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State of charge prediction for new and second-life lithium-ion batteries based on the random forest machine learning technique

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ABSTRACT

Accurate state of charge (SOC) estimation is a critical requirement for the safe and efficient operation of lithium-ion batteries (LIBs), particularly in second-life battery (SLB) applications where battery ageing, nonlinear degradation, and measurement noise introduce uncertainty. Although numerous SOC estimation techniques have been proposed, reliable prediction for new and second-life batteries under varied operating conditions remains challenging. In this study, a comparative investigation of the conventional coulomb counting (CC) method and a data-driven random forest (RF) model is conducted for SOC prediction in new and second-life LIBs. Experimental data are obtained from Murata US18650VTC5D cells under pulse discharge tests (PDT), constant discharge tests (CDT), and dynamic stress tests (DST) across a wide range of C-rates. PDT is conducted at 0.24 C, CDT at 0.2 C, 0.5 C, 1 C, and 2 C, while DST is performed at C-rates ranging from 0.5 C to 4 C at a controlled ambient temperature of 25 °C. The RF model is trained using voltage, current, and time features and evaluated against CC using MAE, MSE, RMSE, and R^2 metrics. Results show that RF consistently outperforms CC under all conditions, particularly for SLBs, achieving significantly lower errors and R^2 values approaching 0.998. These findings confirm the effectiveness of RF-based SOC estimation for intelligent battery management systems (BMS).

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1. INTRODUCTION

Lithium-ion batteries (LIBs) are the support of modern energy storage systems, powering electric vehicles (EVs), renewable energy integration, and portable electronics due to their high energy density and long cycle life. With the rapid growth of EV adoption, sustainability challenges have emerged in managing battery lifecycles. When the state of health (SOH) of EV batteries falls below 80% of nominal capacity, they are retired from first-life use but remain suitable for second-life applications such as stationary storage. These second-life batteries (SLBs) show significant heterogeneity in capacity, internal resistance, and ageing behavior making their management more complex than new cells [1]. Second-life lithium-ion batteries, typically retired from electric vehicles (EVs) at approximately 80% of their original capacity [2], [3]. The cells comprising the second-life battery pack show substantial heterogeneity, characterized by variations in capacity, density, and degrees of ageing [4].

A battery management system (BMS) is essential for optimizing performance and extending the lifespan of rechargeable batteries. Pattern testing validated the system's capability to monitor the battery, maintain cell balance, and provide protection, highlighting its potential to enhance battery performance and durability. A battery management system is essential for optimizing performance and extending the lifespan of rechargeable batteries [5]. The implementation of an advanced battery management system is imperative for the effective regulation of this combination. Moreover, the system must display adaptability, given that each new integrated battery is characterized by unique and distinct properties [6].

The focus is on estimating both the state of charge and the state of health [7]. Estimating the state of charge is a critical function of a battery management system, with most existing approaches predominantly based on model-driven techniques [8]. Moreover, the state of charge represents a critical parameter that delivers essential insights for diverse applications, including the indication of remaining battery energy [9].

Coulomb counting (CC) estimates the state of charge by integrating the battery current over time; even minor errors inevitably accumulate, producing substantial drift under dynamic operating conditions. Although numerous refinements have been proposed to mitigate this drawback, conventional current-based algorithms remain constrained by heavy computational demands and pronounced sensitivity to measurement noise, limiting their reliability in real-world applications [10]. Electric vehicle (EV) lithium-ion batteries are optimized by preventing overcharging and over-discharging while ensuring proper cell balancing. Accurate estimation of the state of charge is critical for battery management systems, ensuring safety, efficiency, and extended service life. However, state of charge prediction is inherently difficult due to nonlinear electrochemical dynamics, measurement noise, and degradation effects. Traditional methods, such as coulomb counting, suffer from drift and error accumulation, while aged batteries introduce further variability that complicates reliable state of charge estimation [11].

Among various influencing factors, measurement noise can significantly increase the error in coulomb counting. To improve accuracy, Kalman filter (KF) based methods are widely employed for state of charge estimation. Extensions such as the extended Kalman filter (EKF) and unscented Kalman filter (UKF) have been developed to address the nonlinear behavior of lithium-ion batteries (LIBs), overcoming the limitation of the original KF to linear systems. The EKF, in particular, applies a recursive framework that reduces estimation error through a linearized Taylor series expansion [12], [13].

While both variants of the Kalman filter continue to be effective in reducing noise-related errors in state-of-charge estimation, the emergence of machine learning has become increasingly significant. By harnessing large datasets and capturing complex nonlinear behaviors, data-driven models offer superior accuracy and adaptability compared to traditional approaches. Consequently, a large amount of research is devoted to applying machine-learning methods for state-of-charge estimation in lithium-ion batteries [14]. Conventional state of charge estimation techniques include coulomb counting, open-circuit voltage (OCV) methods, and model-based approaches such as Kalman filters KF, EKF, and UKF. These methods provide useful insights but are limited by sensitivity to noise, dependence on precise battery models, and reduced accuracy under dynamic operating conditions. More recently, machine learning (ML) approaches, such as support vector regression (SVR), neural networks, and random forest (RF) have demonstrated strong performance by capturing nonlinear relationships and leveraging large datasets. Comparative studies show ML methods can reduce state-of-charge prediction errors below 1%, outperforming traditional techniques [15].

The adoption of machine learning techniques for state-of-charge estimation offers substantial improvements in both accuracy and adaptability compared to traditional model-based methods. Data-driven approaches such as support vector regression (SVR), linear regression, and random forest have shown strong performance across a wide range of operating scenarios, capturing nonlinear relationships that are often difficult to model analytically. However, these methods typically require access to large and diverse datasets to achieve reliable training and generalization, which remains a key challenge in practical applications [16]. Over time, a range of machine learning (ML) and deep learning (DL) techniques have been developed to improve the prediction of battery characteristics across diverse loading conditions [17]. Despite these advances, most state-of-charge prediction studies focus exclusively on new batteries. Limited research addresses second-life batteries, which present unique challenges due to ageing variability. Furthermore, few studies systematically compare traditional and ML-based state of charge estimation methods across both new and second-life cells under varied discharge rates and dynamic stress conditions [18], [19].

