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Research Paper

Harnessing digital twin and IoT for real-time monitoring, diagnostics, and error correction in domestic solar energy storage

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ABSTRACT

This study introduces a cloud-based platform designed for real-time monitoring and comprehensive analysis of lithium-ion battery performance, incorporating a digital twin Battery Management System (BMS). This system overcomes the limitations of traditional local BMS, especially in historical data analysis. It employs advanced data processing and analytics to improve battery performance and enhance prediction accuracy. Key components include a energy measurement correction method, an coulombic efficiency (CE) estimation technique, and SOC estimation using an optimizer algorithm. These strategies are crafted to address sensor errors and dynamically adjust estimations to minimize inaccuracies. The use of sophisticated algorithms to optimize the objective function has led to significant experimental outcomes, notably in reducing the Mean Square Error (MSE) in estimations. The paper also introduces various novel methods for estimating irregular battery data, using the Central Limit Theorem for improved precision. Experimentally, the system identified a battery CE of 0.978 for a specific battery, demonstrating its capability in monitoring battery health. These advancements offer substantial scholarly insights and pave the way for broader application of advanced digital twin BMS technologies in residential battery storage and other areas. The synergy of this system with other smart grid technologies envisions a future where energy storage and management are not only more efficient and reliable but also finely optimized, enhancing the tracking and management of battery life cycles.

1. Introduction

The transition towards renewable energy sources necessitates innovative solutions for efficient and effective energy storage and management. At the heart of this transition, lithium-ion batteries have emerged as a pivotal technology due to their superior energy density, longevity, and rechargeability. However, these batteries pose a set of unique challenges, including the optimization of their performance in life cycle, and the prediction of their State of Health (SOH). Traditional Battery Management Systems (BMS) struggle to cope with these challenges, particularly given the limitations in handling historical data that can inform performance improvements due to the smaller capacity of on-board computer system.

In this context, this study introduces a novel cloud-based system designed to address these challenges. By utilizing a digital twin model of the BMS in a real-time online environment, this research pioneers a transformative approach to the management and analysis of lithium-ion battery performance by utilizes cloud resources. It detail the use of advanced data processing and analysis techniques, along with innovative mechanisms such as a energy measurement correction method and a SOC estimation method. These techniques not only optimize the performance but also enhance prediction accuracy by accounting for sensor errors and adapting to minimize estimation inaccuracies, thereby setting a foundation for more advanced data analysis.

This paper also presents experimental results, demonstrating the effectiveness of the proposed system. For instance, it showcase how adaptive error correction led to a significant reduction in SOC estimation. It further introduce a novel method of estimating irregular pattern data using the Central Limit Theorem (Levin, 2023) and report on the identification of a battery CE equating to 0.978 in one of the batteries.

This research contributes significantly to the academic discourse around lithium-ion battery management. Moreover, it holds substantial practical potential, opening new avenues for the broader application of advanced digital twin BMS in residential battery storage sectors. By integrating this system with other smart grid technologies, move towards a future where energy storage and management become increasingly efficient, reliable, and highly optimized.

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2. Literature on smart batteries solutions

The increasing reliance on renewable energy has bolstered the need for efficient energy storage, bringing lithium-ion batteries into the spotlight (Chen et al., 2018). Recognized for their superior energy density, rechargeability, and longevity, lithium-ion batteries have triggered an influx of research on smart battery solutions (Peters et al., 2017).

The conventional Battery Management Systems (BMS) have been the mainstay for managing lithium-ion battery operations (Manwell and McGowan, 1993). However, traditional BMS have encountered challenges in managing the performance and life cycle of these batteries, particularly in accurate State of Charge (SOC) prediction. A widely-used method for SOC prediction is the Coulomb Counting Method (Zhou et al., 2018), but its inherent simplicity has led to errors when charging and discharging conditions are not consistent. This has necessitated the exploration of novel methods that account for these inconsistencies, and in the study propose using statistical methods to calculate and correct these accumulated errors for precise outcomes.

To address the broader challenges faced by BMS, a number of studies have focused on improving BMS's data processing capabilities and refining SOC estimation methods (Zhang et al., 2019). The rise of cloud computing and the Internet of Things (IoT) has led to new opportunities in the field of battery management (Shafiee et al., 2020). Specifically, digital twin technology, which creates a virtual replica of the physical BMS, has shown promise in enabling real-time tracking and analysis of battery performance (Dinh et al., 2020). The potential of digital twin technology in enhancing lithium-ion batteries' performance and life span has been explored in a range of studies (Tao et al., 2019).

Nevertheless, the effective use of historical data for performance optimization and SOC prediction remains a significant challenge for many BMS (Gao et al., 2021). This has catalyzed research on innovative data analysis techniques that can harness historical data for predictive maintenance and improved operational efficiency (Wang et al., 2017b).

This research unfolds within the context of an evolving academic dialogue. It presents an innovative cloud-based BMS that utilizes a digital twin model. This system is designed to overcome the shortcomings of conventional BMS approaches by leveraging historical data (Vazquez et al., 2019). By addressing the challenges of random and irregular data from real-world applications, this study introduces an energy measurement correction method and an adaptive SOC estimation technique. Furthermore, it proposes a novel method to overcome the limitations inherent in the Coulomb Counting Method. Collectively, these advancements represent significant contributions to the discourse on intelligent battery solutions.

3. System architecture design

The architecture of system is devised to harness the potential of IoT, cloud computing, and digital twin technology, bringing forth an innovative battery management solution. This unique architecture aims to transcend traditional BMS's limitations and effectively utilize historical battery data for improved operational efficiency.

The system architecture consists of three core components: the local battery management system, the cloud server, and the digital twin model (Xia et al., 2021; Grieves and Vickers, 2017).

Here is a breakdown of the design's key components and layers:

Data Acquisition Layer: The smart BMS circuit board, a core component of this layer, is a highly advanced lithium battery protection board specifically developed for home solar energy storage. It boasts voltage balancing for 16 cells, current sensing, and extensive charging/discharging protections. Centered around the Local Battery Management System, plays a pivotal role in the architecture by facilitating the seamless transmission of data. It utilizes IoT-enabled sensors to collect a wide array of real-time battery information, such as charge/discharge current, temperature, voltage, and Geo-location. Once gathered, this data is promptly transmitted to the central system for processing and analysis. The transmission is designed to be swift and secure, ensuring the real-time data is consistently available for accurate SOC calculations and further analysis. This layer's efficient data transmission capabilities are crucial, providing the foundational data flow required for effective monitoring and management of battery performance.

