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Implementation of Integrating PV System Production Forecasting Using Recurrent Neural Networks in Local Weather Station Prototype

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This study examines the use of contemporary technologies like Long Range (LoRa) radio wave modulation technology for real-time data monitoring, as well as the critical function that weather stations play in measuring, gathering, and reporting meteorological data. The weather station is outfitted with sensors for temperature, humidity, sun radiation, and wind to guarantee precise and effective data collecting. At the PEM Akamigas Campus, LoRa technology testing revealed an effective range of roughly ±85 meters, guaranteeing the best possible communication between the Energy Laboratory Building and the Subroto Building. The dependability of weather monitoring is confirmed by data consistency between the Haiwell Human-Machine Interface (HMI) and the Message Queue Telemetry (MQTT) protocol server. In order to improve the accuracy of solar panel energy production estimates, this study also uses a Recurrent Neural Network (RNN) deep learning model to forecast weather and energy output for the PV system at the Subroto Building. The potential is highlighted by an analysis of data from April 1, 2024, to April 22, 2024. With Root Mean Square Error (RMSE) values of roughly 4.9965 for voltage and 0.0081 for current, production forecasting was produced using real-time sensor data that was put in the field on a combination of three series solar panels. This suggests results that are rather satisfactory. The RMSE values for power testing remain inadequate, indicating a need for further model enhancements. With improvements to the model parameters for power data, which is naturally derived from the multiplication of voltage and current parameters, the combination of LoRa technology and the RNN model is anticipated to offer significant insights into dependable weather monitoring and energy production at the PEM Akamigas Campus.

1. INTRODUCTION

Achieving carbon reduction targets continues to be a significant challenge, particularly due to infrastructure limitations in integrating renewable energy—especially solar power—within industrial sectors. According to a study (Bošnjaković, Stojkov, Katinić, & Lacković, 2023), over the past four decades, globalization and increasing energy demands have contributed to higher energy production and CO_2 emissions, with industrial activities being a major source. Although solar technologies like PV and CSP have

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advanced significantly, their adoption still faces challenges—particularly in integrating with existing energy systems, enhancing material efficiency, and addressing storage limitations. Moreover, their performance remains highly sensitive to weather conditions such as temperature, humidity, wind, and solar radiation. According to (Maka & Alabid, 2022), further research is needed to improve the global effectiveness of solar technologies, while (Shaik, Lingala, & Veeraboina, 2023), emphasize the need for innovative solutions to mitigate weather-related impacts.

Weather stations play a key role in addressing the fluctuating output of renewable energy, especially solar power. In Indonesia, although BMKG operated 41 weather radars by 2017, according to (Prakasa & Utami, 2019). The data remained fragmented and sectoral, limiting its broader usefulness. To enhance real-time and comprehensive monitoring, researchers have proposed integrating these systems into a unified national network. However, (Sucipto, Djuni Hartawan, & Setiawan, 2018) have investigated the design of microcontroller-based automatic weather monitoring systems that use sensors to track temperature, humidity, air pressure, wind direction, and wind speed. A microcontroller processes the data before sending it over the internet to a web server. As evidenced by prototype testing in field experiments, several studies have concentrated on creating affordable local weather stations with reasonably accurate data, as shown by the work of (Pourbafrani, Ghadamian, Moghadasi, & Mardani, 2023) and (Rivera, Ponce, Mata, Molina, & Meier, 2023). As a result, it is possible to create local weather stations with greater accuracy and at lower prices, making integration with solar power plants possible.

Numerous experimental investigations have been carried out on the creation of weather stations that send weather data over wireless networks or the Internet of Things (IoT). In order to make paragliding pilot observation easier, a study by (Habibie, 2019) sought to automatically monitor weather conditions. Additionally, to test the Quality of Service (QoS) of IoT applications, (Burhani, Novianto, & Yuliantari, 2023) used IoT technology in tiny weather stations. Even though the outcomes were usually excellent, Long Range (LoRa) radio wave modulation technology performs better than IoT in terms of lower power consumption and lower operating costs, particularly in places with inadequate internet infrastructure or distant regions. LoRa technology's benefits make it ideal for weather stations, which are frequently situated at high elevations with spotty network connectivity. Research by (Stellastral, Hanafi, & Syahroni, 2022) and (Zulafah, Dewatama, & Siswoko, 2022), showed how well LoRa SX1278 monitored meteorological data while using little electricity. The study of (Sianturi, 2021) further supports the association between weather data from weather stations by pointing out that weather stations offer data on solar radiation measured every 10 minutes, with an average daily global radiation accumulation of roughly 4.4 ± 1.0 $kWh/m^2/day$.

