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RESEARCH ARTICLE

Comparative Analysis of the Accuracy of Lithium-Ion Battery State of Charge Estimation Using *Open Circuit Voltage*-State of Charge and Coulomb Counting Methods with Simulink MATLAB

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Abstract

Accurate State of Charge (SOC) estimation is crucial for optimizing battery performance and ensuring the reliability of energy storage systems. As the demand for sustainable and efficient energy solutions grows, improving SOC estimation methods directly benefits society by enhancing battery longevity, safety, and efficiency in clean energy technologies. This study investigates the State of Charge (SOC) estimation of a battery using secondary data from the Samsung INR 18650-20R (2000mAh). The methods employed include the OCV-SOC, Coulomb Counting, and the 1RC equivalent battery model at temperatures of 0 °C, 25 °C, and 45 °C. This research evaluates the accuracy of these methods while assessing the influence of temperature on SOC estimation performance, which is critical for battery management systems in various applications. The equivalent battery model was tested using a 1A current with 10% SOC intervals, while the SOC estimation was performed under a 0.1A current during discharge conditions. The results indicate that the 1RC model demonstrates the smallest error at 25 °C and 45 °C, establishing itself as the most consistent method for SOC estimation across these temperatures. The Coulomb Counting method exhibits superior performance, with an R^2 value nearing 1 across all tested temperatures, showcasing its reliability in accurately reflecting SOC. Conversely, the OCV-SOC method delivers an R^2 range of 0.9757–0.9864, with its best accuracy observed at 45 °C but significantly lower accuracy at 25 °C, especially at low SOC levels (0–10%). The Coulomb Counting method's high accuracy is influenced by its reliance on ideal simulation data, which excludes real-world challenges such as current leakage and sensor fluctuations. Nonetheless, the combination of the 1RC model and the Coulomb Counting method proves more reliable for SOC estimation under diverse temperature conditions compared to the OCV-SOC method. The key contributions of this work include a systematic evaluation of SOC estimation methods under realistic temperature variations and insights into the limitations of each approach, which can guide the development of more robust battery management systems in real-world applications.

Keywords: Estimation accuracy, Lithium-ion battery, OCV-SOC, *Coulomb Counting*, Algorithm complexity, *State of Charge* (SOC)

1. Introduction

In today's technological era, lithium-ion batteries have become a crucial energy source for various electronic devices, ranging from smartphones and laptops to electric vehicles. The advantages of lithium-ion batteries, including high energy density, long lifecycle, and lightweight properties, make them the preferred choice over other battery technologies [1]. However, with the increasing number of applications relying on lithium-ion batteries, it is essential to ensure their performance and reliability remain optimal throughout their lifecycle [2].

One critical aspect of battery management is the ability to accurately monitor and estimate the State of Charge (SOC). SOC is a measure of the remaining battery capacity compared to its full capacity and is vital for applications where energy availability and battery durability predictability are key factors [3]. Inaccuracies in SOC estimation can lead to serious issues such as sudden power outages, damage to electronic components, and, in the context of electric vehicles, may cause inconvenience or even danger to the driver [4]. Several studies have estimated the state of charge using methods such as Coulomb Counting, Modified Coulomb Counting, OCV-SOC, Kalman Filter, and many others [5][6][7].

Two widely used methods for SOC estimation are the Coulomb Counting method and the Open Circuit Voltage-State of Charge (OCV-SOC) method due to their ease of implementation. The Coulomb Counting method is based on the fundamental principle of calculating the total charge that has entered or exited the battery. This method is simple and straightforward, but its accuracy heavily depends on initial calibration and the precision of current measurements. The Open Circuit Voltage-State of Charge (OCV-SOC) method is based on the principle of a direct relationship between the open circuit voltage and the battery's State of Charge (SOC). This relationship is unique and non-linear, depending on the type and characteristics of the battery. This method is relatively simple and accurate when the battery is in a steady-state condition.