This study develops and validates a random forest machine learning framework for state of charge prediction in both new and second-life lithium-ion batteries. Using experimental datasets from pulse discharge tests (PDT), constant discharge tests (CDT), and dynamic stress tests (DST) across multiple C-rates, the random forest model is benchmarked against the conventional coulomb counting method. The analysis demonstrates RF's superior accuracy, robustness to noise, and adaptability to ageing effects, providing a comprehensive evaluation across diverse operating scenarios. By addressing state-of-charge prediction for second-life batteries, this study advances intelligent battery management system design and supports sustainable battery reuse. The findings contribute to extending battery lifecycles, enabling reliable integration of repurposed cells into energy storage systems and promoting circular economy practices in EV and renewable energy sectors.

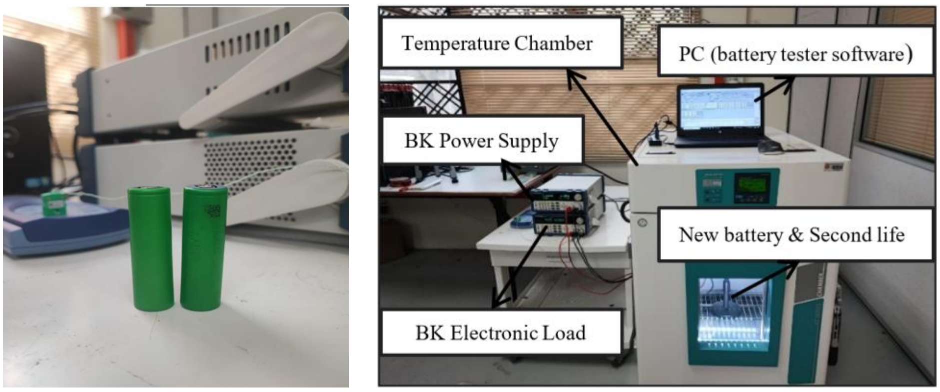
2. METHODOLOGY

2.1. Experimental setup

Various fast-charging methodologies are implemented to enhance the efficiency and reliability of lithium-ion batteries in electric vehicles. A detailed overview of these techniques, including constant current (CC) charge, discharge, and pulse charging methods, is provided, emphasizing their electrochemical principles, charging dynamics, and influence on battery temperature, internal resistance, and degradation behavior [20]. New and second-life lithium-ion batteries, model US18650VTC5D, manufactured by Murata, were used for the test. This battery has a nominal voltage of 3.6 V and a capacity of 2700 mAh. The specifications of the battery are summarized in Table 1. Figure 1(a) illustrates the physical appearance of the lithium-ion battery model US18650VTC5D, while Figure 1(b) presents the experimental setup used for testing both new and second-life batteries. New and second-life lithium-ion batteries extracted from handheld vacuum cleaners were selected for this study. A DC electronic load model 8601, single channel, 120 V/60 A/250 W was used to discharge the battery at a constant current, and a multi-range DC power supply model 9201, single channel, 60 V/10 A/200 W was used to charge it. An environmental chamber model JH-KE was utilized to regulate and monitor the ambient temperature during testing, enabling precise control of the operating temperature over a range of -20 °C to 100 °C. All experimental data were acquired using battery tester software and subsequently stored in Microsoft Excel for data management, analysis, and post-processing.

Table 1. Specification of lithium-ion battery

Battery type	Lithium-ion Murata	Battery type	Lithium-ion Murata
Model	US18650VTC5D	Discharging cut-off voltage	2.5 V
Nominal capacity	2800 mAh	Energy density	567 Wh/l
Nominal voltage	3.6 V	Charging method	Constant current (CC)
Maximum charging voltage	4.2 V		Constant voltage (CV)
		Weight	46.7 g



(a) (b)

Figure 1. The physical appearance of (a) lithium-ion battery model US18650VTC5D and (b) experimental setup for new cells and SLB test

2.2. State of charge estimation methods

The estimation of a battery's state of charge combines conventional techniques with modern machine learning approaches. The process starts with capturing detailed load profile data, which is carefully preprocessed to ensure accuracy and reliability. Conventional methods provide proven and computationally efficient estimates, while machine learning algorithms deliver enhanced adaptability and precision by learning from complex patterns in the data. By evaluating both approaches, this study highlights the strengths and limitations of each, showing how machine learning can complement traditional methods to achieve a more reliable and accurate state of charge prediction [21]. In addition, incorporating a discharge model aligned with C-rate conditions can support the repurposing of batteries for second-life applications. The state of charge is mathematically expressed as (1).

$$SOC = \frac{Q_A}{Q_B} \times 100 \tag{1}$$

Where Q_A represents the available capacity relative to the nominal capacity Q_B specified by the manufacturer. The degradation of Li-ion batteries is evaluated in terms of capacity loss over their operational lifetime [17].

The state of charge is evaluated through traditional and machine learning approaches. As illustrated in the state of charge estimation workflow shown in Figure 2, the framework of this study starts with the experimental data collection of the lithium-ion battery model US18650VTC5D, using constant discharge (CDT), pulse discharge (PDT), and dynamic stress tests (DST) to capture both steady-state and dynamic battery behaviors. The collected data are then preprocessed to improve quality and consistency before being used for state-of-charge (SOC) estimation. Two SOC estimation approaches are investigated: a traditional method based on coulomb counting, which serves as a baseline, and a data-driven approach using machine learning. In the data-driven method, the dataset is split into three parts: training, validation, and testing. A random forest model is then created and trained to learn how battery measurements and SOC are related in a nonlinear way. The performance of both methods is evaluated and compared using standard error metrics, including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and the coefficient of determination (R^2), leading to the final SOC prediction results and overall assessment of model effectiveness. This property is particularly important for second-life batteries, where ageing variability, capacity heterogeneity, and increased internal resistance introduce additional uncertainty. Finally, the predicted state of charge results are analyzed and compared to assess model performance, highlighting the improved precision and robustness achieved by machine learning relative to traditional methods, while Table 2 summarizes the operating parameters of new and second-life lithium-ion cells, including the voltage range, applied C-rates, and test temperatures for the CDT, PDT, and DST profiles.

