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An internet of things-based weather system for short-term solar and wind power forecasting using double moving average

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ABSTRACT

This article presents the design and implementation of an internet of things (IoT)-based weather forecasting system aimed at optimizing operational planning for renewable energy generation. The system leverages a Raspberry Pi as its central controller, integrating pyranometer and anemometer sensors for real-time data collection and predictive analytics. Utilizing the double moving average method, the system provides accurate short-term forecasts of solar and wind power outputs, which are crucial for addressing the intermittency challenges of renewable energy sources. The integration with the Blynk platform ensures user-friendly data visualization and accessibility. Results from a three-day testing phase reveal the system's high accuracy, with prediction errors of 8.79% for solar power and 16.49% for wind power. These findings underscore the system's potential to enhance energy planning, improve efficiency, and support sustainability goals. By enabling data-driven decision-making, this IoT-based forecasting system offers a scalable solution for advancing renewable energy integration into the power grid.

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1. INTRODUCTION

Energy is a fundamental necessity that plays a vital crucial role to large-scale industrial processes. Generally, energy can be classified into various forms, including mechanical, electrical, chemical, and thermal energy. For over a century, fossil fuel such as coal, petroleum, and natural gas have served as the primary energy sources, forming the backbone of industrial and global economic development [1], [2]. However, excessive reliance on fossil fuels has led to numerous adverse effects, including air pollution, environmental degradation, and climate change driven by greenhouse gas emissions [3], [4].

In recent decades, there has been a growing global awareness of the need to mitigate the environmental impacts of fossil fuel usage [5], [6]. This has driven the development of renewable energy as a more environmentally friendly solution [7]. Renewable energy sources, such as sun, wind, water, biomass, and geothermal heat, can naturally replenish themselves within relatively short periods. Beyond being eco-friendly, renewable energy technologies have advanced significantly, becoming increasingly efficient and cost-effective [8].

As a result, renewable energy offers not only a means to address environmental issues but also an opportunity to create more sustainable and independent energy systems [9], [10]. However, despite its vast potential, renewable energy faces significant challenges, particularly its intermittent or non-continuous nature. Power generation from sources like solar and wind energy is highly dependent on weather conditions, which can vary significantly [11], [12]. This dependency introduces uncertainty in energy planning and operation, emphasizing the need for robust technological solutions to enhance the stability and reliability of renewable energy systems.

In the pursuit of achieving the global net zero emission target, which aims to significantly reduce carbon emissions, the development of supporting technologies such as weather forecasting systems has become a strategic initiative [13], [14]. Accurate weather forecasting systems not only assist power generation operators in better operational planning but also enable data-driven decision-making to maximize energy production and minimize the risks of power imbalances in the electrical grid [15].

An internet of things (IoT) based weather forecasting system, supported by technologies such as Raspberry Pi, offers an efficient and scalable solution to address these challenges [16]. Raspberry Pi provides high flexibility for integration with various sensors, such as pyranometers for measuring solar irradiance and anemometers for measuring wind speed [17]. By leveraging IoT technology, weather data can be collected in real-time, processed using predictive algorithms, and delivered directly to users through applications like Blynk. The IoT approach enables real-time monitoring of weather conditions and seamless integration of weather data into power generation systems [18]. Its predictive capabilities, combined with cloud-based platforms such as Blynk, empower operators with timely and actionable insights. This allows for more adaptive and responsive operational planning of power plants, ensuring optimized performance amidst fluctuating weather conditions.

Unlike numerical model-based methods, which require substantial computational resources and expensive infrastructure, the Raspberry Pi-based approach offers a cost-effective and easily implementable solution [19], [20]. Raspberry Pi provides exceptional flexibility for integration with various sensors, such as pyranometers and anemometers, making it ideal for small to medium scale implementations [21]. Additionally, compared to other microcontrollers like Arduino, Raspberry Pi supports more complex data processing and dynamic IoT-based applications [22]. This approach also facilitates further development, enabling the integration of weather data with cloud-based predictive algorithms, enhancing the system's scalability and functionality.