In this research, secondary data is utilized from the A. James Clark School of Engineering, Center for Advanced Life Cycle Engineering, for the INR 18650-20R battery with a capacity of 2 Ah [8]. The battery is fully charged (SoC = 100%) and tested using two methods. The first method is the HPPC test, which employs a 1 A load current with intervals of 10% state of charge to estimate the battery equivalent circuit model. The second method uses a 0.1 A load current to estimate the state of charge through the OCV-SOC and Coulomb Counting methods. After obtaining the data, the experiment will consist of three main steps. The first step is estimating parameters for the lithium-ion battery, the second step is estimating the battery's state of charge using the OCV-SOC method, and the final step is estimating the battery's state of charge using the Coulomb Counting method. All these steps will be conducted using MATLAB Simulink to simulate the tests.

The main contributions of this study are twofold: (1) a comparative analysis of SOC estimation methods—OCV-SOC, Coulomb Counting, and equivalent circuit models (1RC, 2RC, and 3RC)—under varied temperature conditions, and (2) practical insights into the strengths and limitations of each method and model, aimed at enhancing the accuracy and robustness of SOC estimation in battery management systems. These findings are expected to contribute to safer and more reliable battery applications in electric vehicles and renewable energy systems, both of which are essential for sustainable development.

1.1 Comparison Analysis of The Accuracy of Lithium-Ion Battery State of Charge Using Coulomb Counting and OCV-SOC Method with 1RC Equivalent Circuit Model

1.2 Equivalent Circuit Model

Battery models are essential for predicting battery performance through simulation processes, optimizing the structural arrangement of battery packs, and supporting the design of battery management systems [4]. This model streamlines the intricate electrochemical processes within batteries by representing them using electrical elements like resistors, capacitors, and voltage sources. The main benefit of employing ECMs lies in their capability to offer insights into battery behavior without requiring a detailed exploration of the complex internal reactions, which are often computationally demanding and intricate [9][10][11].

A typical structure of an equivalent circuit model is shown in Figure 1. This circuit contains a voltage source Em, a series resistance R_0 to represent instantaneous response when the battery is connected to the load, plus one or more parallel R-C branches connected in series to represent transient an dynamic response of the battery [12]. These models are commonly applied in battery management systems as they offer a good balance between simplicity and accuracy, making them suitable for estimating the state of charge (SOC) and predicting battery performance effectively [13].

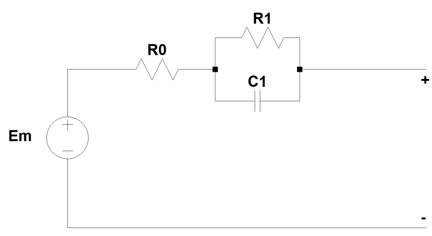

Figure 1. Schematic representation of 1RC Equivalent Circuit Model.

Recent advancements have also led to the development of more sophisticated ECMs that incorporate additional parameters to enhance their accuracy. For example, models that include multiple RC pairs can better capture the dynamic behavior of batteries across varying states of charge and discharge [14]. As shown in Figure 2, which illustrates the equivalent circuit model of a battery with two parallel RC branches.

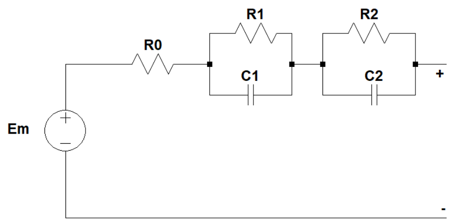

Figure 2. Schematic representation of 2RC Equivalent Circuit Model.

In addition, several studies have also examined the use of an equivalent circuit model of a battery with three parallel RC branches, as shown in Figure 3. Recent studies have demonstrated the efficacy of the 3RC model in various applications. For instance, it has been shown to provide accurate estimations of battery performance during different operational scenarios, including temperature variations and aging effects. The implementation of the 3RC model in battery management systems facilitates improved monitoring and control of battery performance [15]. By accurately estimating SOC and SOH, the model ultimately enhancing the overall efficiency and safety of battery-operated systems [16].

