https://doi.org/10.31436/iiumej.v26i3.3612

CHALLENGES AND STRATEGIES FOR IMPLEMENTATION OF LEAD-ACID BATTERY HEALTH MONITORING AND PREDICTION IN OFF-GRID SOLAR PANEL SYSTEMS

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(Received: 17 February 2025; Accepted: 9 June 2025; Published online: 9 September 2025)

ABSTRACT: This study presents an IoT-based real-time battery health monitoring system that integrates an Equivalent Circuit Model (ECM) with a linear regression approach to estimate internal resistance (IR) and open-circuit voltage (VOC). Unlike conventional electrochemical models or machine learning-based solutions, this method offers a computationally efficient yet accurate approach to predicting battery degradation. The findings demonstrate that increasing IR correlates strongly with declining battery health, reinforcing the necessity of continuous monitoring for predictive maintenance. Additionally, this research highlights the impact of environmental conditions, particularly temperature fluctuations, on battery efficiency, challenging the assumption that heavy rainfall significantly lowers ambient temperatures. Furthermore, this study addresses real-world implementation challenges, including data loss from network disruptions, by proposing a fault-tolerant IoT architecture. These advancements contribute to smart energy storage and provide a scalable solution for remote and off-grid applications, particularly in smart farming.

ABSTRAK: Kajian ini memperkenalkan sistem pemantauan kesihatan bateri masa nyata berasaskan IoT yang terkini, mengintegrasikan Model Litar Ekuivalen (ECM) dengan pendekatan regresi linear untuk menganggarkan rintangan dalaman (IR) dan voltan litar terbuka (VOC). Berbeza dengan model elektrokimia konvensional atau kaedah pembelajaran mesin yang memerlukan sumber pengiraan tinggi, pendekatan ini menawarkan keseimbangan antara ketepatan dan kecekapan pemprosesan dalam meramalkan degradasi bateri. Hasil kajian menunjukkan bahawa peningkatan IR berkait rapat dengan kemerosotan kesihatan bateri, menegaskan kepentingan pemantauan berterusan untuk penyelenggaraan prediktif. Selain itu, kajian ini meneliti kesan persekitaran terhadap prestasi bateri, terutamanya variasi suhu, dan mencabar tanggapan bahawa hujan lebat secara signifikan menurunkan suhu ambien. Kajian ini juga menangani cabaran pelaksanaan di dunia nyata, termasuk kehilangan data akibat gangguan rangkaian, dengan mencadangkan seni bina IoT yang tahan gangguan. Kemajuan ini menyumbang kepada pembangunan sistem storan tenaga pintar dan menawarkan penyelesaian yang berskala untuk aplikasi luar grid, terutamanya dalam bidang pertanian pintar.

KEYWORDS: *Lead-acid battery, IoT monitoring, internal resistance, open-circuit voltage, state of health(SOH).*

1. INTRODUCTION

Rapid advancements in the development of electric vehicles or renewable energy smart power systems, such as smart farming, will require efficient and reliable battery systems to progress. In the field of smart farming, where autonomous systems, sensors, and other IoT devices are indispensable, compromising battery health can reduce availability and pose safety risks. However, the complex nature of battery degradation, influenced by internal mechanisms, manufacturing variations, and the challenging environmental conditions of farming operations, complicates accurate lifetime prediction and health management [1].

Lithium-based batteries have emerged as the most preferred option in many applications due to their lightweight, high energy density, and relatively long lifespan. Compared to lithium-based counterparts, lead-acid batteries generally have a lower energy density and shorter lifespan [2]. Nevertheless, they are still deployed in various applications due to their cost-effectiveness, proven reliability, and robustness. That often makes them an economical option, especially for farming fields or stationary power system applications, where the battery does not need to be removed more frequently.

The lead-acid battery degradation mechanisms, including sulfation, grid corrosion, and electrolyte stratification, have been extensively investigated. There are developed strategies to mitigate these issues and improve these batteries' overall performance and durability [3]. However, predicting the lifespan and managing the health of lead-acid batteries remain complex tasks. This complexity arises from a combination of factors, including intricate internal degradation processes, variations introduced during manufacturing, and the often harsh and unpredictable environmental conditions encountered in farming operations [4]. These challenges are key to ongoing research and innovation in improving battery management systems and predictive modeling. The battery monitors several parameters, such as open circuit voltage and internal resistance [5], essential for developing advanced battery management systems [6].

Implementing a combination of model-based and experimental techniques may have made significant progress in this area, leading to a more reliable and efficient battery-powered system. As batteries age, the model parameters must be updated to reflect their performance accurately. This process relies on the limited sensor data in battery health prediction systems. Optimal sensor deployment is key to estimating battery degradation precisely and effectively over time. High rainfall can worsen this challenge by increasing cloud cover, which reduces solar energy generation and forces the battery to discharge more frequently to meet load demands. Consequently, the increased depth of discharge and cycling accelerates battery degradation.

This study contributes to renewable energy storage and battery management by providing real-world insights into battery degradation patterns and practical challenges. Those challenges and strategies for implementing lead-acid battery health monitoring are delivered especially in remote IoT monitoring. The findings will pave the way for further research on adaptive battery management strategies and provide data parameters for predictive maintenance. In the future, this will result in better cost-effectiveness of battery monitoring and accuracy in predicting battery performance degradation.

2. RELATED WORKS

One approach involves modeling the battery using an electrochemical model and real-time data simulation using fuzzy logic, where the model parameters are estimated online [7].

Machine learning methods can provide insights into battery degradation [8], but implementation can be challenging due to the computational complexity. Internal resistance measurement can also increase the accuracy of State of Charge (SOC) estimation and car mileage [9].

A direct resistance estimation (DRE) technique offers a low-computation alternative that does not require training data [10]. The DRE method estimates ohmic resistance only during sharp current pulses, enabling efficient degraded cell identification within a large battery pack. Results show that DRE maintains high accuracy while significantly reducing computational complexity and advancing diagnostic techniques for battery health monitoring. An alternative approach is to model the battery using an equivalent circuit model and estimate the circuit parameters online. The internal resistance of a battery has proven to increase with aging and can serve as an indicator of the battery's health.