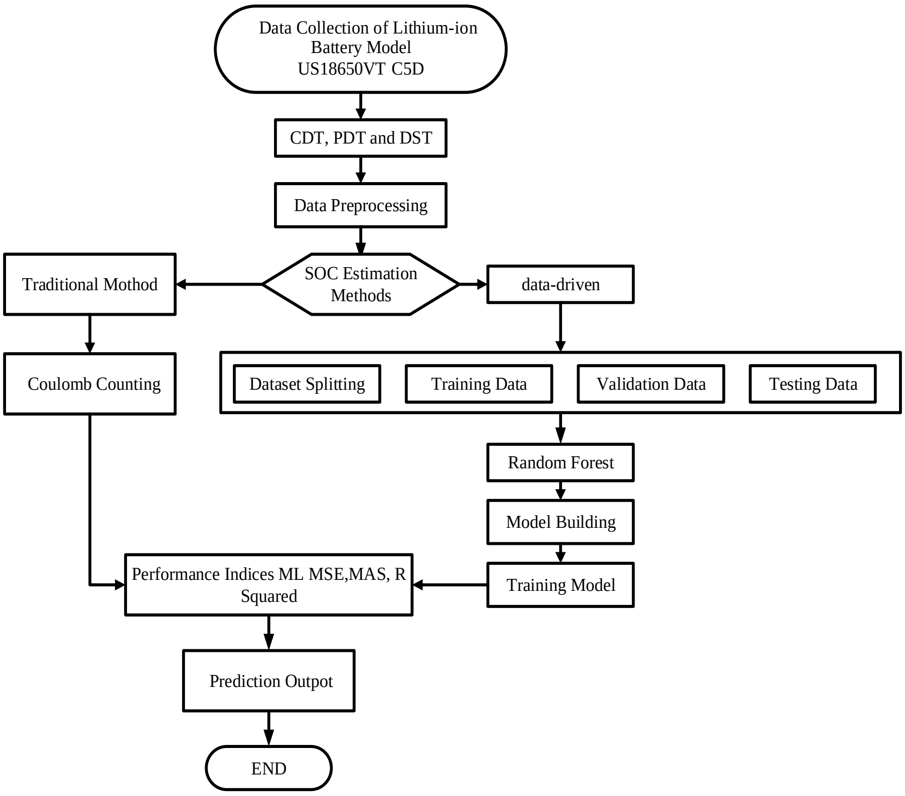


Figure 2. An overview of the framework used in this study

Table 2. Parameters of the new cell and the second life

Test condition	Parameters	Value
CDT	Voltage (V)	2.5 - 4.2 V
	C-rates	0.2 C, 0.5 C, 1 C, 2 C
	Temperature	25 °C
PDT	Current	0.24 C
	Temperature	25 °C
DST	C-rates	0.5 C, 1 C, 2 C, 2.5 C, 4 C
	Temperature	25 °C

2.2.1. Coulomb counting method

Coulomb counting estimates the state of charge by continuously integrating the battery’s current over time. Because cells must operate within safe charge levels during charging, discharging, and storage, the state of charge cannot be directly measured but is instead inferred from measurable parameters. This indirect approach, however, often introduces errors that reduce the accuracy of state-of-charge estimation and may limit the full use of the battery’s capacity. Rather than providing an absolute value, coulomb counting tracks relative changes in state of charge by calculating the net ampere-hours (Ah) supplied to or withdrawn from the battery over specific time intervals. The method relies on a straightforward relationship expressed by (2).

$$\mathrm{SOC}(t) = \mathrm{SOC}(0) \pm \frac{1}{C_{\mathrm{nom}}} \int_0^t I(\tau) d\tau \tag{2}$$

The state of charge SOC(t), is calculated relative to the previous SOC, SOC(0), with the nominal capacity (C_{nom}) expressed in ampere-hours. The current’s sign indicates charging (+) or discharging (–). Accurate state of charge estimation requires precise knowledge of the initial state of charge, often set by fully charging the cell to its maximum allowable voltage to provide a calibration reference. However, coulomb counting remains vulnerable to errors caused by inaccurate initial state of charge, limited current measurement accuracy, integration drift, variations in actual battery capacity, and time synchronization issues [21].

2.2.2. Battery tests

The proposed methodology introduces a two-layer machine learning framework for the autonomous estimation of the state of charge in second-life batteries (SLBs), independent of their capacity or ageing state. In the first layer, a random forest model is developed and trained to characterize based on the heterogeneous features and attributes of second-life batteries. Subsequently, upon identifying the voltage curve, a second random forest model is trained for each curve to provide an accurate state of charge estimation [1]. Three types of battery testing were conducted in this study: pulse discharge test, constant discharge test, and dynamic stress test to evaluate the performance of new and second-life lithium-ion cells. The cells were charged at rates of 0.2 C to 2 C up to a cutoff voltage of 4.2 V and discharged to 2.5 V, while dynamic stress tests were performed at 0.5 C to 4 C under a controlled ambient temperature of 25 °C. All tests employed a BK Precision 8601 electronic load and a BK Precision 9201 programmable power supply, with voltage and current recorded at 1 Hz using battery tester software. Temperature was monitored with a K-type thermocouple, and all time, voltage, current, and temperature data were logged and subsequently saved in Microsoft Excel for storage, analysis, and further post-processing. The dynamic stress test procedure was modified to ensure stable current regulation and reduce battery degradation by extending current pulse durations, excluding deep discharge, and limiting the maximum discharge current from 10.8 A to -5.4 A C-rate. A reference current of 2.7 A (1C), equivalent to 25% of discharge power, was used, where negative values indicate charging and positive values indicate discharging. The revised dynamic stress test profile was applied consistently to new and second-life batteries for comparative evaluation.

2.2.3. Machine learning (ML)

The estimation of the state of charge in lithium-ion batteries has been greatly improved through supervised learning techniques. This improvement stems from their capability to capture the battery's inherent nonlinear dynamics and deliver highly accurate state of charge predictions under diverse operating conditions [22], [23]. The state of charge is estimated via a coulomb counting method, and the corresponding model is implemented and validated in MATLAB/Simulink using extensive datasets obtained from pulse discharge test, constant discharge test, and dynamic stress tests for new and second-life batteries.