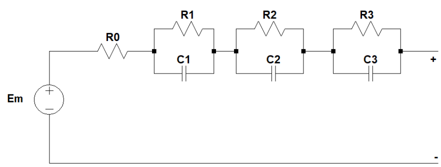

Figure 3. Schematic representation of 3RC Equivalent Circuit Model.

Battery simulation requires an approach to model battery operation using electrical circuit analogies to define behavioral approximations of how battery voltage responds to different current input stimuli [17]. By leveraging knowledge of common electronic components, a circuit can be defined that closely mirrors the observed behavior of a battery cell. The equations describing this circuit also effectively represent the operation of the observed cell.

This model is known as an equivalent circuit model (ECM) of the battery. The circuit elements in the model are not intended to represent the physical construction of the cell. Instead, the circuit serves as a description of the cell's behavior, with various circuit elements acting as analogs for certain internal processes. Because extensive knowledge exists about how circuit elements behave, circuit models leverage this understanding to provide more accurate predictions of how a cell will respond under different usage scenarios.

1.3 Initialization of Equivalent Circuit Model Parameters

Before parameter estimation is performed using MATLAB, the main battery parameters R0, R1, and tau1 are initialized using the following formulas:

$$R0 = \left| \frac{\Delta V_0}{\Delta i} \right| \tag{1}$$

$$R1 = \left| \frac{\Delta V_\infty}{\Delta i} \right| \tag{2}$$

$$C1 = \frac{T_{(s)}}{4R1} \tag{3}$$

In this context, Δ V0 represents the voltage difference when the load is removed, reflecting the instant response of the battery (measured in volts). ΔV_∞ is the voltage difference observed from the moment the load is removed until the voltage stabilizes (also measured in volts). Δi denotes the load current (measured in amperes), and Ts refers to the time required for the battery to reach a stable voltage condition (measured in seconds). These parameters are essential for accurately initializing the battery's equivalent circuit model.

1.4 Coulomb Counting

The Coulomb Counting method is one of the simplest and most widely used techniques for estimating State of Charge (SOC). This method operates on the principle that SOC changes are proportional to the amount of electric charge flowing into or out of a battery. It measures the current entering or leaving the battery and integrates this current over time to determine the change in battery charge[18]. The fundamental formula is:

$$SOC(t) = SOC(0) + \frac{1}{C_{nom}} \int_0^t I(t)dt \tag{4}$$

Where SOC(t) is the SOC at time t (in hours), SOC(0) is the initial SOC at t=, Cnom represents the nominal capacity of the battery in Ampere-hours (Ah), I(t) is the instantaneous current at time t (in Amperes), and t refers to the time of measurement (in hours).

In discrete implementations, such as in digital systems or microcontrollers, the formula becomes:

$$SOC(t) = SOC(0) + \frac{1}{C_{nom}} \int_0^t I(t)dt \tag{5}$$

Where, Δ t represents the time interval between two current measurements (in hours), I(k) is the current measured at the k-th time interval (in Amperes), and N is the total number of time intervals during the measurement process. This discrete approach allows for the calculation of SOC by summing the current values over successive time intervals while considering the battery's nominal capacity.

This method requires accurate current sensors and continuous data logging to ensure all small current changes are recorded. Starting with a known SOC, charge reduction or addition is calculated to update the SOC over time. One of the significant advantages of Coulomb counting is its simplicity and directness. It allows for continuous monitoring of the SOC without the need for complex algorithms or extensive computational resources [19]. However, the method is not without its challenges. The accuracy of Coulomb counting heavily relies on the precision of current measurements and the knowledge of the initial SOC and battery capacity. Errors can accumulate over time due to factors such as current sensor inaccuracies, battery capacity degradation, and variations in coulombic efficiency. Therefore, compensations such as the coulombic efficiency factor, which accounts for charge losses during charging and discharging, are often necessary [20]. Coulombic efficiency is typically less than 1 due to energy losses.