In an Equivalent Circuit Model (ECM), it is essential to identify thermodynamic parameters, such as impedance, and kinetic parameters, including Open Circuit Voltage (VOC). Impedance is particularly significant for State of Health (SOH) diagnosis, as it provides insights into the internal condition of the battery. The ECM offers notable advantages due to its relative simplicity compared to more complex physical models, facilitating more straightforward implementation in simulation software [11]. Moreover, the flexibility of the ECM allows it to be adapted for various types of batteries and applications, including electric vehicles and stationary energy storage systems.

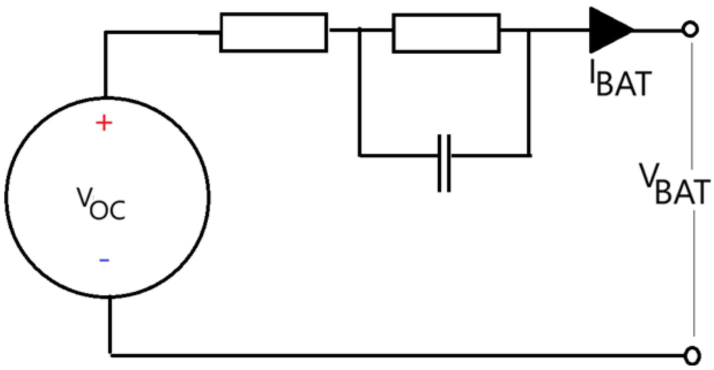

Figure 1. Equivalent circuit model.

The ECM is a widely used approach for representing the behavior of batteries, as shown in Figure 1 [12]. Using this model can help understand the voltage-current (V-I) relationship and the SOH of the battery. By using electrical circuit elements such as resistors, capacitors, and voltage sources, the ECM can simulate the dynamics of the voltage-current characteristic of a battery cell. Characteristics and components of ECM:

- *Resistors and Capacitors*: Resistors cause energy loss due to their resistance, while capacitors can represent the dynamic behavior of the battery during current changes. The impedance analysis may reveal information about the battery's State of Charge (SOC), aging, and potential failure mechanisms, making it a valuable tool for battery management.
- *Voltage Source*: This represents the energy stored by the battery based on its SOC and SOH.

The internal resistance and temperature relationship in commercial batteries is a critical factor influencing their performance. Some research shows that a 4 Ah lead-acid battery with a 70% SOH at room temperature (20 – 35°C) was found to have an internal resistance range between 150 and 200 mΩ [13]. The internal resistance tends to increase due to reduced ion mobility within the electrolyte at lower temperatures, which resists electrical current flow. This condition leads to lowered battery performance, decreased efficiency, and reduced power output. The increased internal resistance at lower temperatures is a well-documented challenge in battery performance. Studies have shown that temperature variations significantly impact the electrochemical processes within batteries, particularly in terms of ion transport and reaction kinetics [14]. For instance, diminished ion mobility at lower temperatures results in higher resistance, which reduces the battery's ability to deliver power and accelerates degradation over time. This highlights the importance of maintaining optimal operating temperatures to ensure consistent performance and longevity of batteries.

3. METHODOLOGY

The methodology consists of several key phases.

3.1. Data Acquisition

To develop a data-driven model for predicting battery capacity fade and lifespan, incorporating various environmental factors, internal mechanisms, and manufacturing variations specific to battery types used in smart farming. The data acquisition site is located in a mushroom farming area in Cikuda Village, Parung Panjang, near the South Tangerang region, Indonesia, at an elevation of 866 meters above sea level. Measurement data was recorded from November to December 2024. The monitoring station is located in our laboratory, Gedung Teknologi 3, KST B.J. Habibie. The distance between the data acquisition site and the monitoring station is approximately 8 km, as shown in Figure 2.

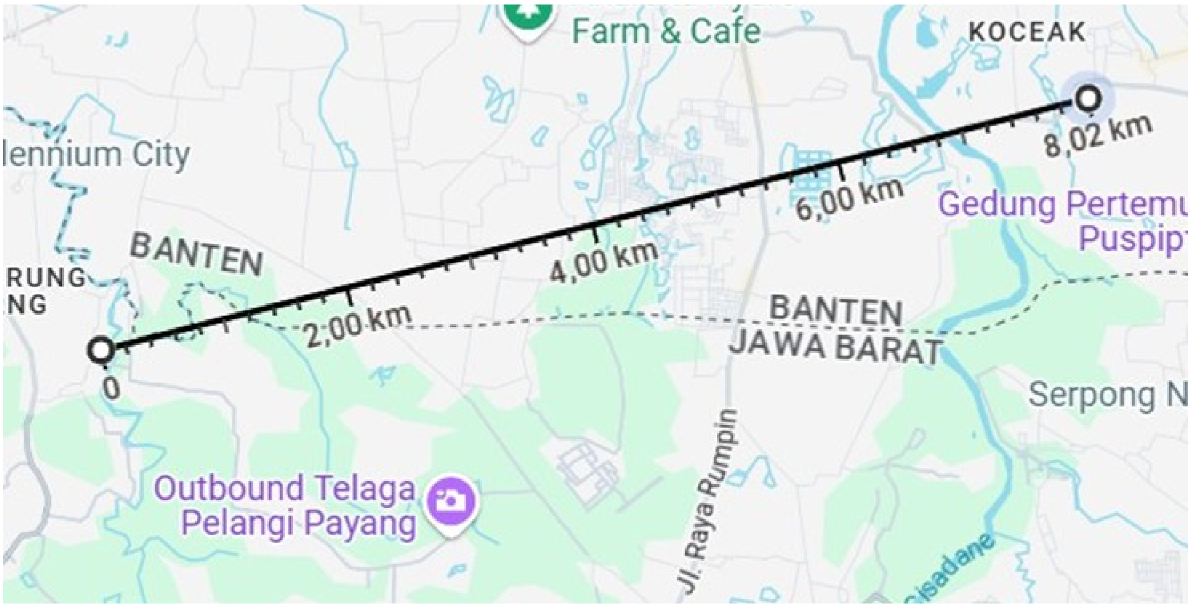

Figure 2. The distance of the measurement location to the monitoring station based on Maps Data © 2025 Google.

