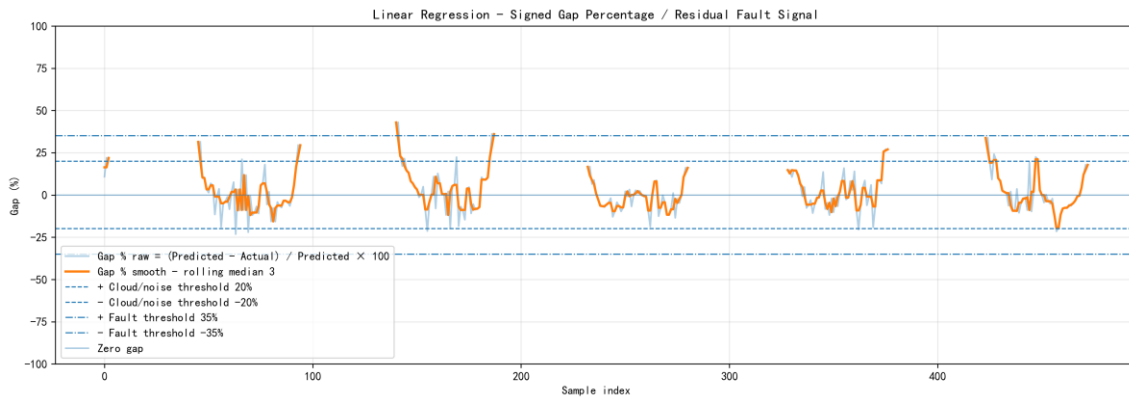


Figure 6. Residuals of linear regression for PV power prediction.

Compared to Linear Regression, the Random Forest model's residual plot displays a more stable smoothed Gap % line with generally smaller error values that are more concentrated around the zero axis. The residuals exhibit fewer significant error peaks and are comparatively steady over time. This shows that the Random Forest model helps lower error variability while simultaneously increasing prediction accuracy (Figure 7).

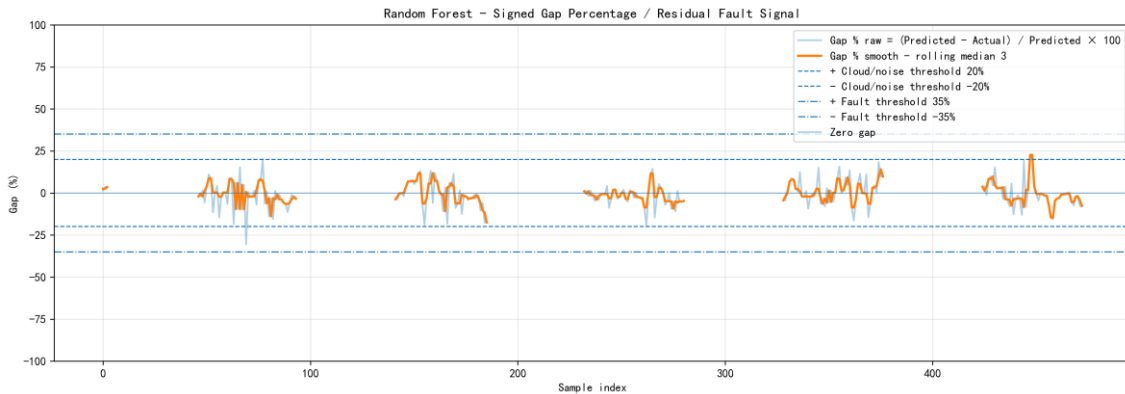


Figure 7. Residuals of random forest for PV power prediction.

3.2. Hardware results

A PV panel, several sensors, a local data gathering device, and a LoRa-based wireless communication module are all integrated into the system. This configuration makes it possible to reliably transmit measured data to a distant receiver for storage and analysis as well as to continuously monitor PV operational conditions.

As seen in Figure 8, Figure 8(a) shows the interior of a LoRa-based receiver device. The data acquisition device, which gathers and prepares sensor signals for transmission, is located on the back side of the PV panel, as seen in Figure 9. The LoRa-based receiving device, which wirelessly receives the measured data and permits real-time monitoring and data logging, is shown in Figure 8(b).

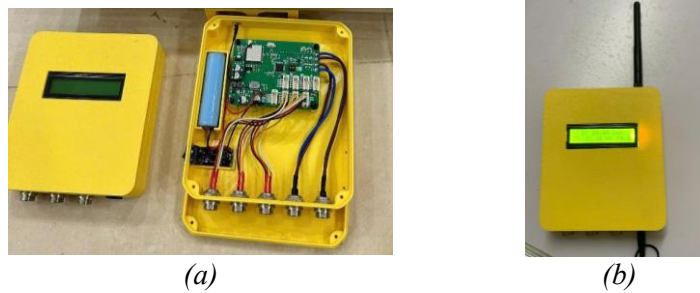


Figure 8. Hardware implementation of the proposed PV data acquisition unit:
(a) inside LoRa-based receiver device, (b) LoRa-based receiver device.