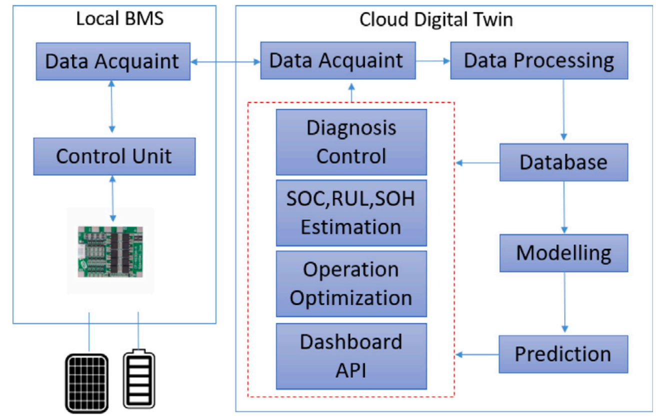

Fig. 1. A Digital Twin Battery BMS System, comprising data storage, alert generation, analysis, and prediction components.

Communication Module: This module ensures seamless data flow, employ a combination of wired and wireless communication protocols to ensure uninterrupted data transmission. Through the Message Queuing Telemetry Transport (MQTT) protocol, the board transmits real-time data to the cloud via WiFi, broadband, or Ethernet connections. Moreover, data is stored on an embedded micro-SD card and is automatically uploaded to the cloud when the internet connection is restored. In this system, the MQTT protocol is used as the standard protocol over TCP/IP through the internet for IoT data transmission (Joonam Park et al., 2020; Tanizawa et al., 2015). This is because IoT messages are small, optimizing network bandwidth. MQTT clients are lightweight and require minimal resources, which is ideal for embedded microprocessors. Battery information usually does not need to be sent very frequently. For instance, a real-world BMS for solar energy storage collects battery data only once per minute, reducing energy consumption.

Cloud Digital Twin: The Cloud Digital Twin constitutes the central structure of the system, orchestrating data storage, processing, and analysis. This sophisticated component utilizes digital twin technology to establish a virtual counterpart of the local BMS on the cloud server. This virtual model accurately reflects the real-time conditions of the battery, facilitating immediate monitoring, analysis, and intervention.

As fresh data is relayed from the local BMS, the digital twin is consistently updated to maintain a precise and current representation of the battery's status. It employs advanced machine learning techniques to refine predictions and understandings of the battery's behavior and potential issues. This continuous flow of data and analysis ensures that the cloud digital twin offers an accurate, real-time depiction of the battery's condition, making it an invaluable tool for proactive management and decision-making. Fig. 1 provides a visual representation of this sophisticated interplay between the real and virtual components, illustrating the cloud digital twin's role in the broader system.

Safety and Security Features: The system is engineered with a comprehensive safety mechanism that vigilantly tracks any anomalies like overcharging, excessive heat, or short circuits. It is programmed to promptly respond to these irregularities, safeguarding the battery system and averting potential damage. Additionally, an information system is in place to display alerts on the user's dashboard or send email notifications for further user action.

Energy Collection and Usage Optimization: The system's design integrates methods for capturing renewable energy, including solar

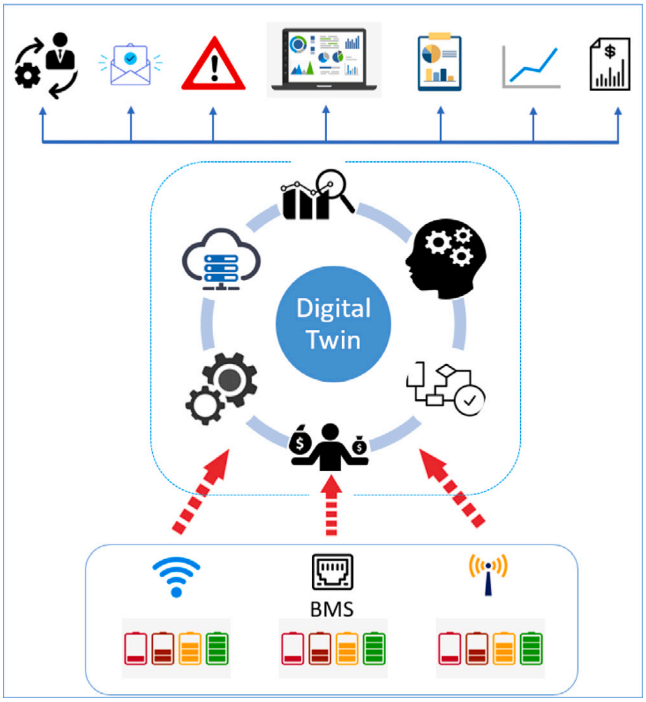

Fig. 2. A depiction of an Advanced Battery Digital Twin System: This setup showcases numerous batteries, each integrated with a distinct Battery Management System (BMS) responsible for sending live data to a digital twin platform hosted in the cloud. The illustration features a cloud server equipped with data storage capabilities and assorted tools designed for analyzing historical data. The image also includes a display of various applications, like real-time data visualization, all developed on this sophisticated technology platform. This visual emphasizes the cutting-edge application of digital twin technology in the field of battery management and data analysis.

power harvesting. Smart load management is employed to maintain an ideal balance between energy storage and consumption. Advanced algorithms are utilized to determine when to switch to grid power, helping to even out peak demand periods on the grid.

Scalability and Flexibility: Central to the system's design is its inherent scalability, enabling it to effectively handle increasing energy requirements. The architecture's versatility suits a wide array of applications, from residential energy storage solutions to the management of batteries in electric vehicles. It facilitates real-time, simultaneous access for numerous users, allowing for efficient monitoring and control of battery status. For instance, users can remotely manipulate the local BMS, including the ability to disable the battery if necessary, demonstrating the system's adaptability and user-centric approach. This scalability and flexibility ensure the system remains robust and relevant in various scenarios and as energy demands evolve.

This system architecture design provides a comprehensive, intelligent, and adaptive solution for managing smart batteries in solar energy storage systems and electric vehicles (Friansa et al., 2017; Stroe et al., 2018). By employing data-driven algorithms, integrating with IoT and digital twins and ensuring safety, this architecture paves the way for future advancements in smart battery technology. See Fig. 2.