3.1.1. Instrumentation Setup

The system utilizes a battery bank connected to a Maximum Power Point Tracking (MPPT) board, serving as a solar charge controller. The battery bank consists of two 12 V, 100 Ah Valve Regulated Lead Acid (VRLA) batteries connected in series. This maintenance-free battery has a rated value of 1.80 V/ cell at 25 °C and an operating temperature range of -15 to

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50 °C. The MPPT board plays a crucial role in managing the charging and discharging of the batteries while simultaneously measuring key electrical parameters, including voltage and current. Measurement and data recording are conducted in real time using IoT technology, as shown in Figure 3.

3.1.2. Data flow

The voltage and current data are transmitted via a serial connection from the MPTT board to a single-board computer (e.g., Raspberry Pi). It processes the information and forwards it to an MQTT broker via cellular telecommunication service over TCP (Internet). A Node.js-based data collector retrieves the data from the MQTT broker and stores it in a PostgreSQL database with a Timescale extension, optimized for time-series data. The entire system is containerized using Docker, ensuring scalability and consistent deployment. This architecture enables efficient and reliable real-time remote measurement.

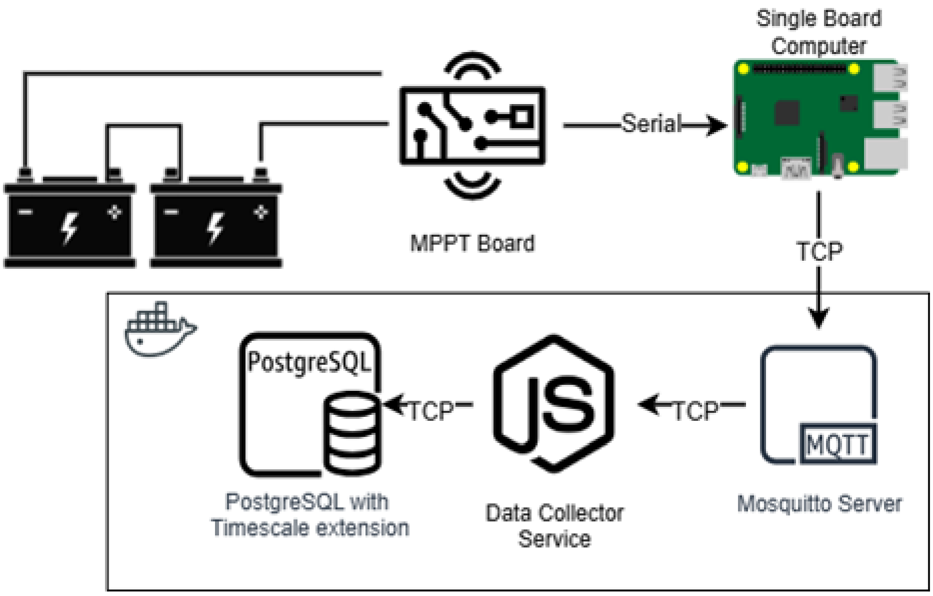

Figure 3. Data acquisition flow chart.

3.2. Data Analysis

To establish a reliable methodology for estimating Open Circuit Voltage (VOC) and internal resistance (IR) under farming environmental conditions using battery voltage and current data.

3.2.1. Data Processing

Data processing is done by analyzing the relationship between the measured voltage and current, as shown in Figure 4, based on direct resistance estimation. Linear regression is an appropriate method for analyzing the relationship between measured current (I_{bat}) and voltage (V_{bat}) in battery systems due to its simplicity, effectiveness, and strong statistical foundation. The voltage-current relationship for a battery under charged-discharge conditions is modeled as a linear Eq. (1).

$$V_{bat} = V_{oc} \pm I_{bat} \cdot R_{int} \tag{1}$$

where V_{bat} notation has meaning, plus when the battery is in a charged condition, and minus when the battery is in a discharged condition. R_{int} is the internal resistance of the battery.

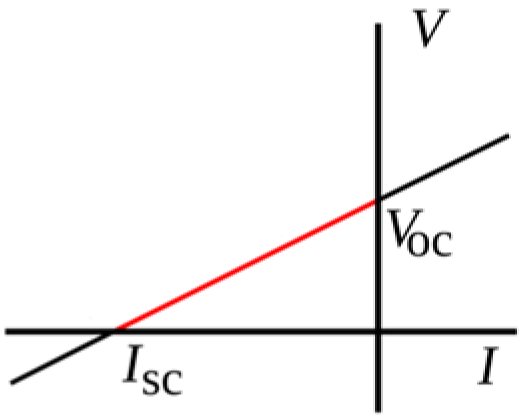

Figure 4. IV Curve relationship.

3.2.2. Data Interpretation

The data interpretation method has a straightforward method that provides easily interpretable results:

- The slope corresponds to R_{int} allowing for direct calculation of the internal resistance (IR).
- The y-intercept corresponds to V_{oc}, representing the open circuit voltage (VOC).
- The x-intercept corresponds to I_{sc}, representing the short circuit current (ISC).

The computational simplicity of linear regression ensures that it can be implemented efficiently, even with large datasets. This efficiency is particularly beneficial in scenarios where extensive cycling data must be analyzed with limited computational resources.

4. RESULTS AND DISCUSSION

Figure 5 provides a clear visual representation of environmental temperature patterns recorded across various dates and times. The vertical axis represents the progression of days, while the horizontal axis captures the time of day. A vivid color gradient, ranging from blue to red, illustrates the temperature spectrum, with cooler readings around 26°C (blue) at midnight transitioning to hotter readings near 36°C (red) at midday. This combination of axes and color coding offers an intuitive overview of temperature fluctuations over time.

Despite the overall consistency of the data, several interruptions were observed. Specifically, data gaps were recorded on November 8, 14, and 15, as well as on December 4, 8, 9, 14, 15, and 16, as shown in Figure 6. In this figure, the availability and continuity of data are represented in the ratio of the number of data points received daily over the maximum number of data points during measurement periods. Furthermore, a complete absence of daily data was noted between November 25 and 28, and again on December 15. These disruptions primarily stem from server downtimes and data transmission issues, common obstacles in large-scale data acquisition systems. While such interruptions may pose temporary challenges, once server functionality is restored and communication channels are re-established, data flow resumes to rerun automatically.