Figure 9. Experimental deployment of data acquisition and monitoring for the PV system.

Once the PV data collecting unit hardware implementation was finished, the system was put into use to gather operational PV panel power output and environmental characteristics. The monitoring interface, which updates the measured parameters every five seconds, displays the gathered data that was saved on Firebase. Important variables including voltage, current, power, energy, irradiance, temperature, and humidity are displayed on the interface (Figure 10).

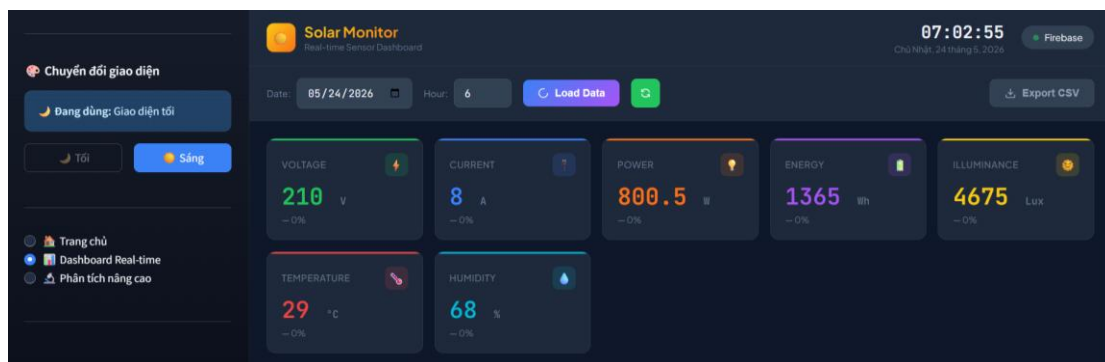


Figure 10. PV system monitoring dashboard.

4. CONCLUSIONS

In order to collect data, this study created a standalone IoT-based PV monitoring system that is integrated with LoRa communication. PZEM-017, BH1750, and SHT31 sensors were used to measure important electrical and environmental factors, which were then sent through ESP-based modules for processing and storage. Environmental, temporal, and lag-based characteristics, two regression models: Random Forest and Linear Regression were used to a public dataset to estimate PV power output. The obtained results will serve as a foundation for the future development of the PV anomaly detection system. While nonlinear behavior and short-term fluctuations were handled differently by both models, the overall daily generation pattern was captured by both.

Future research will focus on developing and implementing a machine learning model that is appropriate for the characteristics of the PV system utilizing the data that is currently being collected. The model will be used to automatically monitor and analyze the operational status of the solar panels.

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TÓM TẮT

Thiết kế và triển khai hệ thống IoT tích hợp LoRa cho giám sát hệ thống quang điện và ước lượng công suất dựa trên học máy

Hệ thống quang điện (Photovoltaic – PV) ngày càng được triển khai rộng rãi như một giải pháp năng lượng bền vững. Tuy nhiên, do đặc tính phụ thuộc mạnh vào điều kiện môi trường và yếu tố thời gian, công suất đầu ra của hệ thống mang tính biến thiên cao trong quá trình vận hành thực tế. Nghiên cứu này đề xuất một hệ thống giám sát PV chi phí thấp dựa trên IoT, tích hợp truyền thông không dây LoRa để ước tính công suất và hỗ trợ phát hiện bất thường. Trước tiên, các mô hình hồi quy học máy được đánh giá trên một bộ dữ liệu công khai, sử dụng cả đặc trưng môi trường tức thời và đặc trưng thời gian như giờ trong ngày cùng các biến trễ để phản ánh ảnh hưởng của điều kiện trước đó, bao gồm quán tính của môi trường ảnh hưởng của tấm pin. Công suất dự đoán sau đó được so sánh với các giá trị đo được để định lượng sai số và phát hiện các bất thường. Kết quả nghiên cứu cho thấy mô hình Random Forest đạt hiệu suất dự đoán ổn định hơn so với Linear Regression, qua đó khẳng định vai trò quan trọng của các mô hình phi tuyến trong bài toán dự báo công suất PV. Những kết quả này tạo tiền đề cho việc phát triển mô hình dự đoán công suất trong tương lai dựa trên dữ liệu thực tế được thu thập từ hệ thống giám sát PV độc lập. Trong hệ thống đề xuất, vi điều khiển STM32F103C8T6 được tích hợp tại nút cảm biến LoRa nhằm thu thập các thông số từ cảm biến môi trường và cảm biến điện, trong khi ESP32 đóng vai trò là cổng LoRa để chuyển tiếp dữ liệu lên nền tảng đám mây. Nhìn chung, kết quả đạt được cho thấy tính khả thi của việc ứng dụng học máy trong dự đoán công suất, đồng thời hỗ trợ định hướng phát triển hệ thống giám sát PV thông minh dựa trên nền tảng IoT.

Từ khóa: Hệ thống quang điện; Học máy; Internet vạn vật; LoRa; Ước lượng công suất.