Accurate and timely weather forecasting is critical for informed decision-making in renewable energy generation [23]. With such a system in place, operators can optimize energy production, reduce inefficiencies, and ultimately contribute to climate change mitigation efforts [24]. By enabling more integrated and efficient energy management, the system can help reduce reliance on fossil fuels, support carbon emission reductions, and directly aid in achieving net zero emission targets [25].

Through this design, we aim to develop an innovative and practical solution to address the challenges of renewable energy management. By leveraging advanced technology and an IoT-based approach, the proposed solution is expected to make a tangible contribution to more sustainable energy management while supporting the transition to an environmentally friendly society.

2. METHOD

The weather forecasting system is designed to optimize the operational planning of renewable energy generation by utilizing IoT-based technology. The core of the system comprises a Raspberry Pi as the central controller, pyranometer and anemometer sensors for data input, and the Blynk application for data output visualization. The system operates based on the block diagram illustrated in Figure 1.

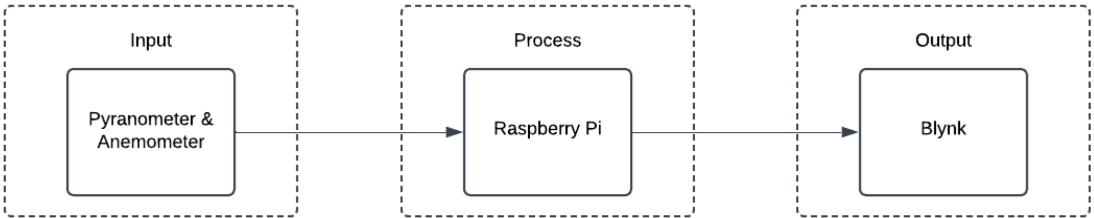

Figure 1. Block diagram of system design

The Raspberry Pi 3 Model B serves as the system’s processing hub, equipped with a quad-core ARM Cortex-A53 processor, 1 GB of RAM, and built-in Wi-Fi and ethernet capabilities. This device serves as the central hub for data collection, processing, and transmission. For solar irradiance measurement, the SEM228A pyranometer is utilized, known for its precision and compliance with international calibration standards. Wind speed is monitored using the VMS-3000 anemometer. Both sensors communicate through RS485 serial output, requiring a RS485-to-USB adapter to establish a seamless interface with the Raspberry Pi. A detailed wiring schematic illustrating the sensor integration with the Raspberry Pi is presented in Figure 2 for further clarity.