Furthermore, this situation also tests the reliability of our monitoring system, which utilizes public telecommunications and other third-party services. The challenges during this period highlight the importance of robust unmanned and remote data collection infrastructure and the need for contingency plans to mitigate the impact of such disruption. This is practical as it eliminates the need to leave highly valuable data recorder equipment unsupervised by on-location personnel and exposed to the weather.

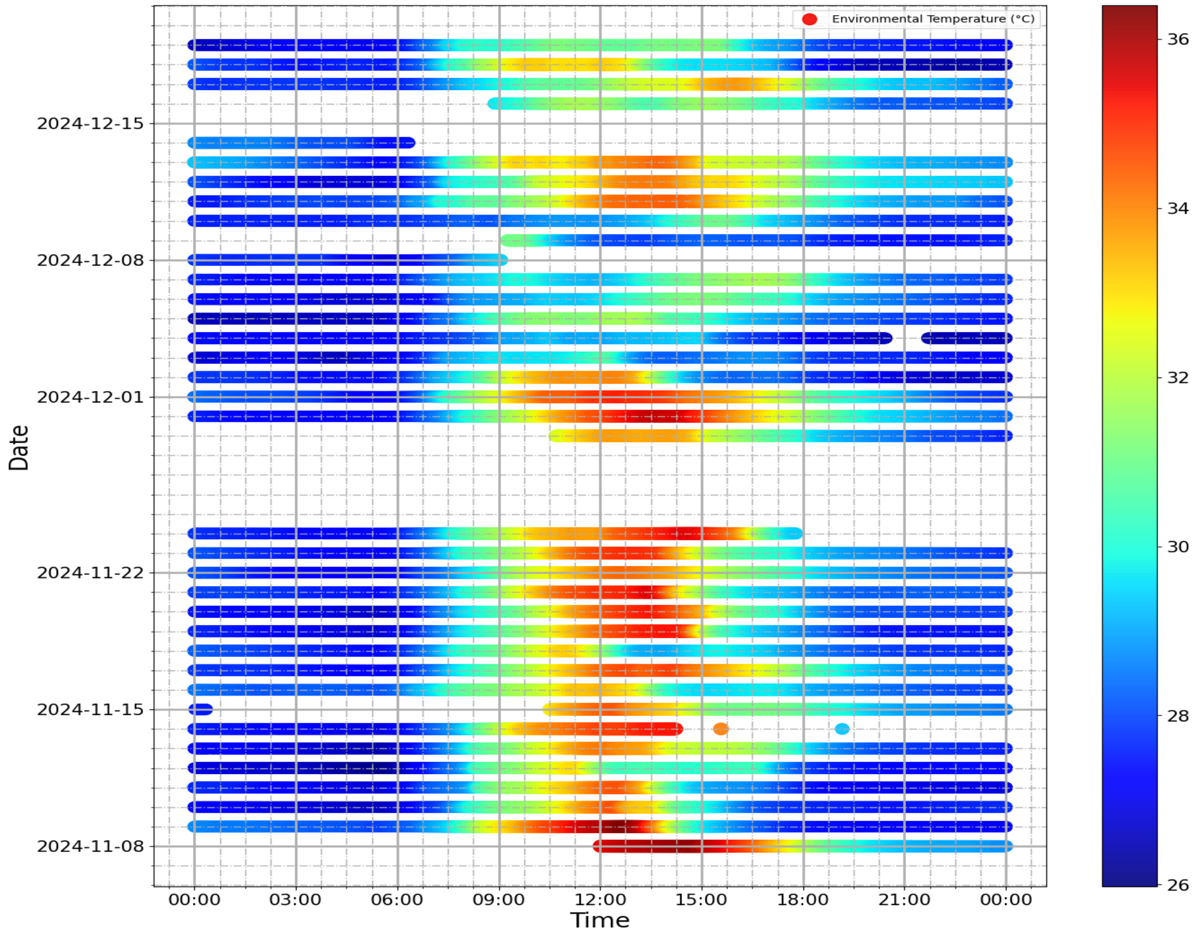

Figure 5. Daily battery environmental temperature record during data acquisition.

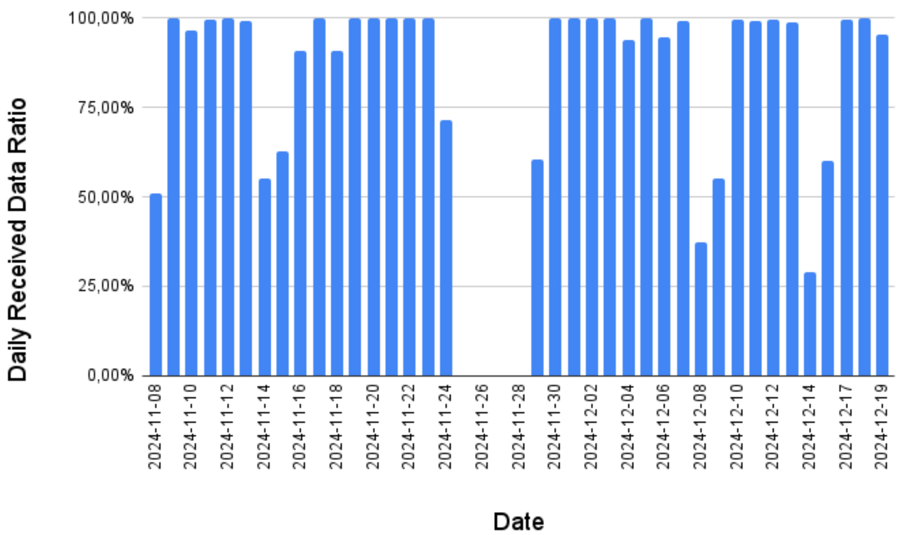

Figure 6. Daily number of data recording.

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Figure 7 illustrates the cycle performance of a battery system over time, presented in 7 days of observation in sub-figures, characterized by its behavior in terms of voltage (plotted on the vertical axis) and current (plotted on the horizontal axis). Each line represents a daily cycle, with different colors and markers corresponding to specific dates. The plot captures the charging and discharging patterns of the battery, providing a comprehensive view of its operation across multiple days. A notable clustering of data points is observed around 0 amperes and a voltage range of 26 to 28.5 volts. This concentration suggests that the battery often remains in a steady-state condition, likely during rest periods or when fully charged.