1.5 Open Circuit Voltage – State of Charge

State of Charge (SOC) estimation is a critical aspect of battery management, especially in electric vehicles (EVs) and energy storage systems (ESS). One of the most commonly used methods for SOC estimation is the Open Circuit Voltage (OCV-SOC) method, which relies on the empirical relationship between the open circuit voltage (OCV) and the SOC of the battery[18]. The relationship between SOC and OCV is well-established, where OCV serves as a reliable indicator of SOC when the battery is at rest and in equilibrium [21][22][23].This relationship is typically expressed as:

$$OCV = f(SOC) \tag{6}$$

where OCV is the open circuit voltage (V), SOC is the battery's state of charge (%), and f represents the empirical or theoretical function linking SOC and OCV. In equivalent circuit models, OCV can also be determined by accounting for internal battery parameters, such as internal resistance, using the formula:

$$OCV = V_{term} + IxRint \tag{7}$$

where Vterm is the terminal voltage (V), I is the battery current (A), and Rint is the internal resistance (Ohm).

The OCV-SOC method is advantageous for its simplicity and high accuracy under stable conditions. The SOC estimation procedure begins with ensuring the battery is in a resting state to eliminate transient currents and polarization effects that could interfere with voltage measurements. The OCV is measured after the system reaches thermal and electrochemical equilibrium, which may require a resting period of several minutes to hours, depending on the battery's characteristics.

Subsequently, the measured OCV value is converted into SOC using an OCV-SOC curve derived from laboratory testing or manufacturer data. This curve represents the non-linear relationship between battery voltage and remaining capacity, influenced by factors such as battery chemistry (e.g., Lithium-ion, Lead-acid), ambient temperature, and discharge rate. The OCV-SOC curve is typically developed through controlled charge-discharge cycles, mapping voltage data at various SOC levels.

In practical applications, voltage sensors measure the OCV at specific times, and the measured value is compared to the reference OCV-SOC curve to estimate the SOC. To enhance accuracy, temperature compensation is often applied, as changes in temperature significantly affect the OCV-SOC relationship. This ensures the method's reliability across varying environmental and operating conditions.

It is important to note that the OCV-SOC method has limitations, particularly its dependence on stable conditions and the requirement for sufficient resting time to achieve equilibrium. This makes the method less effective for systems that require quick responses for real-time SOC estimation. As a result, the OCV-SOC method is often combined with other approaches, such as Coulomb Counting or model-based techniques, to enhance the reliability and accuracy of SOC estimation.