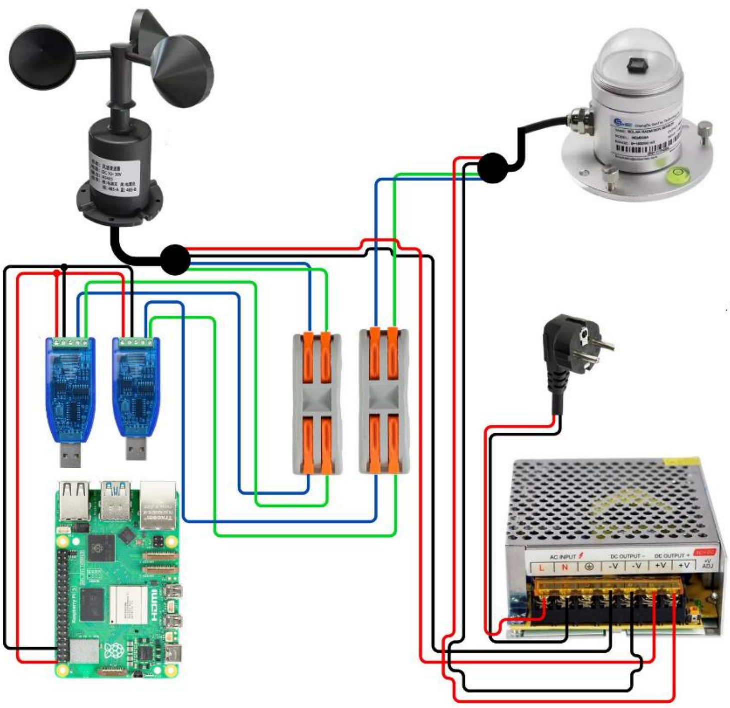

Figure 2. Schematic of weather forecasting design

The system operates by continuously collecting data from the pyranometer and anemometer through the RS485-to-USB adapter. A Python-based first program running on the Raspberry Pi reads the raw sensor data and validates it to eliminate anomalies or noise, ensuring that only accurate and reliable data is processed. Once validated, the data is stored in a CSV format for further analysis and forecasting. In addition to storing the data, the Python program processes the solar irradiance and wind speed values to estimate their corresponding energy outputs. For solar data, the irradiance values are converted into potential solar power output using the standard efficiency of photovoltaic panels. For wind data, the wind speed measurements are transformed into potential wind power output using turbine-specific efficiency factors. This conversion step provides actionable insights into the energy generation potential based on real-time environmental conditions.

The second program in this design is responsible for forecasting future environmental conditions and renewable energy outputs using historical data stored in CSV files. The data is processed with the double moving average method, which smooths short-term fluctuations to provide more stable and accurate predictions. This allows for forecasting trends in solar power and wind power, which helps optimize operational planning for renewable energy systems. Once the data is processed and forecasts are generated, the results are sent to the Blynk IoT platform, where they can be accessed by users. In this setup, the data is transmitted to Blynk via a web server, using HTTP requests facilitated by the Python requests library. The Raspberry Pi communicates with the Blynk server by making HTTP POST requests to send the processed environmental data.

This data is displayed on the Blynk platform in numerical formats, allowing users to view key parameters such as solar irradiance, wind speed, and their corresponding renewable energy outputs. The focus is on providing precise numerical data that enables users to monitor environmental conditions and make informed decisions based on real-time information. The Blynk platform also displays the forecasted values for solar power and wind power, helping users anticipate future conditions. These predictions enable better planning and decision-making in terms of energy production, ensuring that users can adjust their operations based on projected trends. Designing a data retrieval process effectively requires a well-thought-out plan to ensure efficient, secure, and scalable data access, as illustrated in Figure 3.

Figure 3. The weather forecasting system during the data retrieval stage

Upon successful development of the system, the weather forecasting design entered an extensive testing phase aimed at evaluating both system performance and the accuracy of sensor readings. These tests were crucial for ensuring the reliability of the data used in forecasting. The output, comprising real-time and forecasted environmental data, was seamlessly displayed on the Blynk platform in clear numerical formats for efficient monitoring. The testing process confirmed that the system operates effectively in forecasting weather conditions, thereby offering valuable insights for predicting solar and wind power generation in IoT-based intermittent power systems.

3. RESULTS AND DISCUSSION

The data presented in Table 1 represents the input data used to predict solar and wind power generation for the fourth day. Due to the nature of the research and the limitations of the data collection process, the dataset is confined to three days of observation, with measurements recorded hourly between 9:00 AM and 12:00 PM each day. This three-day window provides a comprehensive snapshot of the relevant meteorological and power generation variables, including irradiance, wind speed, solar power, and wind power, which were crucial for developing accurate forecasts. Despite the limited data collection period, this dataset serves as a robust foundation for training and testing the weather forecasting system designed to optimize the operational planning of electrical power generation. The results from this dataset were instrumental in evaluating the forecasting accuracy and identifying the potential for improving power generation predictions based on short-term weather patterns.