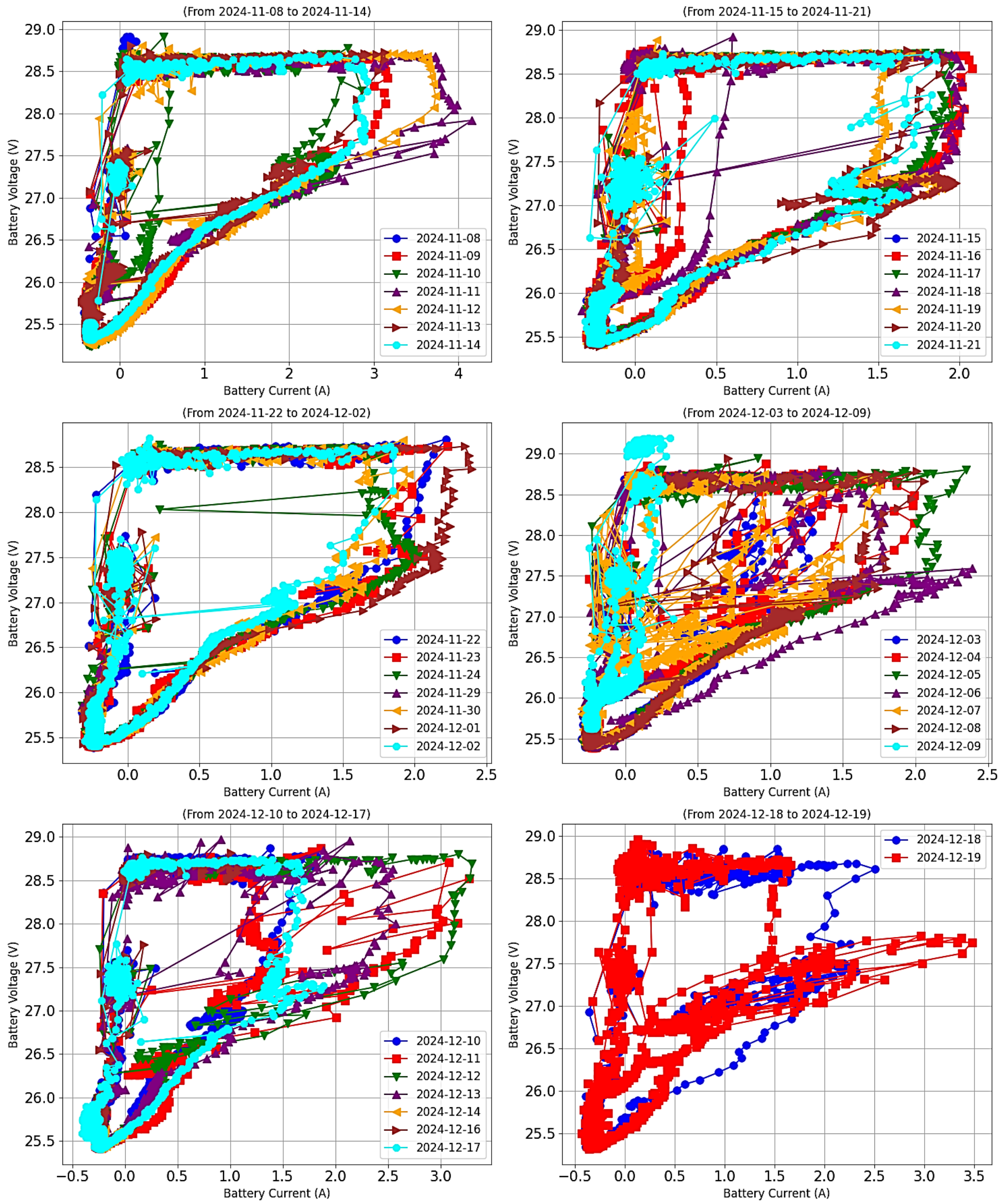

Figure 7. Daily Battery Cycle.

Figure 8 illustrates the daily temperature and rainfall data from the MSN Weather website [15]. A comparison between the MSN-provided temperature data and the measurements recorded by the deployed monitoring system in Figure 5 indicates a high degree of consistency, validating the reliability of both data sources. This alignment enables a more comprehensive analysis of the relationship between ambient temperature and rainfall at the measurement site. The figure demonstrates a weak correlation between daily temperature and rainfall levels. While heavy rain in early December may have induced minor cooling effects through evaporative processes and atmospheric dynamics, the impact appears marginal. To further investigate the influence of temperature fluctuations on battery performance, capacity retention, and degradation mechanisms, additional high-resolution temperature data is required to refine predictive models and enhance the accuracy of battery health assessments.