- Random forest regression method

A two-layer machine learning framework for the autonomous estimation of the state of charge in second-life batteries, independent of their age or remaining capacity. The first layer focuses on developing and training a random forest model to predict the voltage curve using diverse features and characteristics of SLBs. Recently, machine learning techniques, particularly the random forest algorithm, have emerged as powerful tools for state of charge estimation [24]. In mathematical terms, the prediction produced by the random forest model is given by (3).

$$\hat{P}(x) = \frac{1}{S}\sum_{n=1}^{S} y_t \quad (3)$$

The (3) shows that the final prediction $\hat{P}(x)$ of a random forest is the average of the predictions made by all the individual decision trees in the ensemble. S is the total number of trees, and $y_t(x)$ is the state of charge value predicted by the t^{th} tree for the input x is time, voltage, current, and temperature. Random Forest was selected for state of charge estimation due to its strong capability to model complex nonlinear relationships between battery input variables and state of charge without requiring a clear electrochemical model. Unlike conventional methods, random forest employs an ensemble of decision trees trained on randomly sampled data and feature subsets, which enhances generalization performance and reduces sensitivity to measurement noise. This property is particularly important for second-life batteries, where ageing-related variability, capacity heterogeneity, and increased internal resistance introduce significant uncertainty. Furthermore, random forest is less prone to overfitting compared with single-tree or shallow learning models and shows stable performance under dynamic operating conditions and varied C-rates. These characteristics make random forest well-suited for robust state-of-charge estimation in both new and second-life lithium-ion batteries. The performance of the random forest model in predicting the state of charge is evaluated using key metrics, including mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2). These indicators collectively assess the model’s accuracy and effectiveness in estimating the state of charge of the battery.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \quad (4)$$

$$\text{RMSE} = \sqrt[i=1]{\text{MSE}} \quad (5)$$

$$\text{MAE} = \frac{1}{n}\sum^{n}|e_i| \quad (6)$$

$$R^2 = 1 - \frac{\sum_i^{i=1} e_i^2}{\sum_i (y_i - \bar{y})^2}, \text{ with } \bar{y} = \frac{1}{n}\sum_i y_i. \quad (7)$$

3. RESULTS AND DISCUSSION

3.1. Experimental results and performance comparison

To clearly illustrate the performance differences between coulomb counting and random forest, side-by-side comparison plots are presented for voltage, state of charge profiles, and error metrics under identical operating conditions. This presentation enables a direct visual assessment of estimation accuracy and robustness across pulse discharge test, constant discharge test, and dynamic stress test profiles for both new and second-life batteries.

3.1.1. Constant discharge test

Figure 3 presents the voltage and time behavior of a new and second-life lithium-ion battery during charging and discharging at 25 °C. In Figure 3(a), charging profiles at 0.2 C to 2 C show smooth voltage increases. However, charging for the second-life cells was limited to 4.0 V to prevent lithium plating, extreme overpotential, and accelerated ageing typical above this voltage. In Figure 3(b), discharge responses recorded at the same C-rates show that the cutoff voltage for second-life cells was set to 2.7 V to avoid over-discharge, copper dissolution, and thermal instability. Across all current rates, new cells withstand higher voltages and longer charge-discharge durations, demonstrating lower internal resistance and superior charge efficiency, whereas second-life cells reveal greater polarization and capacity fade caused by electrode degradation and increased impedance.

3.1.2. Pulse discharge test

After charging, new and second-life lithium-ion batteries were rested before pulse discharge testing. The new cell was charged to 100% SOC, while the second-life cell was limited to 80% SOC to prevent lithium plating, overpotential, and additional ageing, consistent with safe operating limits for aged cells. Each was discharged at 0.24 C (0.648 A) for 6 minutes, followed by a 12-minute rest to allow voltage relaxation [25]. This sequence was repeated until the new cell reached its 2.5 V cutoff and the second-life cell 2.7 V.

Figures 4 and 5 show the corresponding voltage and current pulse profiles, showing that despite identical current pulses, the second-life cell displays lower voltages, greater polarization, and slower recovery. Although the initial SOC change, the comparison focuses on voltage response behavior and internal resistance effects under identical load conditions.

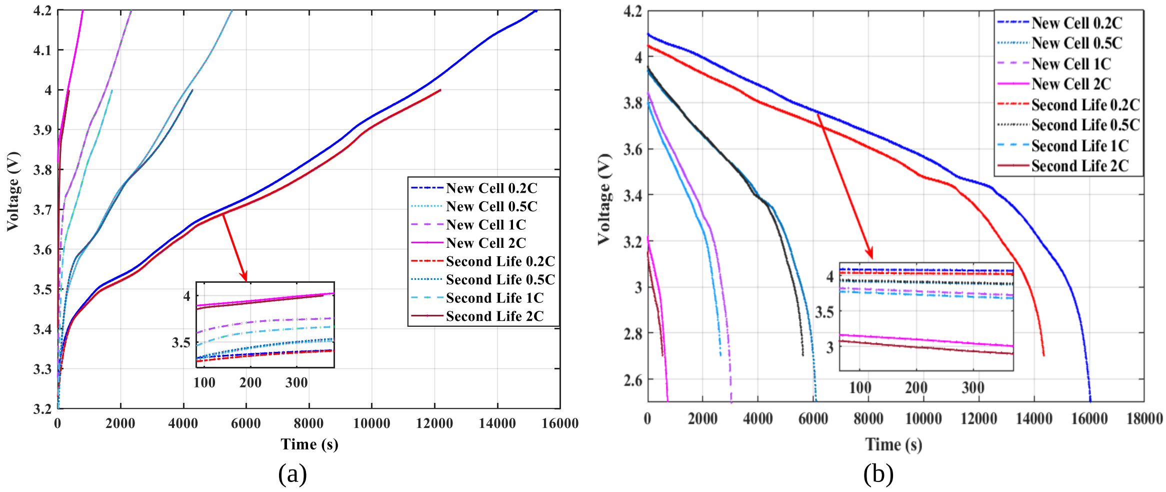


Figure 3. The voltage signals and time at (a) four charge currents for new and second-life cells and (b) four discharge currents for new and second-life cells at 25 °C

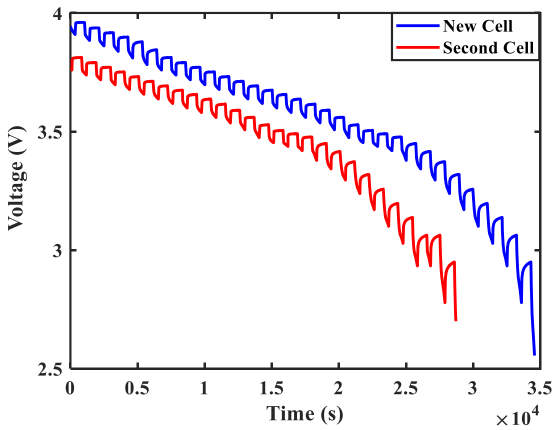


Figure 4. Voltage pulse discharge test of new and second-life lithium-ion batteries