Table 1. Data in three days

Day	Timestamp (GMT-7)	Irradiance (W/m^2)	Wind speed (m/s)	Solar power (W)	Wind power (W)
1	09:00 16/12/2024	846.0	6.2	126.9	1.3
	10:01 16/12/2024	545.2	7.2	81.8	1.4
	11:00 16/12/2024	594.6	11.4	89.2	2.3
	12:00 16/12/2024	1029.6	5.6	154.4	1.1
2	09:00 17/12/2024	798.2	2.4	119.7	0.5
	10:00 17/12/2024	961.6	9.0	144.2	1.8
	11:00 17/12/2024	486.4	2.0	73.0	0.4
	12:00 17/12/2024	428.2	8.2	64.2	1.6
3	09:00 18/12/2024	483.4	4.2	72.5	0.8
	10:00 18/12/2024	1200.0	7.0	180.0	1.4
	11:00 18/12/2024	468.2	3.8	70.2	0.8
	12:00 18/12/2024	576.8	3.5	86.5	0.7

The data in Table 1 provides a detailed account of the variations in meteorological conditions and their direct impact on solar and wind power generation, offering key insights into the dynamics of renewable energy production. For instance, on day 1, solar irradiance peaked at 1029.6 W/m² at noon, resulting in a solar power output of 154.4 W, showcasing the capability of solar panels to perform optimally under favorable irradiance conditions. Conversely, on day 2, a lower irradiance value of 428.2 W/m² led to a reduced solar power output of 64.2 W, emphasizing the sensitivity of solar energy systems to fluctuating irradiance levels. These values were derived using a conversion coefficient of 0.15, representing the efficiency of the mini solar panel in converting incoming irradiance into electrical power. This coefficient plays a vital role in modeling the performance of solar panels and ensures the accuracy of solar power estimations in varying environmental scenarios.

Similarly, wind speed variability significantly influenced wind power generation during the observation period. On day 1, wind speeds reached a high of 11.4 m/s, producing a peak wind power output of 2.3 W, which highlight is the potential of wind turbines to generate substantial energy when wind conditions are optimal. In contrast, on day 2, wind speeds as low as 2.0 m/s resulted in a minimal wind power output of 0.4 W, underlining the dependence of wind energy systems on sufficient wind velocity for meaningful power generation. These wind power values were calculated using a conversion coefficient of 0.2, which reflects the efficiency of the mini wind turbine in harnessing kinetic energy from wind. This standardized approach ensures that the derived values accurately represent the energy potential of the system under different wind conditions.

Based on the data presented in Table 1, the power output forecast for the fourth day is generated using the double moving average method, a widely recognized statistical approach for smoothing time series data and predicting short-term trends. This method leverages the solar and wind power output values observed over the three-day period to calculate an average that represents the estimated power output for the following day. By applying the moving average technique, the forecast accounts for variations in meteorological conditions, enabling a more accurate projection of energy production from renewable sources.

The forecasted values are then integrated into the Blynk platform, where they are displayed as the "Forecasted Power Output Tomorrow," as shown in Figure 4. In the figure, the predicted values for the next day include a forecasted solar power output of 105.8 W and a wind power output of 1.13 W. The weather condition for the following day is anticipated to be cloudy, with the wind categorized as normal.