4. Estimations method

A range of data analysis techniques were employed in the estimation study.

SOC is a critical parameter in battery management as it indicates the current energy level in the battery compared to its maximum capacity (1). In this paper, propose a novel method for SOC estimation that employs both the Coulomb Counting method and an adaptive model-based approach. This innovative method enhances accuracy and accounts for various factors that typically impact the SOC estimation.

To begin with, the SOC is mathematically defined as the ratio of the current battery charge to its fully charged capacity:

$$SOC = SOC_0 + 100 * \frac{Q}{Q_{max}} \tag{1}$$

Additionally, the State of Health (SOH) of a battery, which is a measure of its current maximum capacity relative to its rated capacity, is defined as (2):

$$SOH = 100 * \frac{Q_{max}}{C_r} \tag{2}$$

Here, Q_{max} represents the current maximum capacity of the battery, C_r is the nominal battery capacity, and SOH signifies the current state of the battery's health.

In the Coulomb Counting method, a simple yet widely-used technique, the SOC is estimated by integrating the current flowing through the battery over time. However, this method can incur errors due to measurement noise and sensor drift. To address these shortcomings, research introduces a modified version of the Coulomb Counting method with error correction. The equation for the Coulomb Counting method is:

$$SOC_t = SOC_{t-1} + \frac{\epsilon \cdot \Delta C_t}{C_r} \tag{3}$$

where SOC_t is the SOC at time t, SOC_{t-1} is the SOC at the previous time step, and $\Delta C_t = I_c(t)\Delta t$ represents the change in charge during the time step, it is a measure of how much electric charge has been added to or removed from the battery between two consecutive time steps. ϵ represent charging efficiency. In this formula, the SOC is updated by adding to the previous SOC the proportion of the battery's rated capacity that has been charged (or discharged) during the time interval Δt. The charging efficiency modifies this addition to account for energy losses in the process. This method is commonly used in battery management systems for tracking SOC over time.

The Coulombic efficiency, CE, is calculated using the following function:

$$CE_k = \frac{Q_{dis,k}}{Q_{cha,k}} \tag{4}$$

In this equation, $Q_{dis,k}$ represents the discharge capacity, and $Q_{cha,k}$ denotes the charge capacity of the battery within cycle k.

The degradation index (η) quantifies the decline in a battery's capacity resulting from degradation over time. Additionally, η is broadly employed to denote the overall efficacy of a process, extending beyond just electrochemical applications. It is calculated as the proportion of the actual useful output of a process to its theoretical maximum output, under the assumption of perfect efficiency. η is close refers to a measure or index that reflects the overall health and efficiency of a battery, considering various factors such as capacity fade, power fade, increase in internal resistance, and other aging mechanisms. It take into account the Coulombic Efficiency as one of its components, among other factors. While Coulombic Efficiency is a direct and specific measure of charge transfer efficiency, the battery degradation index is a broader term that encompasses CE along with other parameters to give a more holistic view of the battery's health and performance over time. Nevertheless, the terms Coulombic Efficiency (CE) and degradation index (η) are often used synonymously to refer to battery efficiency and an indicator of battery degradation.

In the study, calculate CE by merging the Coulomb Counting method with a Gaussian curve fitting technique, the Coulomb Counting method is used to compute the charging and discharging capacity. Applying the curve fit function to fit the charging and discharging capacity data with a Gaussian curve. This fitted Gaussian curve is then used to determine the peak charging and discharging capacities, denoted as $Q_{cha,max}$ and $Q_{dis,max}$, respectively. Utilize this curve to calculate the Coulombic Efficiency for the current cycle k as per Eq. (4). The central point of the Gaussian fit, represented by (σ), corresponds to the most prevalent value of Coulombic Efficiency.

The estimated CE values provide vital insights about the battery's health and performance. A decreasing trend in CE over time signifies increased parasitic reactions and battery degradation. SOH has positive correlations with CE but it is not linear (Ng et al., 2009), this can be further explore using battery life cycle data.

In light of the inherent inaccuracies posed by factors such as thermal energy dissipation, the historical degradation of batteries, and the intermittent nature of data in Coulomb Counting methods, a more robust approach is necessitated. To this end, a third-degree polynomial function has been employed to better capture the complex relationship between the dependent variable P(x), indicative of energy levels, and the independent variable x, representing the original value:

$$P(x) = ax^3 + bx^2 + cx + d \tag{5}$$

In this context, P(x) represents the corrected energy levels, and x represents the cumulative energy discrepancy between charging and discharging processes over time. The coefficients a, b, c, and d intricately determine the shape of the polynomial curve, with a non-zero a ensuring a cubic characteristic.

The cubic term allows for the modeling of data with two inflection points, providing a nuanced fit capable of adapting to more intricate data behaviors than linear or quadratic models. This refined model is instrumental in detrending energy data, thereby enhancing the fidelity of energy measurement and prediction. This is particularly useful for adapting to intricate patterns in battery energy data, enhancing the accuracy of energy measurements and predictions.

Additionally, this research employs Broyden–Fletcher–Goldfarb–Shanno (BFGS) for SOC estimation (Mesbahi et al., 2017). The BFSG method is a heuristic search algorithm that is used for minimizing a function in a multidimensional space. This method considers maintains a simplex of n+1 points for an n-dimensional space. The method then iterative performs a series of operations that reflect, expand, contract, or shrink the simplex in search of a minimum. In the context of searching for the minimal MSE in SOC estimation using the charge coefficient (nc) and discharge coefficient (dc), the method can be quite effective.

$$SOC_n = \begin{cases} SOC_{n-1} + \frac{nc \cdot I_c(t) \cdot \Delta t}{C_r}, & \text{for charging} \\ SOC_{n-1} + \frac{dc \cdot I_c(t) \cdot \Delta t}{C_r}, & \text{for discharging} \end{cases} \tag{6}$$

C_n: Cumulative charged capacity at time n. C_{n-1}: Cumulative charge capacity at the previous time step (n-1). nc: Charging efficiency coefficient, this accounts for the efficiency of the charging process. dc: Discharging efficiency coefficient, this accounts for the efficiency of the discharging process. $I_C t$: Current at time t. Δt: The time interval between the current and the previous measurement.