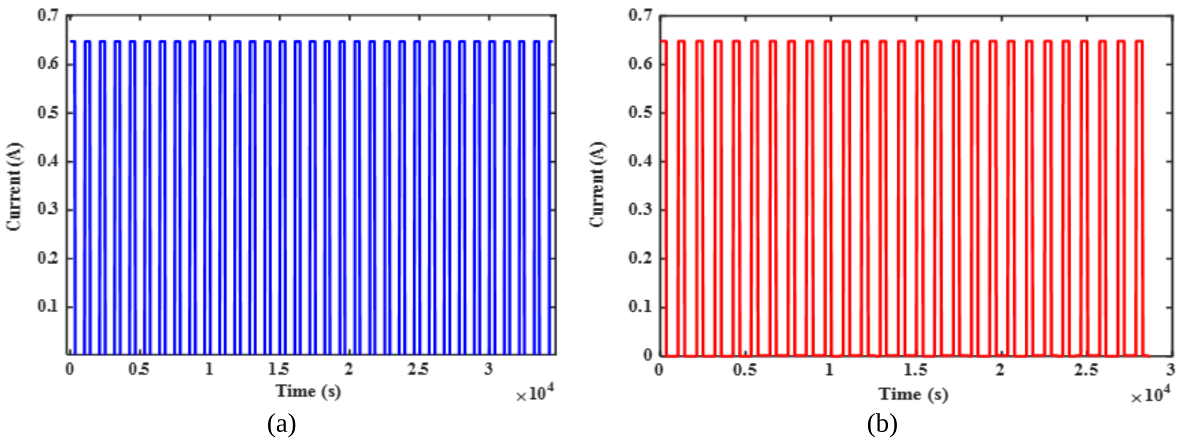
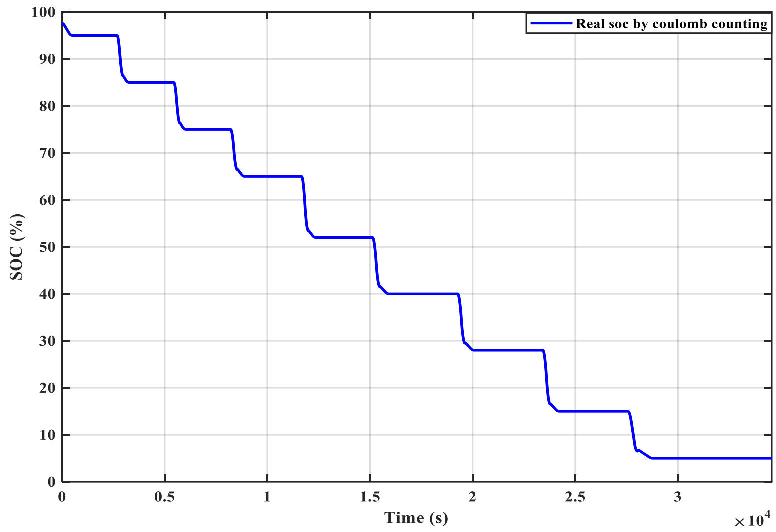
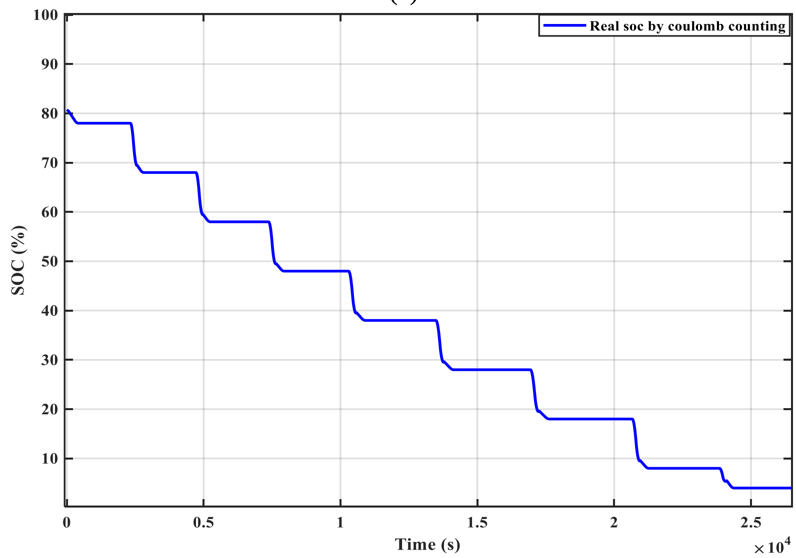


Figure 5. Current pulse discharge tests for (a) a new lithium-ion cell and (b) a second-life lithium-ion battery

Figures 6 and 7 illustrate the state of charge behavior of lithium-ion batteries for new and second-life lithium-ion batteries under the pulse discharge test. Figure 6 shows the state of charge profiles estimated using the coulomb counting method. In both cases, the state of charge decreases stepwise over time, reflecting sequential discharge stages under constant current conditions. The new cell shows a smoother and more linear decline, indicating higher efficiency and lower internal losses, whereas the second-life cell shows slightly compressed discharge durations, revealing reduced usable capacity due to aging. Figure 7 presents a comparative analysis between the real and predicted state of charge profiles obtained using the random forest estimation model, demonstrating strong alignment between the two curves and confirming the high accuracy of the random forest method. The zoomed-in sections further highlight the model's ability to capture stepwise discharge transitions and dynamic variations precisely. Collectively, these figures validate the reliability of the random forest approach in accurately estimating the state of charge for new and second-life batteries with minimal error. Figure 8 compares the performance of the random forest and coulomb counting methods for state-of-charge prediction in Figure 8(a) new and Figure 8(b) second-life lithium-ion batteries. The random forest method shows lower MAE, MSE, and RMSE values than the coulomb counting method. This indicates higher prediction accuracy and smaller estimation errors. The R^2 value of the random forest model is close to one, confirming strong agreement with the actual SOC. In contrast, the coulomb counting method shows higher errors and lower R^2 values. Overall, the random forest model provides a more reliable state of charge estimation for new and second-life batteries.