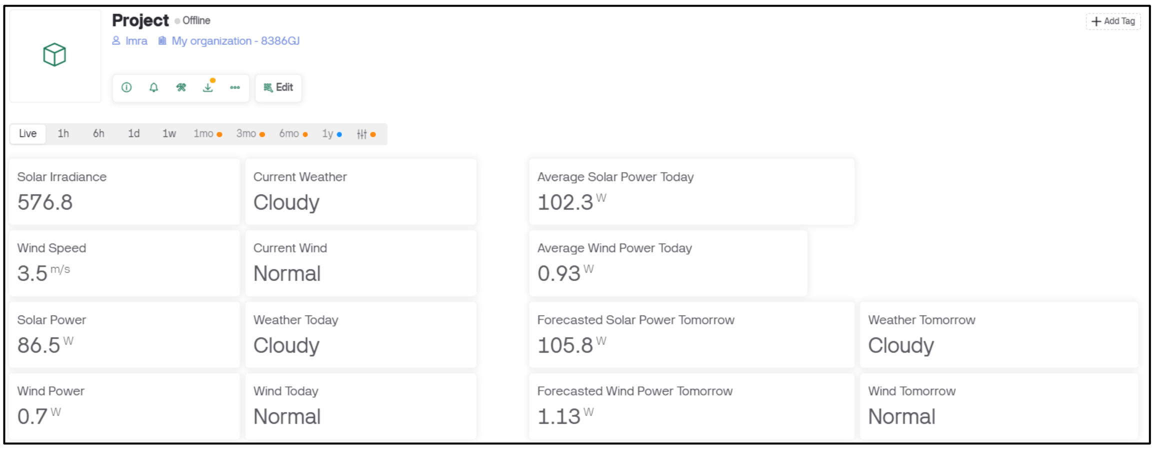

Figure 4. Blynk dashboard for monitoring and predicting renewable energy data and weather conditions on the third day

In addition to displaying the predicted values for the next day, the system also provides real-time monitoring data for the latest values of irradiance intensity, wind speed, solar power, wind power, and the daily averages of solar and wind power, as illustrated in the Figure 4. This real-time data allows users to assess the current energy generation conditions effectively. The system also incorporates weather conditions and wind classifications derived from the measured values of irradiance intensity and wind speed. Specifically, the weather is categorized based on the irradiance intensity, where values greater than 800 W/m^2 are classified as "Sunny", values between 400 and 800 W/m^2 are considered "Cloudy", and values below 400 W/m^2 indicate "Overcast" conditions. Similarly, the wind condition is determined by the wind speed, where speeds exceeding 12 m/s are categorized as "Strong", speeds between 8 and 12 m/s as "Moderate", and speeds below 8 m/s as "Normal".

To validate the accuracy of these predictions, data collection will be conducted on the fourth day to compare the predicted values with the actual measured data. This process aims to evaluate the reliability of the prediction model in estimating solar and wind power outputs, as well as the associated weather and wind conditions. The results of this comparison will provide valuable insights into the model's performance, highlighting any discrepancies between predicted and actual values. These findings will be crucial for refining the prediction algorithm and improving its precision for future applications. The collected data and the corresponding analysis will be presented in Table 2, which will illustrate the actual values recorded on the fourth day alongside the previously predicted values. This visual representation will serve to demonstrate the system's predictive capability and its potential to support effective energy planning and management.

Table 2. Data on the fourth day

Day	Timestamp (GMT-7)	Irradiance (W/m^2)	Wind speed (m/s)	Solar power (W)	Wind power (W)
4	09:00 19/12/2024	445.8	3.4	66.9	0.7
	10:00 19/12/2024	773.2	5.8	115.8	1.2
	11:00 19/12/2024	885.0	6.0	132.8	1.2
	12:00 19/12/2024	489.6	4.0	73.4	0.8

Table 2 presents the actual measured data collected on the fourth day, encompassing key parameters such as irradiance intensity, wind speed, solar power output, and wind power output recorded at specific timestamps. The data reveal notable variations throughout the observation period, with the highest irradiance intensity reaching 885.0 W/m² at 11:00 AM, resulting in a solar power output of 132.8 W. Similarly, the peak wind speed of 6.0 m/s at the same time contributed to a wind power output of 1.2 W. These measured values will be used to validate the predictive model by comparing them with the predicted values described previously.

The Blynk display shown in the Figure 5 provides a concise summary of the data collected on the fourth day, which includes irradiance intensity, wind speed, solar power, and wind power. Focus of this display is the calculated average solar power for the day, which is 97.23 W. This average value serves as the primary metric for comparison with the predicted solar power provided earlier. Similarly, the average wind power for the day, recorded at 0.97 W, is used to validate the wind power prediction.