The purpose of this study is to propose the design and development of a local weather station prototype with real-time weather data monitoring utilizing LoRa Aurora V2 technology, which supports enhanced solar energy utilization. While previous studies have separately explored LoRa-based weather stations or LSTM/RNN-based PV forecasting, few have integrated real-time meteorological data from a custom-built local station with deep learning forecasting models in a single, unified system. Compared to LoRa SX1278, LoRa Aurora V2 offers improved integration, connectivity, and development flexibility, making it more suitable for continuous monitoring. This study addresses this gap by combining a locally developed weather station using LoRa Aurora V2 with a Recurrent Neural Network (RNN) model to forecast solar power generation. Such integration is expected to provide more accurate, scalable, and low-cost energy forecasting, particularly in decentralized renewable systems like those in educational or vocational institutions.

2. METHODS

As noted by (Murdyantoro et al., 2019) and (Nurdin, Munadi, & Sidiq, 2022), placing local weather station prototypes on rooftops ensures a clear line of sight between transmitter and receiver, allowing sensors to capture accurate environmental data. Accordingly, the prototype adopted a similar approach, installing its weather station prototype on the rooftop of the Subroto Building to maximize exposure and measurement accuracy. The system incorporates key sensors including a pyranometer for solar irradiance, DHT11 for temperature and humidity, as well as wind speed and direction sensors mounted on a dedicated transmission tower, as shown in Figure 1 below.

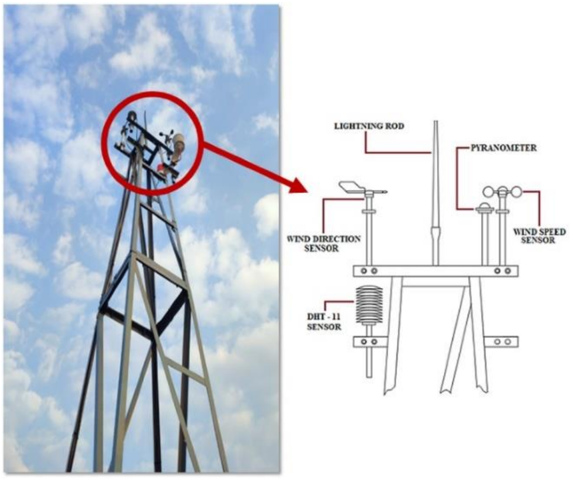

Figure 1. Sensors installation on Transmitter Tower

The weather sensors installed on the transmission tower are types of sensors related to input parameters that influence the magnitude of solar energy generation, as follow:

1. RK200-04 Solar Radiation Sensor to measure the level of irradiance It has a supply voltage of 12 VDC, an output voltage range of 0–5 VDC, and a measurement range of 0–1500 W/m²;
2. DHT-11 Temperature and Humidity Sensor with Casing to measure ambient temperature and humidity. Its specifications include an operating voltage of 3.5–5.5 VDC, a temperature range of 0°C to 50°C, a humidity range of 20% to 90%, and an accuracy of ±1°C and ±1%;
3. QS FS01 Wind Speed Sensor to measure wind speed with a measurement precision of ±1 m/s. It has a measurement range of up to 32.4 m/s, Vin = 7–24 VDC, Vout = 0.4–2 VDC or 0–5 VDC, and an output pulse speed of 0.88 m/s per pulse;
4. QS FX01 Wind Direction Sensor to indicate wind direction with Vin = 7–24 VDC, Vout = 0.4–2 VDC, a measurement range of 0–360 degrees, and 16 directional points.