(a)



(b)

Figure 6. SOC by coulomb counting for (a) new and (b) second-life lithium-ion batteries

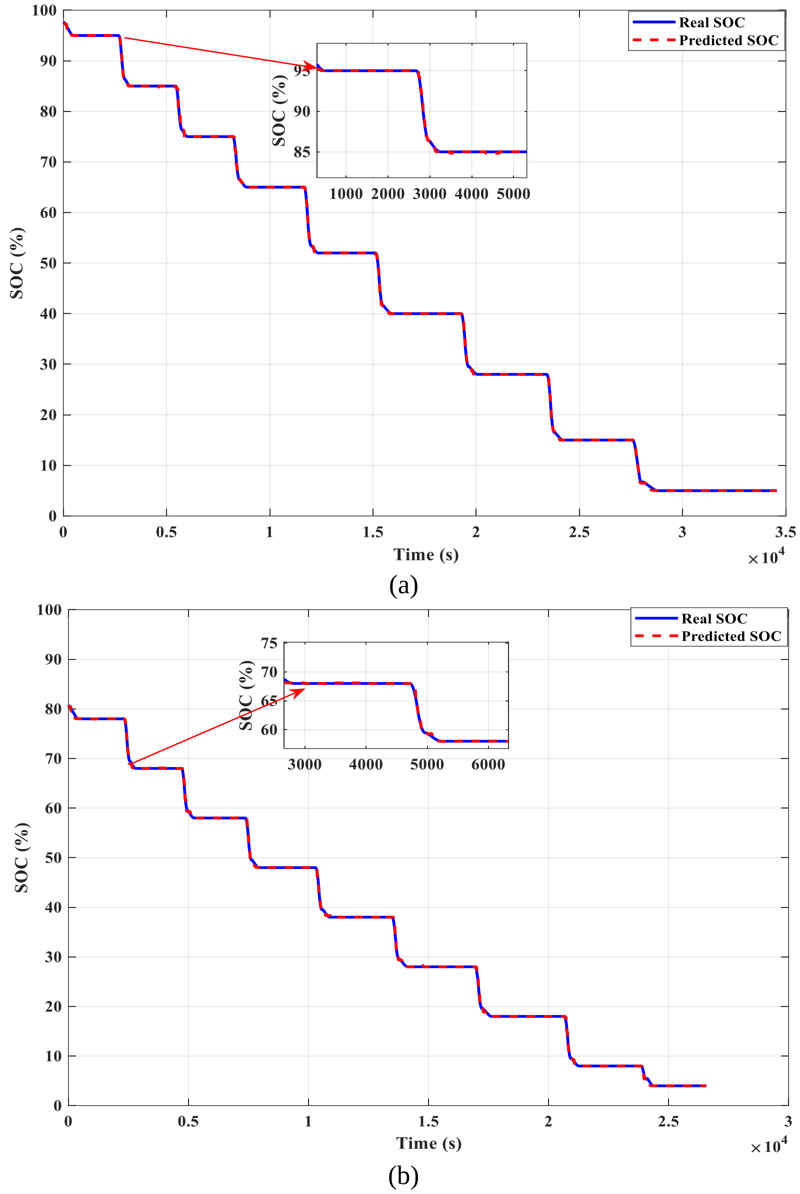


Figure 7. Comparison of real and predicted state of charge for (a) new and (b) second-life lithium-ion batteries using a random forest model

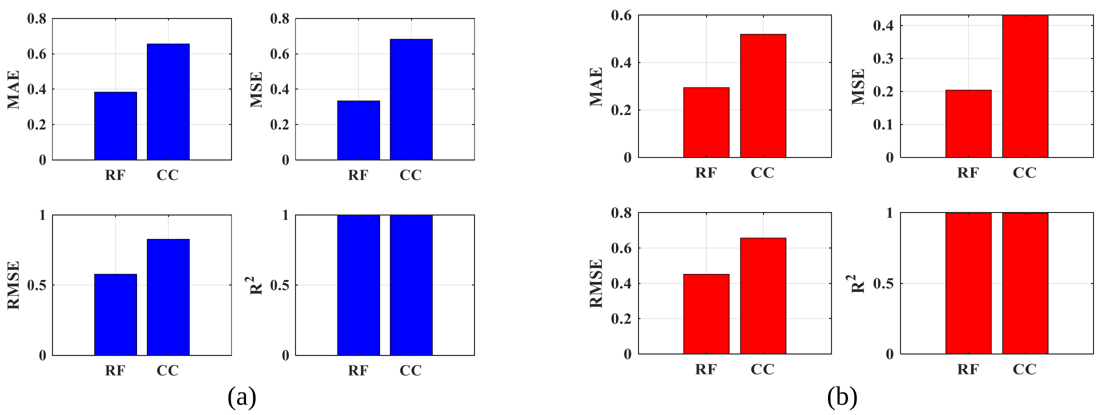


Figure 8. The performance metrics of PDT are evaluated using both the random forest and coulomb counting methods for state of charge prediction in (a) new and (b) second-life lithium-ion batteries

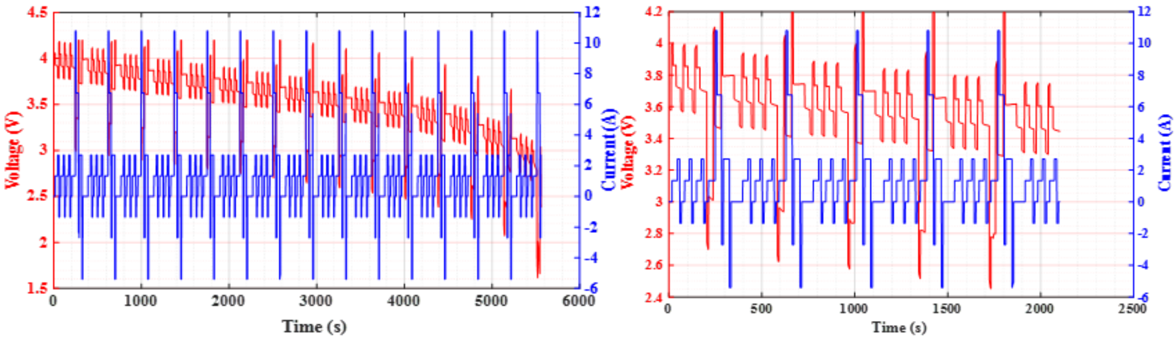
Table 3 shows the comparison of the SOC prediction performance of coulomb counting (CC) and random forest (RF) under pulse discharge test (PDT) conditions at 25 °C for both new and second-life lithium-ion cells. While both methods display high accuracy ($R^2 > 0.997$), RF consistently outperforms CC. For the new cell, RF reduces MAE from 0.6555% to 0.383% and RMSE from 0.826% to 0.5773%, with a higher R^2 of 0.9988. Similarly, for the second-life cell, MAE decreases from 0.5193% to 0.2943% and RMSE from 0.6567% to 0.4515%, with R^2 improving to 0.9987. These results demonstrate that RF provides superior accuracy and robustness by effectively capturing nonlinear SOC dynamics and reducing the cumulative integration errors associated with CC, particularly under aging conditions.