2. Research Methods

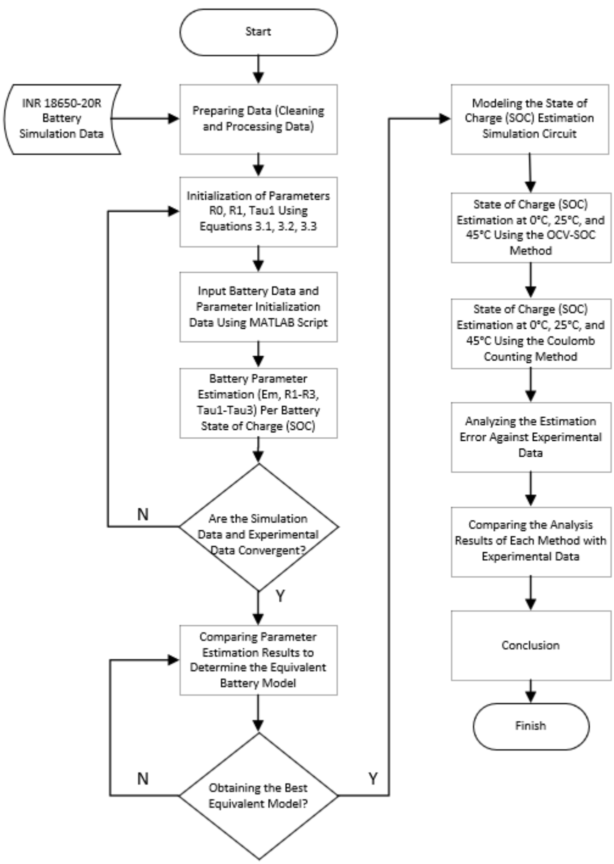

Figure 4. Research Flowchart

Figure 4 outlines the research workflow. The first step involves collecting battery test data, including parameters such as time, voltage, and current. This data is obtained from verified secondary sources on the internet. The collected data is then cleaned using Microsoft Excel by removing NaN values and duplicate entries before being imported into MATLAB for further analysis. After data cleaning, initial parameters such as R0, R1, and tau1-tau3 are initialized using formulas (1), (2), and (3). These parameters represent the basic characteristics of the battery and serve as the starting point for modeling and simulation.

Once the initial parameters are set, the battery data and parameters are input into a MATLAB script for further processing. In MATLAB, advanced battery parameter estimation is performed to derive values such as Em (the equivalent battery voltage), R1-R3 (resistances in different battery layers), and tau1-tau3 (time constants for each battery component) based on the battery's State of Charge (SOC). These results are compared with experimental data to check for convergence between simulation and experimental results. Convergence is a critical indicator of the model's accuracy and relevance to the actual battery conditions.

If the results show that the simulation and experimental data are not yet convergent, the process loops back to previous stages, such as additional data cleaning, parameter adjustments, or MATLAB script optimization. Once convergence is achieved, the study progresses to the next phase is estimating SOC under three different temperature conditions: 0 °C, 25 °C, and 45 °C. This estimation employs the OCV-SOC (Open Circuit Voltage-State of Charge) method with three equivalent battery models: 1RC, 2RC, and 3RC. Each model uses distinct mathematical representations to capture the dynamic behavior of the battery, enabling a deeper analysis of the impact of temperature on battery performance.

After SOC estimation, the next step involves analyzing estimation errors by comparing simulation results with experimental data. This analysis evaluates the accuracy of each model in predicting SOC across various temperature conditions. Subsequently, the results from the three equivalent battery models 1RC, 2RC, and 3RC are compared to identify which model is the most accurate and consistent under different operational conditions. This comparison considers metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

The final phase of the research is to draw conclusions based on the analysis results. These conclusions include recommendations on the most suitable equivalent model for specific applications and suggestions for future research to refine the methods used.

This research flow provides a systematic approach to modeling, analyzing, and optimizing battery SOC estimation under various temperature conditions using the OCV-SOC method equivalent circuit models.

3. Analysis of State of Charge Estimation Using OCV-SOC and Coulomb Counting

3.1 Parameter Estimation for Equivalent Circuit Models

The results of the parameter estimation for the equivalent battery models show improvements with each model. However, having more parallel RC circuits does not necessarily result in a better battery model, as the characteristics of the battery and the data used vary. The following analysis will present the parameter estimation results for the 1RC, 2RC, and 3RC equivalent battery models at battery temperatures of 0 °C, 25 °C, and 45 °C. Figure 5 below shows the visualization of the parameter estimation results for the 1RC, 2RC, and 3RC equivalent battery models at a battery temperature of 0 °C, sequentially from top to bottom.

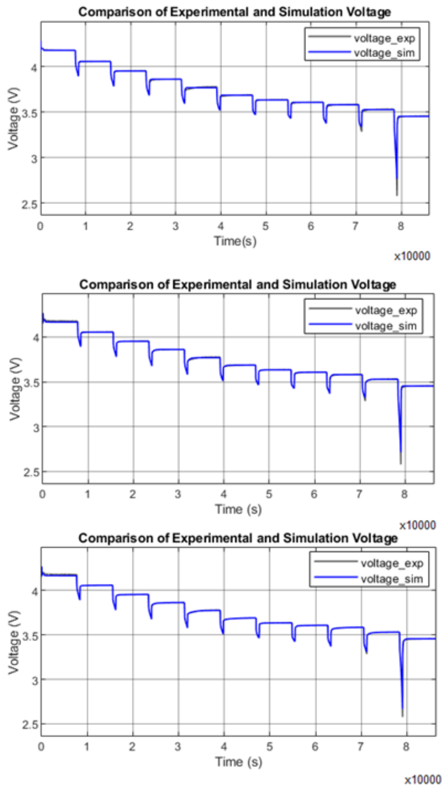

Figure 5. Comparison of Experimental and Simulation Voltage 1RC, 2RC, and 3RC Equivalent Circuit Model at Tbat 0 °C