Research present an approach to estimate Coulombic Efficiency (CE), defined as the ratio of actual energy delivered by the battery to the energy supplied during charging. Estimating CE is essential for evaluating battery health and identifying degradation over time. It approach employs a Gaussian curve fit to estimate the CE based on the battery's charging and discharging profiles (Ren et al., 2019).

In summary, the SOC estimation method integrates a modified Coulomb Counting technique with an adaptive model-based approach, resulting in higher accuracy and reliability. This novel method proves to be highly effective in managing battery health and energy levels for various applications including solar energy storage systems and electric vehicles.

5. Formulating the objective function

Crafting an effective objective function is paramount in advancing battery performance and management. This function acts as a quantifiable representation of the ultimate aims the BMS is designed to achieve. It is shaped and refined through sophisticated control algorithms and strategic management approaches.

In contexts of home solar energy storage systems or electric vehicles, the objective function typically integrates various factors. These include enhancing the battery's lifespan, optimizing SOC, ensuring safe operation, and improving energy efficiency.

By fine-tuning this objective function, the control of BMS can adeptly navigate the intricate balance between prolonging battery life, optimizing energy use, and maintaining safety. This balance is especially critical in solar energy storage and electric vehicles, where both longevity and efficiency are key.

This research focused on an objective function centered around SOC estimation algorithms to minimize predictive errors, employed the Mean Squared Error (MSE) as a metric to gauge the accuracy of SOC estimation.

MSE is particularly advantageous in this setting. It accentuates larger discrepancies by squaring the difference between actual and predicted values, making it highly sensitive to significant variations crucial for practical scenarios. Moreover, its differentiable nature creates a conducive landscape for optimization algorithms, facilitating more effective model training. As an absolute measure, it directly mirrors the error magnitude in squared units, offering a clear understanding of the model's performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \tag{7}$$

Here, n represents the number of data points, the actual value, the predicted value, and $\sum$ denotes summation. The aim is to minimize this metric concerning the charge efficiency coefficient nc and the discharge efficiency coefficient dc. Consequently, the objective function for minimizing the MSE is:

$$\begin{aligned} &\text{minimize ObjectiveFunction}_{\text{MSE}}(nc, dc) = \\ &\qquad \frac{1}{N}\sum_{t=1}^{N}\left(SOC_{\text{actual}}(t)\right. \\ &\qquad \left. - f\left(C(t-1) + nc \cdot I_{\text{charge}}(t) \cdot \Delta t + dc \cdot I_{\text{discharge}}(t) \cdot \Delta t\right)\right)^2 \end{aligned} \tag{8}$$

The objective function incorporates nc and dc as variables to calculate SOC's estimation MSE. Utilizing the BFGS optimization method, the system iteratively refines nc and dc to minimize this function, thereby diminishing MSE and bolstering SOC estimation precision.

The BFGS technique, a simplex-based method, iteratively refines the values of nc and dc by navigating the function's landscape through reflection, expansion, contraction, and shrinkage. This method does not necessitate derivative calculations, making it highly suitable for scenarios requiring quick and reliable solutions. Thus, it is an invaluable asset in BMS for dynamically balancing battery health, energy use, and safety, providing a strategic edge in the management and optimization of sophisticated battery systems.

6. Calculating coulombic efficiency

Calculating the Coulombic Efficiency (CE) of Lithium-ion batteries is an important metric for assessing their health. The performance loss of a Lithium-ion battery is caused by three aging processes: loss of lithium inventory, loss of active material, and an increase in internal resistance (Chang, 2013; Dong et al., 2011; Nitika et al., 2021; Zhang et al., 2020). CE is the ratio of discharge quantity to charge quantity within the same cycle and is usually less than 1. However, obtaining an accurate CE value in online conditions is challenging due to irregular charging and discharging, missing data, and other factors. This makes it difficult to calculate each cycle's CE, battery discharge capacity fade, and internal resistance accurately.

To tackle this problem, experimental online battery is utilized to produce a CE fading curve. The battery was charged via a solar panel during the day and discharged randomly at various times. Under optimal weather conditions, the battery typically achieves a fully charged state. For simplicity, assumed that one day represented one battery cycle to compare CE with each day's changes. However, in reality, the randomness of the battery's operation, errors in measurement, and missing data transmission led to uneven charge and discharge quantities throughout the day. As a result, the CE displayed an irregular pattern that varied from one day to the next.

To enhance the precision of the Coulombic efficiency CE measurement, here leveraged the Energy Conservation Law, which dictates that input energy equals output energy. Thus, despite variations in charging and discharging quantities on a daily basis, the total amount of charged and discharged energy should be approximately equal over a certain number of days. To calculate the CE, it used the average CE of each day as a single data point. To ensure accuracy, it applied the Central Limit Theorem, which states that the sample mean approaches the population means as the sample size increases. Specifically, it calculated a single CE value using one-day data consisting of 1440 data points and obtained the final mean value of CE by computing the average of 100 days' worth of samples.

Fig. 3 (c) presents a histogram that illustrates the energy consumption during charging and discharging over a period of year 2022–2023. It applied a Gaussian curve fit function to analyze the data and identify the center of the mean distribution (σ), which corresponds to the CE value. This approach eliminates outliers and reduces calculation errors stemming from inaccuracies in the data. Consequently, the mean CE value represented by the center of the Gaussian distribution, can serve as a dependable metric for assessing battery health. In this study, it determined a value of CE = 0.978 in a battery. Overall, the methodology enables a more precise estimation of the CE for Lithium-ion batteries operating under real-world conditions, which can facilitate the monitoring of battery health and the extension of battery lifespan.

A smaller value of CE indicates greater self-consumption of the battery, but it does not necessarily mean that the battery is in a degraded state. The Battery Degradation Index η value is affected by many factors, including Coulombic Efficiency, but also factors like capacity fade, internal resistance, cycle number, temperature effects, and other aging mechanisms. Therefore, it is necessary to use multiple indicators to evaluate the health of a battery, rather than relying solely on the CE value.

The significance of choosing an optimal averaging period for Coulombic Efficiency (CE) in evaluating battery degradation is underscored in Fig. 4. This figure shows that using a 400-day average for CE results in a nearly flat curve, suggesting that such a lengthy period might be too extensive to detect significant degradation during the initial life cycles of the battery. Conversely, a very brief averaging period may emphasize short-term irregularities that do not necessarily reflect the battery's long-term health trends. Nevertheless, a consistent decline in CE over time is a critical indicator, pointing towards increasing parasitic reactions and progressive battery degradation. This reduction in CE serves as a preliminary alert to declining battery performance. Therefore, further research and experimental work are crucial to ascertain the most effective averaging period that accurately reflects battery health and identifies signs of degradation.