The LoRa Aurora V2 board is a wireless communication system used in IoT applications and sensor networks. It uses LoRa technology and transmits data via a transmitter antenna to a receiver antenna. The board includes an ESP32 microcontroller board, RFM95W LoRaWAN chip, 12-bit analog pins, I2C and UART pins, digital I/O pins, and 520 KiB SRAM memory. A Power Supply Unit (PSU) powers all devices, and a current-to-voltage converter ensures voltage-form output signals. A Canadian Solar CS6X-325P solar panel is connected to PZEM-017 sensor module measures voltage output generated by the solar panels, but an additional TTL to RS485 converter module is required due to its compatibility with the LoRa Aurora V2, as shown in Figure 7 below.

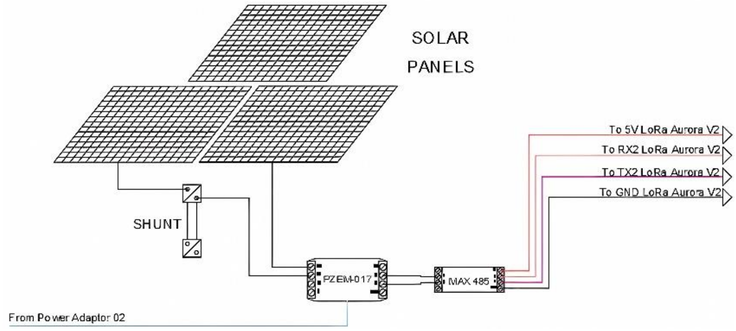

Figure 2. Solar panel wiring diagram

The receiver panel box consists of a 24 VDC PSU, a LoRa Aurora V2 device for data reception, and a Haiwell Human Machine Interface (HMI) for weather data display. These components are connected via the HiveMQ MQTT Broker protocol, a widely used protocol in industrial environments. The system, as shown in Figure 8 below, uses wind speed, wind direction, temperature, humidity, and solar radiation sensors to transmit data wirelessly to another LoRa Aurora V2 device. The data is then transmitted to the Haiwell B7H-W HMI using the HiveMQ MQTT Broker protocol, allowing for visual representation of weather data.

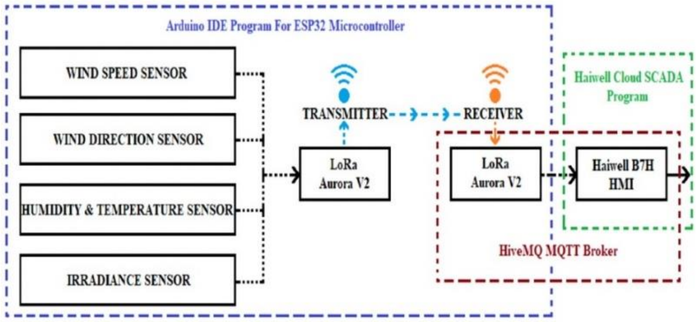

Figure 3. Overall weather station system diagram

RNN, particularly LSTM, are effective for time-series prediction due to their ability to retain and process sequential data. LSTM also addresses the vanishing gradient issue found in basic RNNs by regulating information flow. According to (Wang, Addepalli, & Zhao, 2020), RNNs are widely applied in Remaining Useful Life (RUL) prediction with high accuracy. In weather forecasting, especially solar radiation studies by (Kumari & Toshniwal, 2021), and (Tanjung, Listiani, & Lestari, 2024), show that LSTM outperforms traditional models such as regression and simple neural networks, achieving lower RMSE values for temperature, humidity, wind speed, and air pressure.

Studies on predicting or forecasting solar energy production using LSTM, a variant of RNN, have been extensively explored by (Hossain & Mahmood, 2020), (Sarmas, Spiliotis, Stamatopoulos, Marinakis, & Doukas, 2023), and (Campos, Sousa, & Barbosa, 2024). These three studies demonstrate significant improvements in forecasting accuracy with the use of LSTM. (Hossain & Mahmood, 2020) highlighted the capability of LSTM in processing time-series data, particularly in capturing long-term dependencies crucial for accurate photovoltaic (PV) energy predictions. Their work showed that LSTM outperforms traditional models such as regression and simple neural networks by effectively mitigating the vanishing gradient problem inherent in basic RNN architectures. (Sarmas et al., 2023) advanced this research by integrating numerical weather prediction (NWP) data with LSTM models, achieving enhanced forecasting results by leveraging weather variables like solar irradiance, temperature, and wind speed. The study by (Campos et al., 2024) demonstrated the adaptability of LSTM in handling multi-dimensional inputs and its superiority in dynamic environmental conditions. They also showed that hybrid models, like LSTM combined with CNN, improve feature extraction from weather datasets, providing an edge in complex forecasting scenarios.