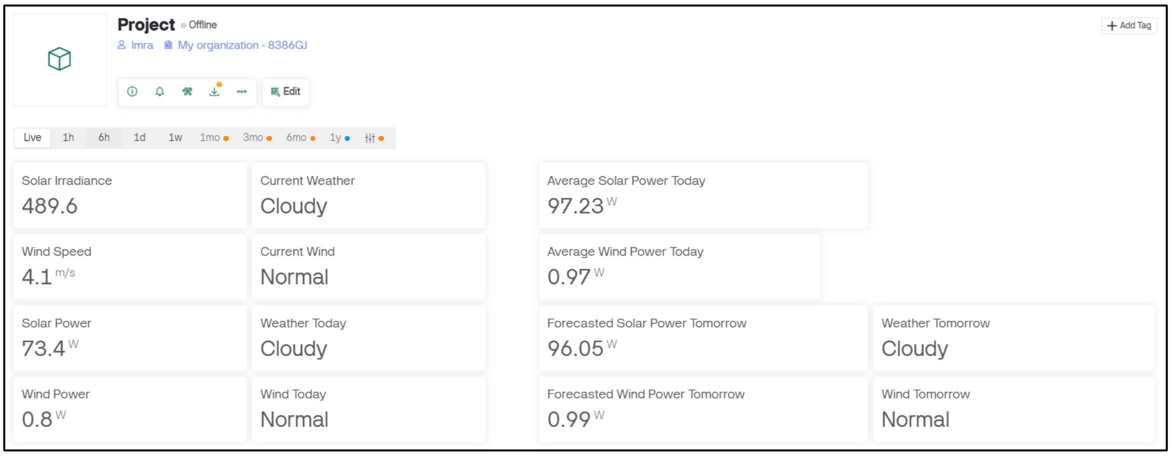

Figure 5. Blynk dashboard for monitoring and predicting renewable energy data and weather conditions on the fourth day

To validate the accuracy of the prediction model, the average values of solar and wind power recorded on the fourth day were compared to their respective predicted values using the percentage error as (1):

$$Error = \frac{|\,Prediction\ Value - Actual\ Value\,|}{Actual\ Value}\ x\ 100\% \qquad (1)$$

For the solar power, the predicted value was 105.8 W, while the actual average measured value was 97.23 W. Substituting these values into the formula yields (2):

$$Error_1 = \frac{|\,105.8 - 97.23|}{97.23}\ x\ 100\% = 8.79\% \qquad (2)$$

For the wind power, the predicted value was 1.13 W, and the actual average value was 0.97 W. Substituting these values gives (3):

$$Error_2 = \frac{|1.13-0.97|}{0.97} \, x\, 100\% = 16.49\% \quad (3)$$

These results indicate that the prediction model achieved an error of 8.79% for solar power and 16.49% for wind power on the fourth day. While the solar power prediction demonstrates a relatively high level of accuracy, the wind power prediction exhibits a slightly higher error, suggesting the need for refinement in modelling wind-related variables.

This comparative analysis underscores the importance of validating predictive algorithms with actual data. The calculated error percentages provide a quantitative assessment of the prediction model's performance, highlighting its strengths and identifying areas for improvement. The findings confirm the utility of the model in renewable energy forecasting while emphasizing the need for iterative refinement to enhance precision, particularly in wind power predictions. These insights form a solid foundation for further development and optimization of the prediction system, ensuring its reliability in supporting energy planning and management initiatives.

4. CONCLUSION

The results of this system highlight the effectiveness and reliability of the predictive model in estimating solar and wind power outputs under varying environmental conditions. The comparison of predicted and actual data collected on the fourth day revealed an error rate of 8.79% for solar power and 16.49% for wind power, demonstrating the model's strong predictive capability for solar energy and identifying areas for improvement in wind energy forecasts. The systematic analysis of average values and percentage errors validates the accuracy of the predictive system while emphasizing the importance of continuous data collection and refinement. The findings indicate that the prediction model is well-suited to support renewable energy management, providing reliable forecasts essential for energy planning and optimization. These results confirm that the predictive model is a valuable tool for advancing renewable energy forecasting. However, the higher error in wind power predictions suggests that further refinements in the algorithm are necessary to account for complex wind-related variables. Overall, this study provides a strong foundation for improving predictive algorithms to enhance the precision and reliability of renewable energy systems in real-world applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [S], upon reasonable request.

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