7. Energy measurement correction

The energy involved in charging and discharging is calculated by multiplying voltage, current, and time.

Accurate voltage and current measurements are crucial for analyzing the performance of battery systems, especially smart batteries. Various factors, including sensor limitations, measurement inaccuracies, and environmental conditions, can cause discrepancies between the actual and measured energy values in these systems. Therefore, it is essential to correct these measurements to ensure data precision and reliability. This correction is vital for effective battery management.

In line with the energy conservation principle, a battery's energy inputs and outputs should ideally balance each other. To uphold this principle and tackle discrepancies in measurement, an adaptive error correction method can be implemented. This method involves comparing the actual energy values obtained from charging and discharging cycles against a theoretical ideal of zero deviation. Through this comparison, the system can dynamically adjust its energy calculations.

The use of historical data plays a crucial role in this process, significantly improving the accuracy of battery performance assessments and enhancing the overall functionality of the battery management system. Each new measurement allows the error correction algorithm to update its parameters, continually honing its precision based on the variances between the measured values and the expected zero deviation.

Integrating this error correction method into the broader framework of the battery management system is essential. It ensures a more accurate and reliable evaluation of battery health and performance, thereby maintaining the balance between energy input and output as per the energy conservation law. This approach not only corrects immediate discrepancies but also contributes to the long-term reliability and efficiency of the battery system.

By factoring in the specifics of each battery system, including the unique characteristics of the sensors used, the environmental conditions, and the particular application of the battery, the error correction method can be different tailored to suit each scenario, leading to improved precision in energy measurement, ensure the accuracy and reliability for effective and efficient battery management.

The study utilizes an iterative method to adjust the parameters of the correction function, which substantially improves the precision of daily energy calculations. Incorporating a third-degree polynomial fit counteracts the influence of environmental disturbances. Insights from the application of function 5, as depicted in Fig. 5, demonstrate a notable decrease in daily energy computation errors. This figure illustrates the corrected current values obtained through this method, alongside the calculated daily energy and the associated errors across a 600-day timeline. The figure clearly conveys the increased accuracy attained via daily energy correction.

The results affirm that the refined energy values significantly elevate the precision of daily energy computations, effectively reducing the error accumulation and preventing the energy calculations from straying from their actual values. The graph notably indicates that the error rate maintains relative stability, even amidst data fluctuations, underscoring the strength and efficiency of the correction method applied. For sustained accuracy in daily energy estimations over prolonged periods, it is imperative to routinely revise the correction function parameters. The adaptive method takes into account sensor discrepancies that could alter energy readings and autonomously adapts to minimize computational errors. This process of continual refinement further increases the trustworthiness of the daily energy estimation process. To validate a model against empirical data, especially in the context of energy charge and discharge where actual values are not readily available, presents a unique set of challenges.

8. Enhancing SOC estimation with optimization techniques

This section delves into the application of the statistical method to optimize the charge coefficient (nc) and discharge coefficient (dc) for minimize the MSE in SOC estimation.

Given the unpredictable nature of battery usage, online data frequently show erratic charging and discharging patterns. This complexity is intensified by energy dissipation as heat, which makes precise SOC estimation based solely on data from complete charge–discharge cycles becomes impractical. The nc and dc is a pivotal element in battery SOC estimation, indicative of the efficiency and energy loss during charging and discharging. As noted earlier, SOC is deduced from daily energy inputs and outputs, with nc dc being critical factors in formula (6). Influenced by variables such as temperature, battery age,