The study suggests that LSTM, a machine learning architecture, can be effectively used in renewable energy systems for short-term PV energy prediction. Its ability to handle complex temporal relationships in sequential data makes it ideal for optimizing grid management and energy dispatch strategies. The integration of wireless data transmission technologies like LoRa Aurora V2 can further streamline energy forecasting systems.

3. RESULT AND DISCUSSION

The LoRa transmitter's range and Arduino IDE program display were tested between the Subroto Building of PEM Akamigas and the Energy Laboratory of PEM Akamigas, covering a distance of 85 meters (278.88 ft). The data packets transmitted accurately reflected real-time conditions, including temperature, humidity, solar radiation, wind direction, and wind speed. The data was forwarded to the HiveMQ MQTT server for further processing, as demonstrated in Figure 9 below.

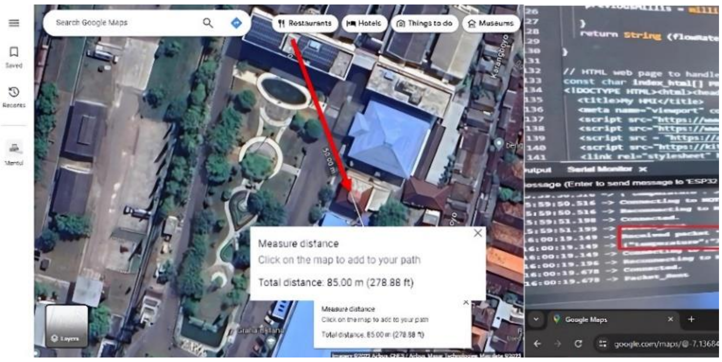

Figure 4. LoRa point-to-point distance testing

In this study, to evaluate the accuracy and performance of the forecasting model, RMSE was used. The formula can be expressed as follows:

$$RMSE = \sqrt{\frac{\sum(Actual\ Value - Prediction\ Value)^2}{n}} \tag{1}$$

The LSTM forecasting method uses InfluxDB voltage data as training to understand seasonal trends. The data is divided into training, validation, and testing subsets, with the training subset providing insights into voltage fluctuations. The validation data, consisting of 2,500 data points, spans from April 17, 2024, to April 18, 2024, with an average output voltage of 37.98 V. The optimal number of epochs for processing the data is 11, with the 11th epoch yielding a value of 4.995. The RMSE result for data validation is 4.995. The voltage validation and test result, shown in Figure 10 below. The voltage prediction results during both validation and test phases closely follow the actual values, although some fluctuations and deviations appear during sudden drops, indicating areas for model improvement in dynamic conditions.

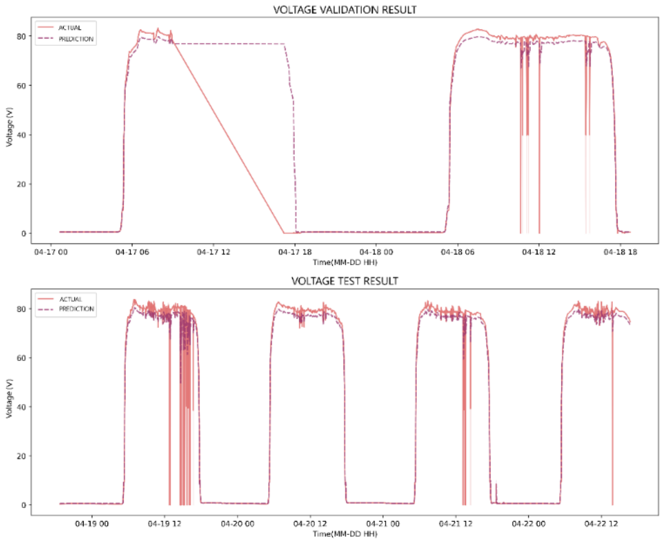

Figure 5. Voltage validation and test result

The current data was used to train a model to recognize seasonal patterns, with the dataset split into training, validation, and testing sets. The model performed best at the 8th epoch, reaching an RMSE of 0.0081, likely influenced by low solar irradiance and frequent rain. As shown in Figure 11, the predictions follow actual current trends well in stable periods, but struggle during sudden spikes above 0.4 A, highlighting the model's limitations in capturing rapid changes.