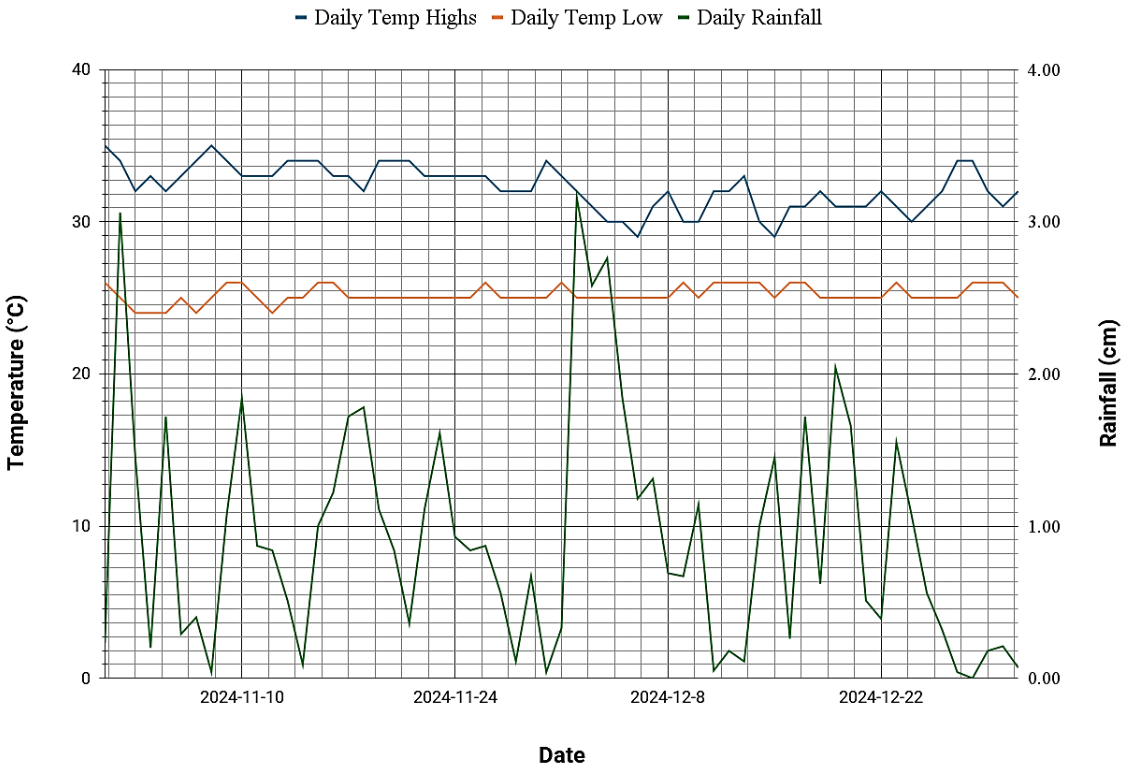

Figure 8. Daily weather record during November - December 2024.

Figure 9 illustrates the relationship between battery voltage and current, with the battery temperature represented through a color map scale. Similar to Figure 7, a notable clustering of data points is observed around 0 amperes within the voltage range of 26 V to 28.5 V, indicating that the battery frequently enters a steady-state condition. This trend suggests prolonged periods of either full charge retention or minimal load conditions, where the battery is neither actively charging nor discharging significantly. Such observations provide critical insights into battery utilization efficiency, depth-of-discharge cycles, and potential long-term degradation trends.

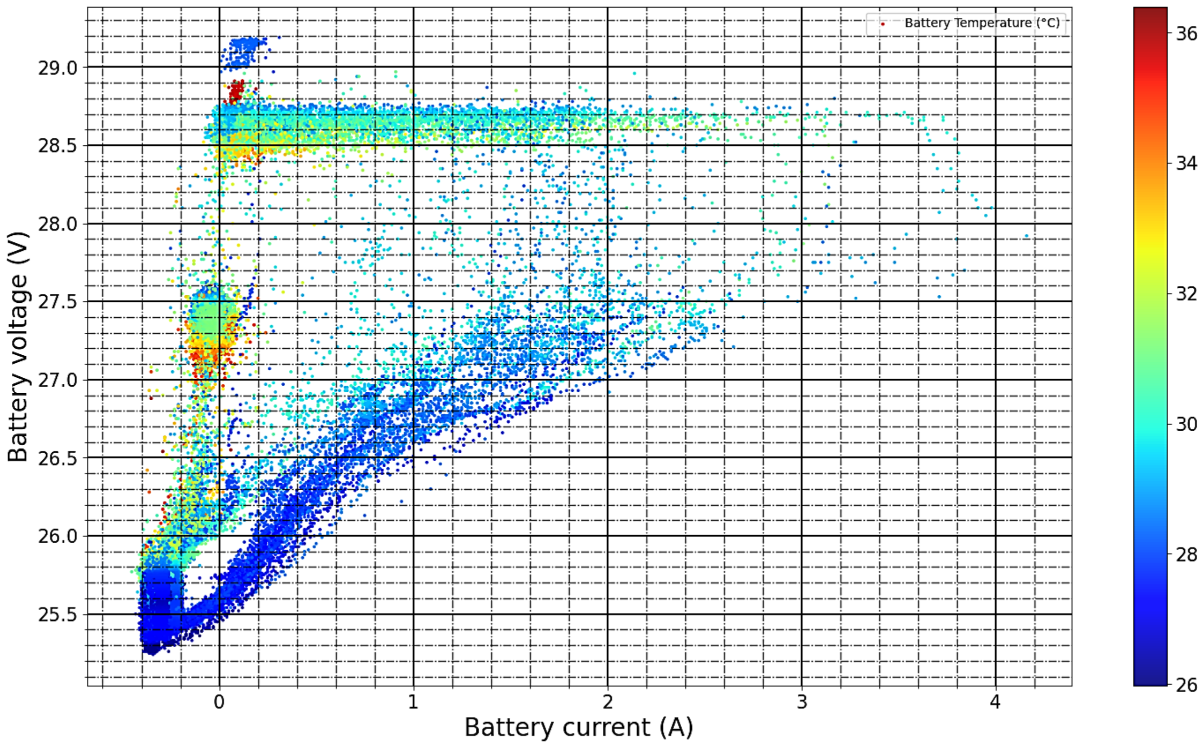

Figure 9. Effect of battery temperature on voltage and current relationship.

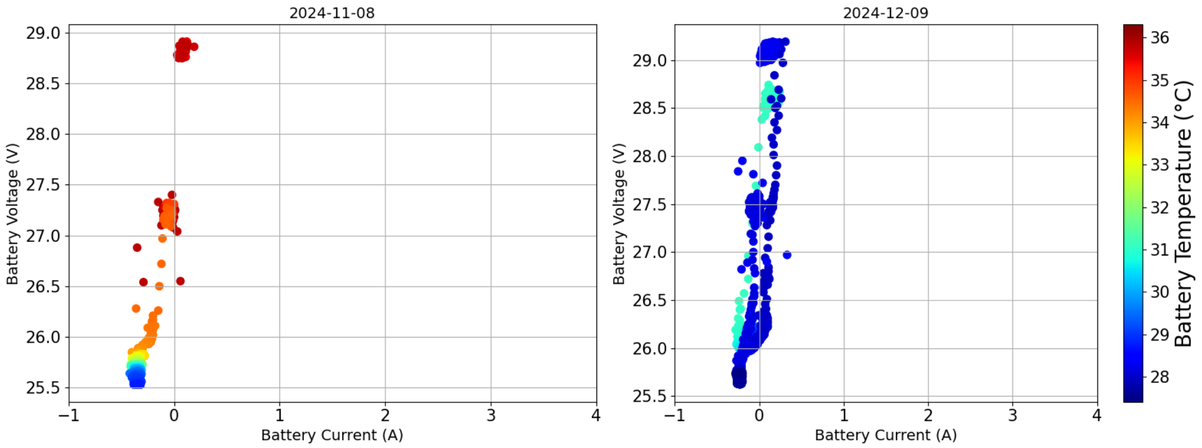

Figure 10. Anomalous data recorded by the monitoring system.