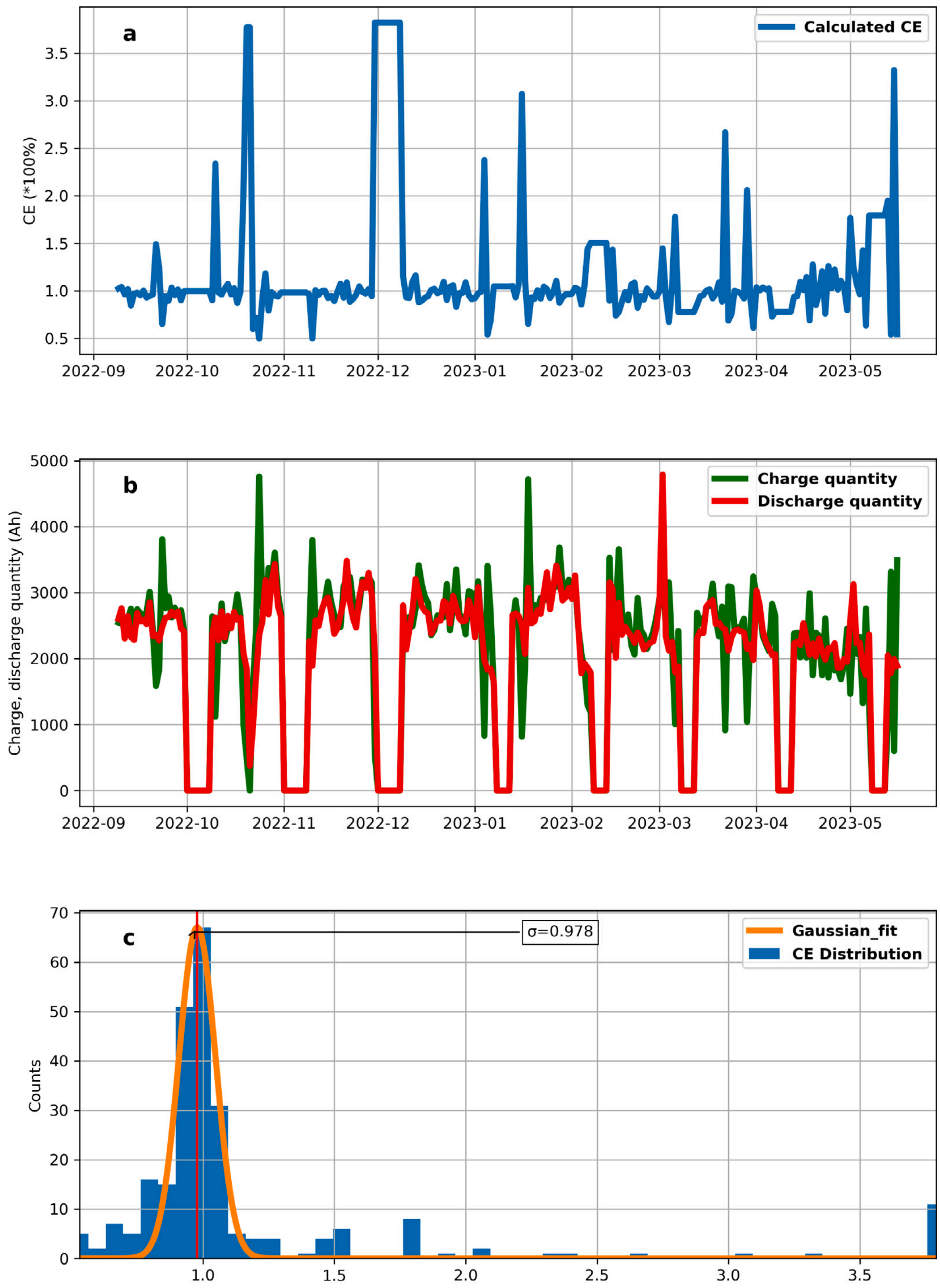

Fig. 3. Analysis of Coulombic Efficiency (CE) Using Gaussian Curve Fitting: (a) Variations in CE attributed to inconsistent charging and discharging cycles. (b) Analysis including real-time data from irregular charging and discharging patterns, encompassing over 400,000 data points. (c) Estimation of CE via Gaussian fitting; the mean value is obtained from the apex of the curve. In accordance with the Central Limit Theorem, the distribution of sample means tends towards a normal distribution as the sample size increases, irrespective of the population distribution's form. Consequently, if large random samples are taken from a population and their means are calculated, those means will typically form a normal distribution centered (σ) around the actual population mean.

and discharge rates, a precise nc and dc value is essential for accurate SOC calculation, as it directly impacts the integration of current over time. A standard SOC estimation model might overlook the dynamic nature of nc, dc, resulting in progressive inaccuracies. The goal of optimizing nc and dc is to minimize MSE as outlined function (7) within the overarching objective function (8). This optimization aims to correct the deviations and significantly improve the accuracy and reliability of the overall model.

Our investigation included a detailed assessment of various optimization algorithms, with a special focus on the 'L-BFGS-B' method, an enhancement of the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm [28]. This sophisticated method is particularly adept at optimizing differentiable functions subject to specific boundaries, making it a key tool in Multivariate Optimization to identify the minimum of a function across numerous variables. It is especially effective in

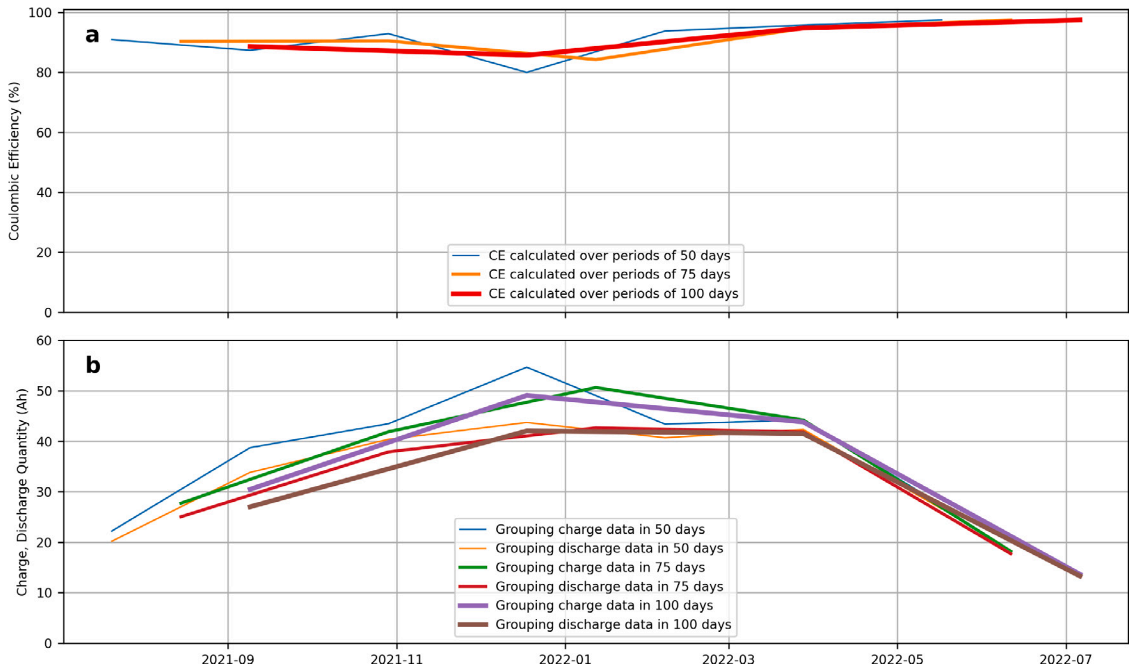

Fig. 4. Coulombic Efficiency (CE) Analysis: Coulombic Efficiency (CE) Analysis is an essential technique for evaluating the performance of batteries over time. This method becomes more effective and accurate when the period for calculating CE is extended. In this analysis, (a) the observation of a nearly flat trend (indicated by the red line) on the graph is encouraging. It signifies that there is minimal early degradation of the battery, as the CE value approaches the ideal mark of 1. (b) The other trend lines represent the average CE values, calculated by grouping the charge and discharge data over intervals of 50, 75, and 100 days. These lines demonstrate the expected fluctuations in energy quantities that occur during typical charging and discharging cycles. Particularly noteworthy is the trend line for the 100-day interval over an extended 400-day period. This line shows a more consistent pattern, indicating that longer periods of data for calculating CE can yield a more reliable gauge of battery efficiency. Such insights are crucial for accurately forecasting the long-term performance and health of batteries. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