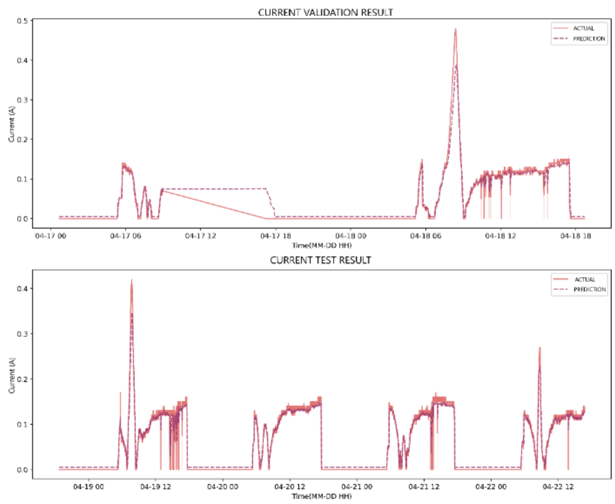

Figure 11. Current validation and test result

The actual power data, collected every second, reflects the DC output of the solar panel calculated from voltage and current. As shown in Figure 12 below, the predicted power closely matches the actual data, especially during stable periods. However, during sharp peaks above 30 W, the model tends to underpredict, indicating room for improvement in capturing rapid power changes.

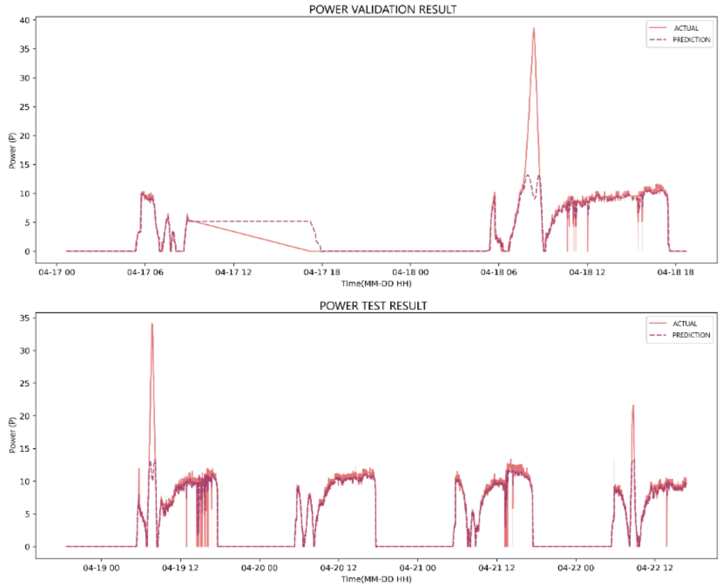

Figure 6. Power validation and test result

Since power data is the result of multiplying voltage and current, using an LSTM prediction model is not recommended for data derived from calculations involving other data parameters. This indicates the need for model improvement. Figure 26 above illustrates this. Although the data validation shows good results, when tested, there is a significant deviation.

4. CONCLUSION

The local weather station device underwent tests before installing a LoRa device on the Subroto Building and the Energy Lab of PEM Akamigas. The device successfully reached a maximum communication range of 185 meters and received data from the transmitter. Data transmission delays, recording intervals, and accuracy were assessed. Data consistency was verified by comparing weather data with external sources, indicating the reliability of the sensors used. A minor discrepancy in temperature data was found between external sources, possibly due to differences in measurement locations or methods. The forecasting model using LSTM, a variant of the RNN method, showed adequate capability in forecasting voltage and current data parameters, even with large datasets and time frames per second. However, for power data forecasting, the system requires additional calculations involving voltage and current parameters, necessitating future model improvements.

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