Figure 5 compares the experimental and simulated voltage profiles of 1RC, 2RC, and 3RC equivalent circuit models at a battery temperature of 0 °C. The top, middle, and bottom panels depict the 1RC, 2RC, and 3RC model simulations, respectively. Visual inspection reveals that the 3RC model most closely aligns with experimental data, particularly during transient phases. Based on these results, an error analysis was conducted to evaluate the performance of each model using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) as presented in the equation (6) and(7). The result of this equation is presented in Table 1 below.

$$MSE = \frac{1}{N}\Sigma_{I=1}^{N}(Yi - \acute{Y}i)^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{2}\Sigma_{I=1}^{N}(Yi - \acute{Y}i)^2} \tag{9}$$

Table 1. Calculation Results of MAE and RMSE for Battery Equivalent Model Performance at Tbat = 0 °C

0 °C			
	1RC	2RC	3RC
MAE	0.0001	0.0046	0.0039
RMSE	0.0083	0.0682	0.0621

Based on the table 1 results, the 1RC Model demonstrates the lowest error with an MSE of 0.00001 and an RMSE of 0.0083, indicating the highest accuracy in representing the battery voltage profile compared to the other models. The 3RC Model, with an MSE of 0.0039 and an RMSE of 0.0621, performs better than the 2RC Model but is still less accurate than the 1RC Model. The 2RC Model, on the other hand, has the highest error with an MSE of 0.0046 and an RMSE of 0.0682, reflecting the lowest performance among the three models. Overall, it can be concluded that the 1RC Model is the most optimal for representing battery voltage dynamics at 0 °C, followed by the 2RC Model, and lastly the 3RC Model. Increased model complexity positively contributes to improving estimation accuracy.

Figure 6 below shows the visualization of the parameter estimation results for the 1RC, 2RC, and 3RC equivalent battery models at a battery temperature of 25 °C, sequentially from top to bottom.

Figure 6 compares the experimental and simulated voltage profiles of 1RC, 2RC, and 3RC equivalent circuit models at a battery temperature of 25 °C. The top, middle, and bottom panels depict the 1RC, 2RC, and 3RC model simulations, respectively. Visual inspection reveals that the 3RC model most closely aligns with experimental data, particularly during transient phases. Based on these results, an error analysis was conducted to evaluate the performance of each model using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), as presented in Table 2 below.

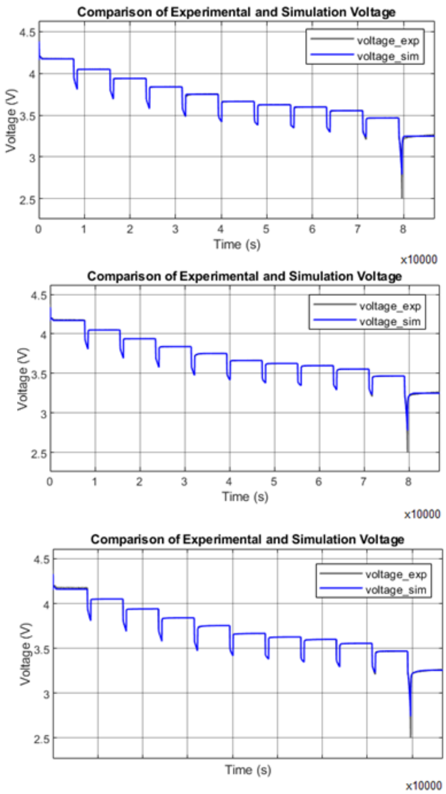

Figure 6. Comparison of Experimental and Simulation Voltage 1RC, 2RC, and 3RC Equivalent Circuit Model at Tbat 25 °C