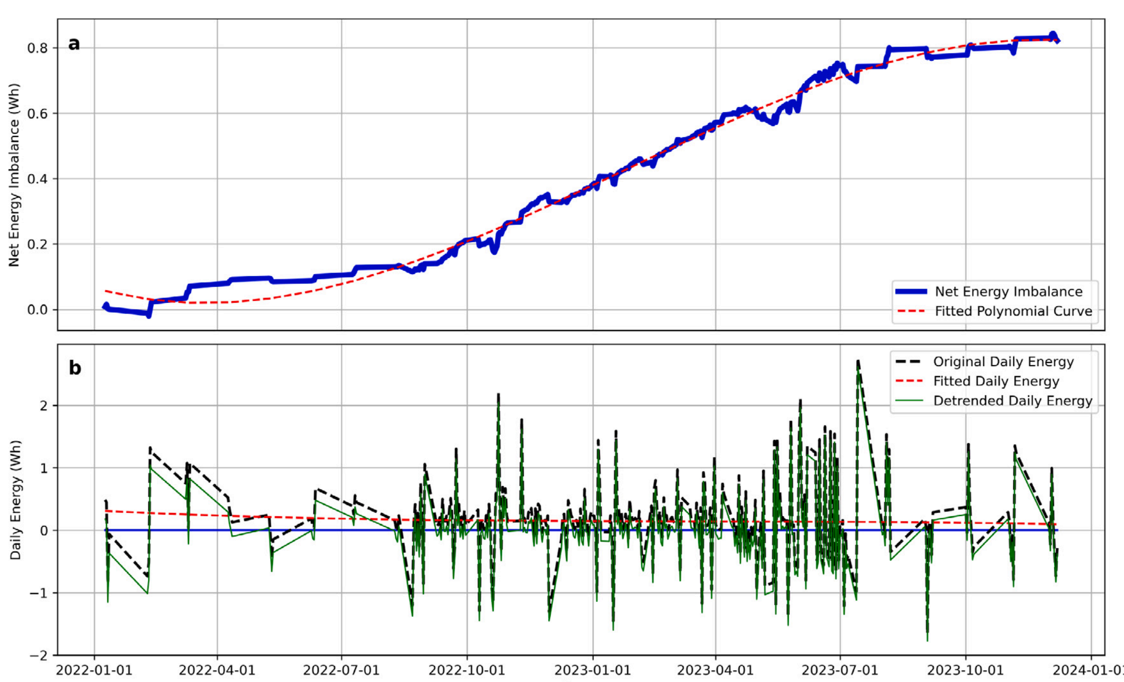

Fig. 5. Analysis of Net Energy Trends and Corrections: (a) Across over 600 days, the chart depicts the cumulative trend in battery energy balance, with subtle fluctuations indicative of systematic drift. The application of a third-degree polynomial fit reveals a well-aligned model, underscoring the critical importance of precise trend analysis for subsequent data utilization. (b) The second graph showcases the application of a third-degree polynomial for trend extraction from daily energy data. The resulting green line demarcates the detrended data, crucial for isolating transient errors and enhancing the accuracy of future estimations. This step is pivotal in refining the data for more granular analytical endeavors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

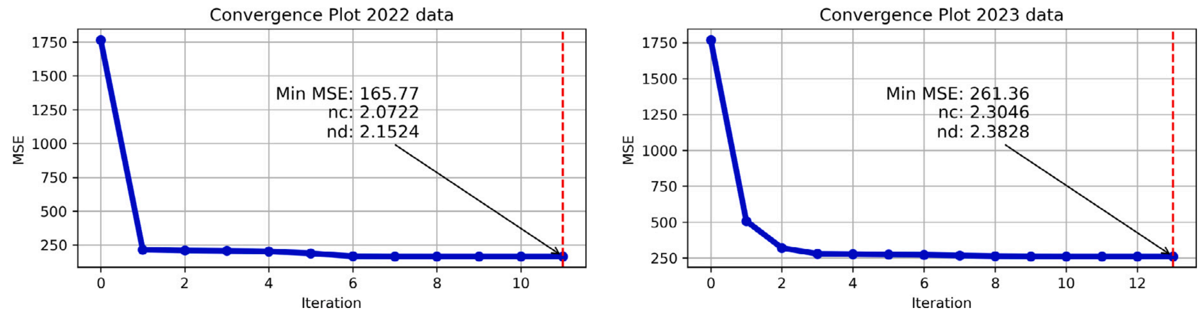

Fig. 6. Optimization Trajectories for SOC Estimation Accuracy: This pair of graphs illustrates the progression of MSE reduction across iterations using an optimization algorithm. The charts compare the minimization process for two distinct datasets from 2022 and 2023, highlighting the algorithm's effectiveness in fine-tuning SOC estimation parameters nc, dc for improved accuracy. Key metrics such as the minimum MSE achieved are annotated, showcasing the optimizer's performance in searching local optimum.

minimizing the MSE, thereby significantly boosting the precision and reliability of SOC estimation models for batteries.

The 'L-BFGS-B' method stands out for its ability to fine-tune critical parameters like the charging efficiency coefficient nc and discharging efficiency coefficient dc, significantly reducing estimation inaccuracies. This optimization, depicted in Fig. 6, demonstrates the method's effectiveness through the convergence of optimal values from two distinct data sets.

Crucially, the 'L-BFGS-B' method performs iterative adjustments of nc and dc to minimize the MSE. During this process, nc is applied during the charging phase, and dc is used during discharging. Notably, this method operates independently of the derivative of MSE with respect to nc or dc, providing an advantage in complex scenarios where an analytical derivation is challenging or impossible.

The 'L-BFGS-B' optimizer functions through an iterative, bounded, and memory-efficient approach. It employs a limited memory strategy, approximating the inverse Hessian matrix using a restricted number of previous updates. This significantly reduces memory usage and computational load, particularly beneficial in scenarios involving a large number of parameters. Each iteration assesses the gradient of the objective function, determines the search direction, and performs a line search to find a suitable step size. The optimizer's handling of bound constraints ensures solutions remain within feasible and logical ranges.

This method's intelligent navigation of the objective function's landscape, making informed adjustments at each step, results in an efficient convergence towards the optimal values. This balance between precision and computational feasibility makes the 'L-BFGS-B' an invaluable tool in complex optimization scenarios, underlining its importance in enhancing SOC estimation accuracy and battery management systems.

In a particular dataset analysis, after 11 iterations of calculation, the values of nc = 2.0722 and nd = 2.1524 were determined. These values correspond to the minimum MSE in estimating the SOC for this dataset.