Two significant conditions can be identified and analyzed from the data: the saturation phase of charging and the ohmic relationship at voltages below 28 V.

4.1. Saturation phase of charging

The saturation phase occurs as the battery nears full charge, characterized by a voltage plateau between 28.5 V and 29 V as it approaches maximum capacity. Data plotting reveals a temperature-dependent voltage increase, consistent with theoretical expectations, where higher temperatures correlate with elevated voltage levels due to the impact of thermal variations on electrochemical processes. As shown in Figure 10, anomalous voltage behavior was observed in the data recorded on November 8, where the battery voltage exceeded the expected saturation voltage, likely due to higher operating temperatures. However, a similar anomaly occurred on

December 9, 2024, where the measured voltage again exceeded the expected saturation voltage despite operating at a lower temperature.

The unexpected behavior observed on December 8 was probably caused by oversaturated charging, which was triggered by intensified electrochemical activity, as indicated by a rapid rise in battery voltage and temperature. This condition activated the controller's protection cutoff mechanism to protect the battery from overheating or further damage, resulting in the load system going offline. During this period, power supply to the load was interrupted, and no data was transmitted. On December 9, internal chemical stabilization may have occurred, allowing the voltage to drop within the operational range. This enabled the system to resume normal operation. However, the anomaly is interesting in that it indicates potential irregularities in internal resistance, warranting further investigation into its root causes and implications for long-term battery performance.

4.2. Ohmic relationship at voltages below 28 V

At voltages below 28 V, an ohmic relationship becomes apparent, predominantly during the initial charging stages and at temperatures below 30 °C. This relationship is defined by a linear increase in voltage relative to current, under Ohmic Law ($V = IR$). The behavior in this region is predominantly influenced by the battery's internal resistance, which causes the voltage to rise proportionally as the current increases. Understanding this region is crucial for analyzing the battery's internal dynamics and efficiency, as excessive resistance can lead to heat generation and a decline in charging efficiency.

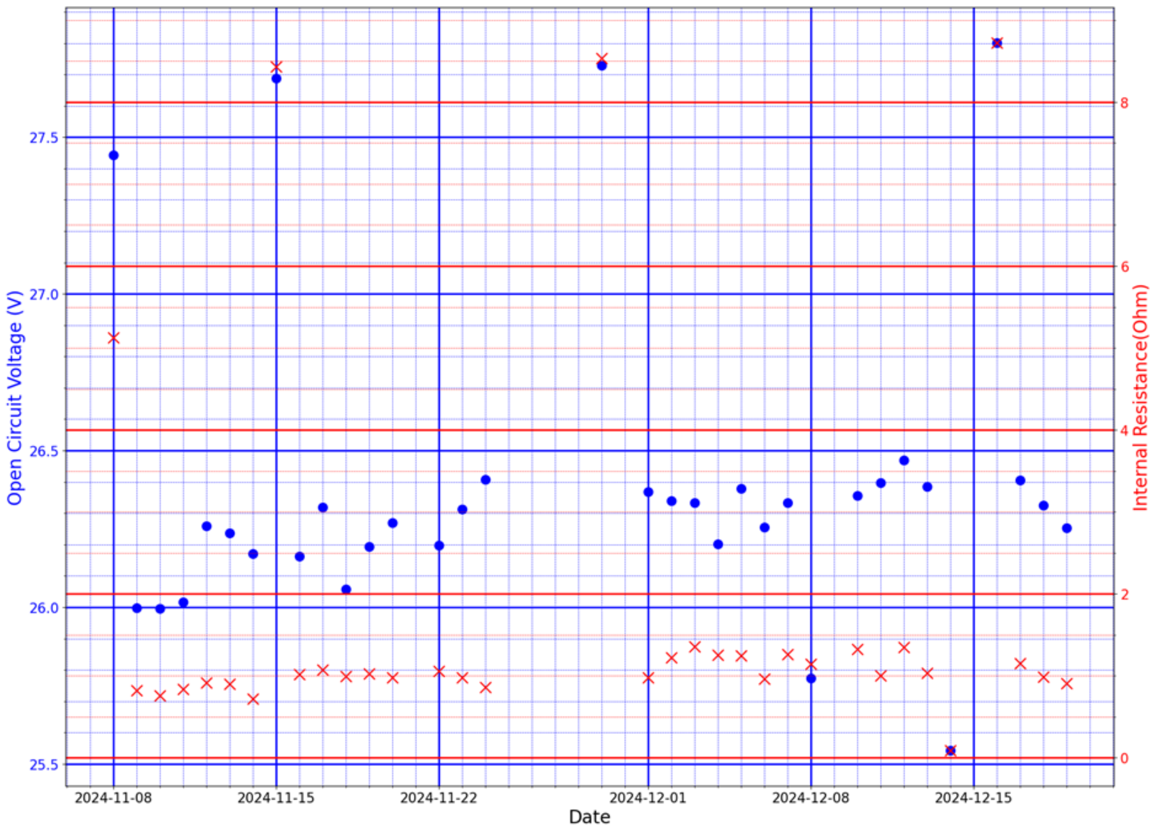

Figure 11. Daily prediction of open circuit voltage and internal impedance of the battery.

Figure 11 illustrates the trends of VOC (represented by blue dots) and IR (represented by red crosses) over time, based on linear regression analysis of current and voltage measurements. The VOC estimation was performed using an equivalent circuit model and regression analysis, mapping the voltage-current relationship during battery charging and discharging cycles. The results indicate that VOC remained relatively stable, ranging between 26.0 V and 26.5 V. However, a sudden increase beyond 27.0 V was observed toward the end of the measurement period. This anomaly could be attributed to gaps in data collection on specific dates (e.g., November 8, 15, and 28, 2024) as referenced in Figures 5 and 6, or potential changes in battery operating conditions that were not fully captured.

VOC also indicates the battery's energy-holding capacity, where a decrease in VOC signifies a reduction in available energy storage [16]. Conversely, the ISC represents the battery's ability to deliver electrical current; a higher ISC value indicates better performance in supplying power. ISC displayed a negative mean outflow current from the battery. A more negative ISC value indicates better performance, as the battery degrades, and ISC decreases or is less negative, reflecting a decline in capacity to provide sufficient current [17][18]. This trend is also illustrated in Figure 12, which presents the calculated ISC values, further highlighting the correlation between battery health and current delivery capability.