Table 3. Error metrics analysis of state of charge prediction between the coulomb counting and random forest for pulse discharge test

Temperature 25 °C							
Type	Methods	Initial SOC (%)	Working condition	MAE (%)	MSE (%)	RMSE (%)	R^2
New cell	CC	100	PDT	0.6555	0.6823	0.826	0.9975
	RF	100	PDT	0.383	0.3333	0.5773	0.9988
Second life	CC	80	PDT	0.5193	0.4312	0.6567	0.9974
	RF	80	PDT	0.2943	0.2039	0.4515	0.9987

3.1.3. Dynamic stress tests

Although these techniques have demonstrated effectiveness in state-of-charge estimation, they frequently require extensive historical datasets for individual batteries or operate under the assumption of uniform aging behavior. Such dependencies constrain their applicability to second-life batteries (SLBs), which are characterized by substantial variability. Conversely, random forest represents a well-established machine learning methodology [1] This dynamic driving profile is widely employed to evaluate vehicle performance and to validate model accuracy or algorithm effectiveness [26]. Figure 9 illustrates the dynamic stress test voltage and current profiles of a new and second-life lithium-ion battery at 25 °C. In this test, both cells were subjected to identical current pulse sequences alternating between discharge and charge phases. Each discharge pulse lasted approximately 60 s, followed by a 30 s rest and a 20 s charge recovery period to simulate real-world fluctuating loads. The dynamic stress test protocol was modified to ensure stable current regulation and minimize degradation by extending pulse durations, omitting deep discharge segments, and reducing the maximum discharge current from 10.8 A to -5.4 A. A reference current of 2.7 A (1C), equivalent to 25 % of the rated discharge power, was used, where negative currents denote charging and positive currents indicate discharging. This reviewed profile was consistently applied to new and second-life batteries for comparative analysis. The new cell showed smooth, stable voltage transitions with a gradual decline from 4.2 V to 2.4 V, signifying low internal resistance and strong electrochemical stability, while the second-life cell showed larger voltage drops and slower recoveries, reflecting polarization effects and reduced capacity due to aging. These characteristics suggest that the second-life cell is unsuitable for high discharge current rates and demanding applications such as electric vehicles (EVs).

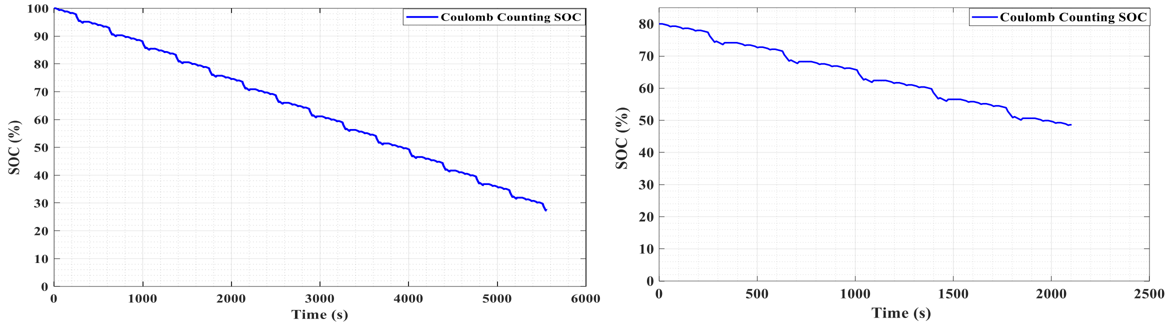


(a) (b)

Figure 9. DST voltage and current profile at 25 °C for (a) new and (b) second-life batteries

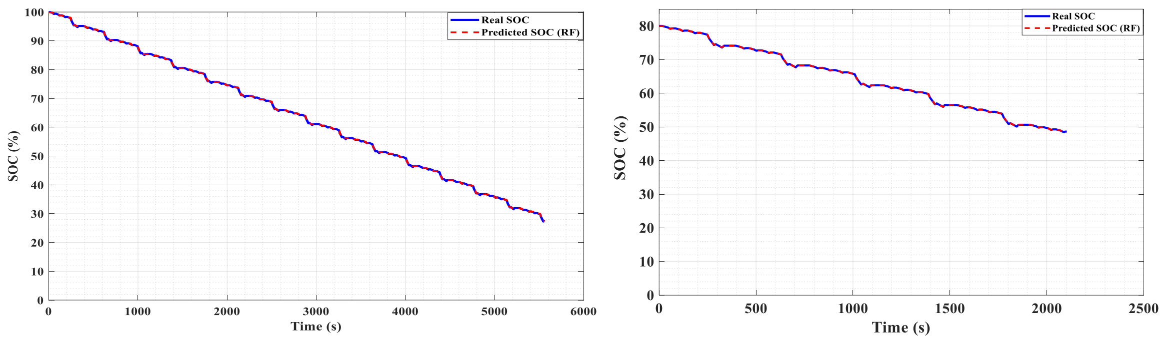
Figure 10 illustrates coulomb counting state-of-charge measurements during discharge testing for new versus second-life lithium-ion batteries. Figure 10(a) shows a new battery starting at 100% SOC and discharging steadily to approximately 30%, demonstrating the full capacity and extended discharge duration typical of new batteries. In contrast, Figure 10(b) shows a second-life battery that begins at 80% SOC and drops to about 50%, reflecting the reduced capacity and shorter operational time characteristic of batteries that have undergone previous use cycles. This behavior can be attributed to the dynamic stress test profile being originally developed for new batteries, wherein the elevated charge-discharge current rates are not fully compatible with the electrochemical and performance characteristics of second-life batteries. The coulomb counting method tracks state of charge by integrating the current flow over time, and these results clearly demonstrate how second-life batteries display diminished energy storage capacity and faster discharge rates compared to new batteries.

Figure 11 shows the comparison of the measured SOC with the random forest (RF) predicted SOC for Figure 11(a) the new and Figure 11(b) the second-life lithium-ion batteries under dynamic stress test (DST) conditions. In both cases, the RF model closely tracks SOC throughout the discharge process, demonstrating strong performance under dynamic current variations. For the new battery, the predicted curve nearly overlaps with the real SOC, indicating accurate modelling of nonlinear battery behavior. For the second life battery, although minor fluctuations appear due to ageing-related effects, the overall agreement remains high. These results confirm the robustness and generalization capability of the RF-based SOC estimator for both new and second-life cells under realistic operating conditions.