Table 2. Calculation Results of MAE and RMSE for Battery Equivalent Model Performance at Tbat = 25 °C

	25 °C		
	1RC	2RC	3RC
MAE	0.00004	0.0048	0.0039
RMSE	0.0069	0.0689	0.0623

Based on the table 2 results, the 1RC Model has the lowest error with an MSE of 0.0046 and an RMSE of 0.0682, making it the most accurate model among the three at 25 °C. The 2RC Model has slightly higher error values, with an MSE of 0.0048 and an RMSE of 0.0689, indicating some deviations, particularly during the transition phases between battery discharge cycles. The 3RC Model also performs well, with an MSE of 0.0047 and an RMSE of 0.0689, showing that the addition of extra resistors and capacitors slightly improves the accuracy in representing the battery voltage profile at 25 °C. Overall, the 1RC Model is the most optimal for predicting battery voltage at 25 °C, followed by the 3RC Model and then the 2RC Model.

Despite the minor differences, the results highlight the trade-offs between simplicity and complexity in model structures.

Figure 7 below shows the visualization of the parameter estimation results for the 1RC, 2RC, and 3RC equivalent battery models at a battery temperature of 45 °C, sequentially from top to bottom.

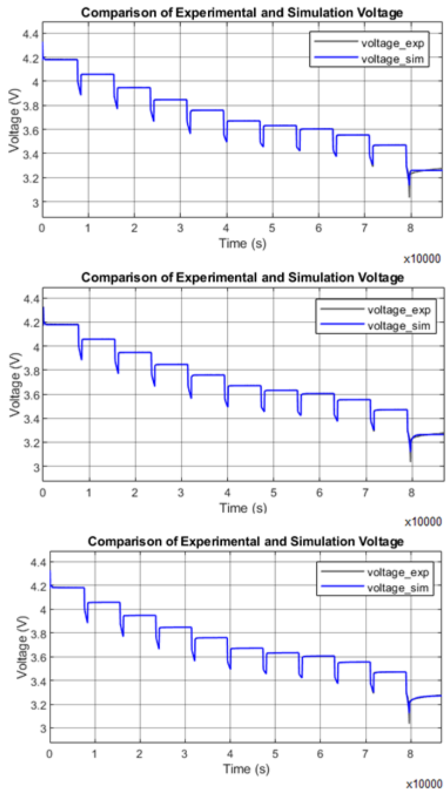

Figure 7. Comparison of Experimental and Simulation Voltage 1RC, 2RC, and 3RC Equivalent Circuit Model at Tbat 45 °C

Figure 7 compares the experimental and simulated voltage profiles of 1RC, 2RC, and 3RC equivalent circuit models at a battery temperature of 45 °C. The top, middle, and bottom panels depict the 1RC, 2RC, and 3RC model simulations, respectively. Visual inspection reveals that the 3RC model most closely aligns with experimental data, particularly during transient phases. Based on these results, an error analysis was conducted to evaluate the performance of each model using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), as presented in Table 3 below.

Table 3. Calculation Results of MAE and RMSE for Battery Equivalent Model Performance at Tbat = 45 °C

	45 °C		
	1RC	2RC	3RC
MAE	0.00002	0.0047	0.0039
RMSE	0.0053	0.0689	0.0624

Based on the table 3 results, the 1RC Model has an MSE of 0.0039 and an RMSE of 0.0621, indicating good performance with a low error rate, though some deviations remain during the transition phases between battery discharge cycles. The 2RC Model has an MSE of 0.0047 and an RMSE of 0.0689, showing results very close to the 1RC Model. This suggests that the addition of extra resistors and capacitors does not significantly enhance the model's accuracy at this temperature. Similarly, the 3RC Model has an MSE of 0.0039 and an RMSE of 0.0624. While its error values are slightly higher than those of the 1RC and 2RC Models, the differences are minimal and statistically insignificant. This indicates that at 45 °C, the added complexity of the 3RC structure does not provide a meaningful improvement in voltage estimation accuracy.