Fig. 7 illustrates the comparison between SOC estimations from cloud computing and local BMS SOC readings. Formula (6) was utilized in these calculations, with the values of nc and dc being derived from an optimization function. This suggests that the minimal MSE was achieved using an optimization algorithm.

9. Discussion

The research delves into enhancing digital twin using adaptive error correction, statistical analysis, and machine learning, showing improved estimation and battery health monitoring. It addressed traditional BMS limitations, notably historical data handling and error accumulation, by significantly reducing MSE in SOC estimations with adaptive strategies and a novel CE calculation.

Importantly, this research has paved the way for analyzing random data in real-world applications. The data collected in actual scenarios, with their inherent complexity, differ significantly from controlled laboratory data. Consequently, achieving the same level of accuracy as lab-generated results is challenging, underscoring the complexity and unpredictability of real-world data. This aspect highlights the necessity for continuous innovation in battery management systems, particularly given the increasing dependence on renewable energy solutions.

The importance of a flexible objective function that adapts to real-time conditions and various applications, extending our methods' applicability across different battery types and scenarios. This work not only boosts the reliability and efficiency of renewable energy systems but also paves the way for further advancements in BMS technology to meet the growing demand for sophisticated renewable energy solutions.

The research's extension of local BMS functions to include cloud-based remote control is a significant advancement. Allowing users to set up battery operation parameters or strategies remotely not only enhances convenience but also optimizes battery performance in the long run. By facilitating adjustments that can improve economic returns or prolong battery longevity, the system offers a dynamic and responsive approach to battery management.

Incorporating this system into the broader smart grid and renewable energy ecosystem can indeed provide a more comprehensive view of its significance. As part of a larger network, the cloud-based BMS can contribute valuable real-time data and control capabilities. It could interact with other elements of the smart grid to optimize energy distribution and storage, responding to changes in demand or supply quickly. Moreover, its integration with renewable energy sources can help maximize the efficiency and utilization of these resources, promoting a more sustainable energy landscape.

By interacting with and adapting to the broader ecosystem, the system not only improves individual battery performance and longevity but also contributes to the overall efficiency and reliability of the energy grid. This holistic approach emphasizes the potential of the research to play a pivotal role in advancing smart grid technologies and renewable energy management.

10. Conclusion

In summary, this research offers a cutting-edge methodology for enhancing and managing battery performance within the realms of residential solar energy storage and electric vehicles. By employing adaptive error correction techniques, comprehensive statistical analyses, and advanced machine learning algorithms, the study has notably advanced SOC estimation accuracy on the on-line data, thereby addressing the inherent limitations of conventional BMS approaches.

Significantly, the application of an optimization algorithm has effectively reduced the MSE in SOC estimations, reflecting a marked improvement in precision. The study's innovative use of the Central Limit Theorem to derive a unique degradation index signifies efficient

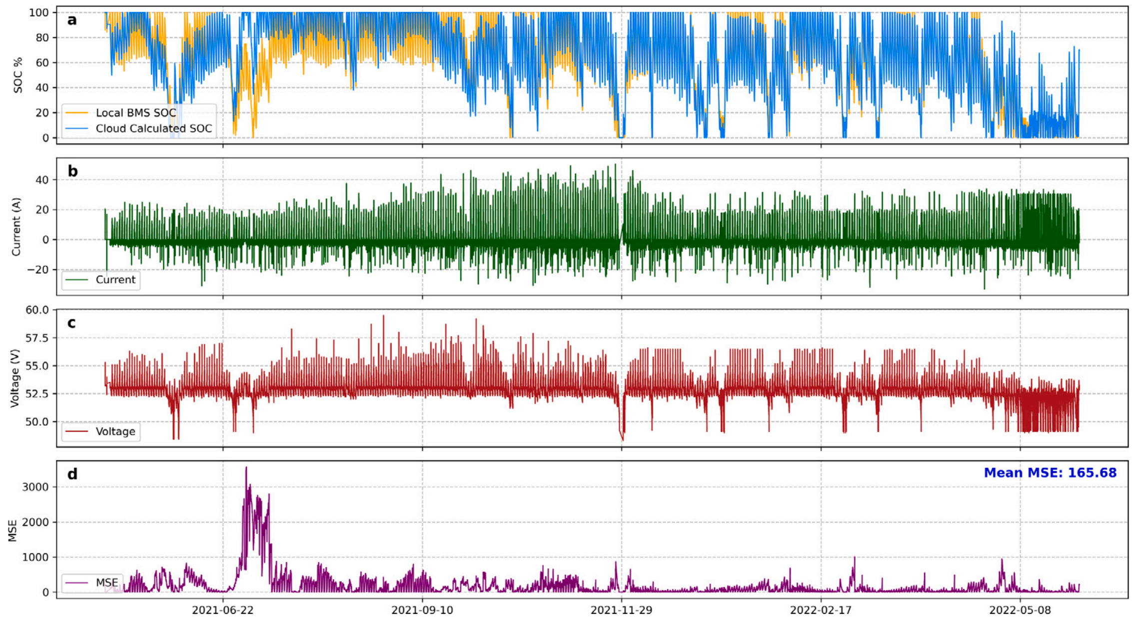

Fig. 7. Enhancements in SOC Estimation Accuracy via MSE Reduction: (a) Comparison between Estimated SOC from Digital Twin and Actual readings from the local BMS. (b)(c) Collected current and voltage data for battery unit across the period 2022–2023. (d) Temporal analysis of the SOC Estimation Error represented as MSE.

battery operation. Moreover, the tailored objective function, which considers various battery parameters, enables dynamic management tailored to specific application demands on real-time conditions.

This investigation underscores the critical need for continual innovation in battery management systems, especially in light of the escalating reliance on renewable energy solutions. The methodologies developed here are versatile, applicable to diverse battery types, and contribute substantially to enhancing the reliability, efficiency, and eco-friendliness of renewable energy storage systems.

The strategies and insights gleaned from this study lay a solid foundation for further exploration into additional factors affecting battery performance, the development of more sophisticated prediction algorithms, and the integration of these methods with intelligent control strategies for optimized functioning. As the future leans increasingly towards a dominant role for renewable energy systems, the significance and potential for further advancements in battery management systems are unmistakably clear.

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CRediT authorship contribution statement

Fang Chen: Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.egyr.2024.03.024.

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