(a) (b)

Figure 10. Coulomb counting for (a) new and (b) second-life lithium-ion batteries during dynamic stress test



(a) (b)

Figure 11. Real state of charge and random forest predicted for (a) new and (b) second-life lithium-ion batteries during dynamic stress test

Figure 12 shows the performance metrics mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and the coefficient of determination (R^2) for the random forest and Coulomb counting methods in predicting the state of charge of new and second-life lithium-ion batteries. The results show that the random forest model achieves significantly lower MAE, MSE, and RMSE values than the coulomb counting method, indicating superior prediction accuracy and reduced estimation error. Additionally, both methods show comparable R^2 values, confirming a strong correlation between predicted and actual SOC. Overall, the random forest algorithm demonstrates higher robustness and reliability in capturing the nonlinear state of charge behavior, while the coulomb counting method, though simpler, is more prone to cumulative errors and less effective for aged battery cells.

Table 4 presents a comparative evaluation of SOC prediction accuracy using coulomb counting and random forest methods under dynamic stress test (DST) conditions at 25°C for both new and second-life lithium-ion cells. Under dynamic loading, the error values are generally higher than those observed in pulse discharge conditions, reflecting the increased complexity of rapidly varying current profiles. For the new cell, RF significantly improves prediction accuracy compared to CC, reducing the MAE from 1.0084% to 0.6000% and the RMSE from 1.2708% to 0.9073%. The coefficient of determination also increases from 0.9975 (CC) to 0.9987 (RF), indicating better agreement with the reference SOC. A similar improvement is observed for the second-life battery, where RF lowers the MAE from 0.8243% to 0.4125% and the RMSE from 1.0423% to 0.6324%, while achieving a higher R^2 value of 0.9990. Overall, the results demonstrate that the RF model provides superior robustness and accuracy under highly dynamic operating conditions, effectively mitigating cumulative integration errors inherent in CC and capturing nonlinear ageing-related effects in second-life batteries.

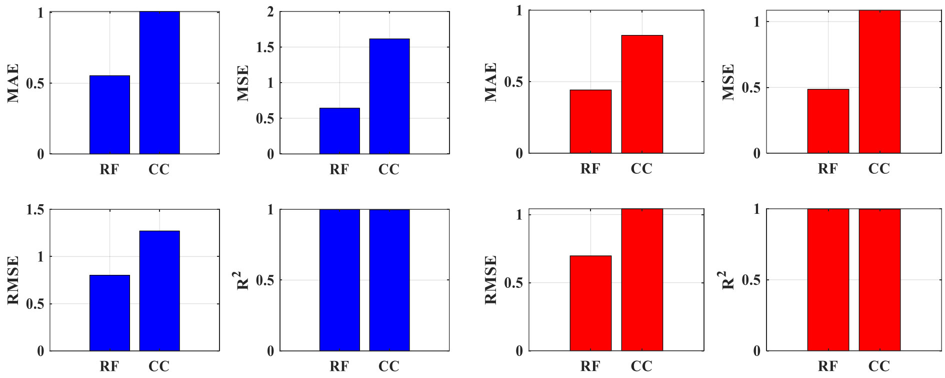


Figure 12. The performance metrics of DST are evaluated using both the random forest and coulomb counting methods for state of charge prediction in (a) new and (b) second-life lithium-ion batteries

Table 4. State of charge prediction errors metrics between the coulomb counting and random forest methods, dynamic stress test

			Temperature 25 °C				
Type	Methods	Initial SOC (%)	Working condition	MAE (%)	MSE (%)	RMSE (%)	R^2
New cell	CC	100	DST	1.0084	1.6149	1.2708	0.9975
	RF	100	DST	0.6000	0.8233	0.9073	0.9987
Second life	CC	80	DST	0.8243	1.0864	1.0423	0.9974
	RF	80	DST	0.4125	0.4000	0.6324	0.9990

3.2. Discussion and practical implications

To clearly illustrate the performance differences between coulomb counting and random forest, side-by-side comparison plots are presented for voltage, state of charge profiles, and error metrics under identical operating conditions. This presentation enables a direct visual assessment of estimation accuracy and robustness across pulse discharge, constant discharge, and dynamic stress test profiles for both new and second-life batteries. The superior performance of the random forest model is particularly evident for second-life batteries, which show increased variability due to capacity fade and internal resistance growth. These results directly address the research gap identified in the Introduction, where limited attention has been given to state of charge estimation under ageing heterogeneity. Unlike coulomb counting, which accumulates error under such conditions, random forest effectively adapts to variability by learning nonlinear relationships from data, demonstrating enhanced robustness for second-life applications. Compared with model-based approaches such as EKF and UKF, which typically report state-of-charge estimation errors in the range of 1-2% under dynamic conditions, the random forest model achieves comparable or improved accuracy without requiring an explicit battery model.

Furthermore, while deep learning-based state of charge estimation methods have demonstrated high accuracy, they often demand large datasets and higher computational complexity. In contrast, random forest provides a favorable balance between accuracy, robustness, and computational efficiency, making it well-suited for practical battery management system applications. The demonstrated robustness and accuracy of the random forest model indicate strong potential for real-time battery management system implementation. Since RF relies on readily available measurements such as voltage, current, and time, it can be embedded into battery management system architectures to support online state of charge estimation for both new and second-life batteries. This capability enhances operational safety, energy utilization efficiency, and lifecycle management in battery energy storage systems. Despite the promising results, this study was conducted under controlled laboratory conditions using a limited experimental dataset, which may constrain direct generalization to real-world operating environments. Future work will focus on expanding the dataset to include a broader range of ageing states and operating conditions, as well as validating the proposed approach using field data from real-world electric vehicle and stationary energy storage applications.

4. CONCLUSION

This study presented a comparative evaluation of the conventional coulomb counting method and a data-driven random forest model for state of charge estimation in new and second-life lithium-ion batteries under varied operating conditions. Experimental validation was conducted using pulse discharge, constant discharge, and dynamic stress tests across multiple C-rates. The results demonstrate that RF consistently outperforms coulomb counting, reducing the mean absolute error by approximately 40-50% and achieving coefficient of determination (R^2) values close to 0.998, particularly for second-life batteries. These findings confirm the robustness of random forest against measurement noise, dynamic loading, and ageing variability, whereas coulomb counting shows cumulative error under such conditions.

However, the study was performed under controlled laboratory conditions using a limited dataset, which may constrain direct real-world generalization. Future work will focus on larger datasets, hybrid machine learning frameworks, and real-world electric vehicle validation. Overall, the proposed random forest-based state of charge estimation approach supports intelligent battery management system design and enables reliable state of charge estimation for sustainable electric vehicle battery reuse in second-life energy storage 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	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

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 data that support the findings of this study are available from the corresponding author upon reasonable request.

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