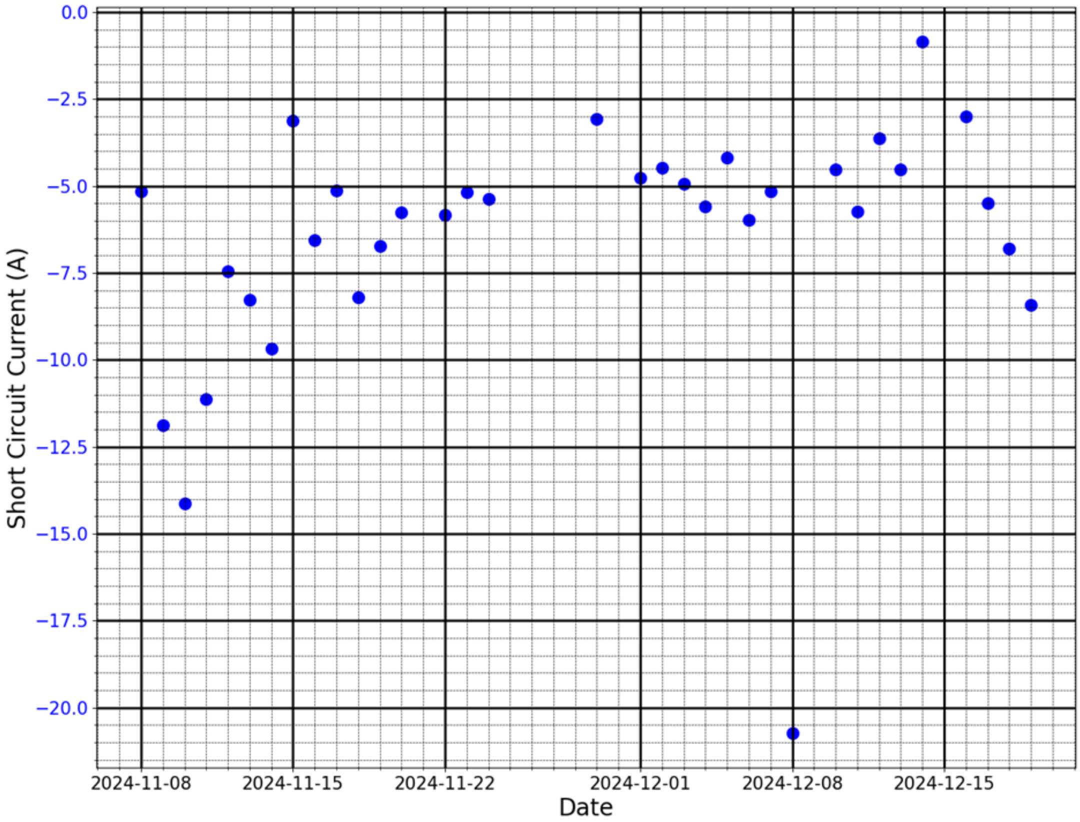

Figure 12. Daily prediction of the short circuit current of the battery.

The internal resistance calculation results align with these findings, showing that IR generally ranges between 0 and 2 Ohms, with a gradual increase over several days, consistent with the observed ISC decline. Interestingly, periodic decreases in internal resistance were also detected, likely due to reversible electrochemical reactions within the electrolyte. In sealed lead-acid (SLA) batteries, oxygen and hydrogen gases generated during charging can recombine to form water, temporarily stabilizing internal resistance [19]. This phenomenon highlights the dynamic nature of battery degradation and the necessity for continuous monitoring. The findings demonstrate that our remote monitoring system effectively tracks and calculates internal impedance, a key parameter for assessing battery health status. Furthermore, enhancing sensor network efficiency through adaptive data collection and wireless transmission techniques is crucial for overcoming these challenges and ensuring accurate long-term battery health monitoring in solar power stations.

5. CONCLUSION AND FUTURE WORK

This study proved that IoT-based real-time monitoring and predictive maintenance systems effectively maintain lead-acid battery health within off-grid solar power systems, particularly in high-rainfall regions. The developed system provides valuable insights into battery degradation mechanisms by continuously monitoring voltage, current, and temperature. The findings indicate that increasing internal resistance is a key indicator of declining battery performance, affecting the state of health (SOH). Additionally, temperature fluctuations have a significant impact on battery efficiency, underscoring the need for dynamic monitoring and adaptive maintenance strategies. The study showed that integrating predictive analytics in remote monitoring systems can enhance reliability and reduce operational costs. This cost reduction is achieved by lowering labor and transportation expenses for manual inspection and enabling condition-based maintenance, rather than adhering to fixed schedules. Moreover, the research identified challenges in data acquisition due to network disruptions, underscoring the need for more robust infrastructure to ensure consistent, real-time monitoring.

Future research should develop a monitoring system with machine learning integration to improve battery health prediction, while considering computational complexity in resource-constrained environments. It will also enable the examination of the seasonal variations' impact on battery degradation and the exploration of adaptive energy management strategies to optimize battery usage. Additionally, expanding the monitoring framework to support multiple battery chemistries, such as lithium-ion batteries, would provide valuable comparative insights into their performance under similar environmental conditions. This development has substantial implications for real-world deployment, particularly in remote or rural areas where manual maintenance is costly and infrastructure is limited. By enabling autonomous and adaptive monitoring, this system can enhance the reliability of solar-powered installations for off-grid communities, health clinics, and disaster-relief operations. Furthermore, the extension to lithium-ion batteries opens up opportunities for integration into smart grid systems and electric mobility applications, where accurate state-of-health monitoring is critical.

ACKNOWLEDGEMENT

The authors wish to thank the Indonesian Endowment Fund for Education (LPDP) – Ministry of Finance of the Republic of Indonesia for funding this research through the Research and Innovation for Advanced Indonesia (RIIM) program at the National Research and Innovation Agency (BRIN) under grant number B-1468/II.7/FR/10/2022, and PT Jamur Cikuda Nusantara, our research partner, for providing materials and facilities for this research.

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