Overall, all three models demonstrate nearly identical performance at 45 °C, with the 1RC Model showing a slight advantage due to its lower RMSE compared to the other models. This suggests that at higher temperatures, the additional complexity of models like 2RC and 3RC does not significantly impact accuracy improvement.

3.2 State of Charge Estimation Using Coulomb Counting and OCV-SOC Method at Tbat = 0 °C

The graph below illustrates the comparison between the estimated State of Charge (SOC) of the battery using the Coulomb Counting (CC SOC) method and the experimental results at a temperature of 0 °C.

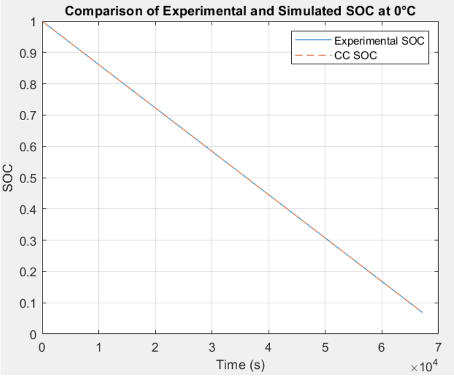

Figure 8. State of Charge Estimation Results Using the Coulomb Counting Method at 0 °C

Figure 8 compares the State of Charge (SoC) estimation results using the Coulomb Counting method at 0 °C. The two curves, represented by a solid blue line (experimental) and a dashed orange line (simulation), overlap perfectly at 0 °C, indicating excellent performance with MSE of 0, RMSE of 0.0001, and R^2 of 1. This demonstrates high accuracy for the Coulomb Counting method under ideal simulation conditions, though practical applications may be affected by external factors such as sensor noise and battery self-discharge.

The graph below shows the comparison between the estimated State of Charge (SOC) of the battery using the Open Circuit Voltage-State of Charge (OCV-SOC) method and the experimental results at a temperature of 0 °C.

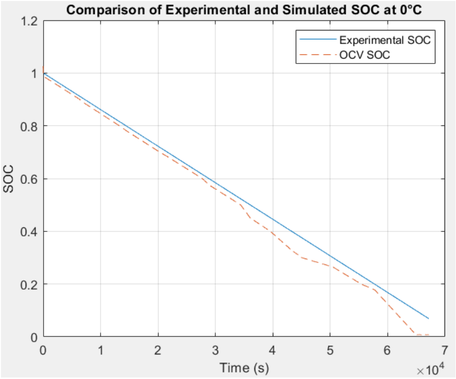

Figure 9. State of Charge Estimation Results Using the OCV-SOC Method at 0 °C

Figure 9 compares the State of Charge (SoC) estimation results using the OCV-SOC method at 0 °C. The solid blue line (experimental) and dashed orange line (OCV-SOC simulation) show deviations, especially at lower SOC levels. With an MSE of 0.002, RMSE of 0.045, and R^2 of 0.9775, the OCV-SOC method demonstrates strong correlation but higher errors compared to the Coulomb Counting method, indicating limitations in accuracy at lower SOC levels.

Table 4. Performance Comparison of Coulomb Counting and OCV-SOC at Tbat = 0 °C

Method	Parameter	0 °C
Coulomb Counting	MSE	0
	RMSE	0.0001
	R^2	1
OCV-SOC	MSE	0.0016
	RMSE	0.0403
	R^2	0.9775

Based on the table 4 results, at a temperature of 0 °C, the Coulomb Counting method outperforms the OCV-SOC method with lower error rates and better prediction accuracy. This indicates that the Coulomb Counting method is more stable and reliable for use in low-temperature conditions.

3.3 State of Charge Estimation Using Coulomb Counting and OCV-SOC Method at Tbat = 25 °C

The graph below illustrates the comparison between the estimated State of Charge (SOC) of the battery using the Coulomb Counting (CC SOC) method and the experimental results at a temperature of 25 °C.

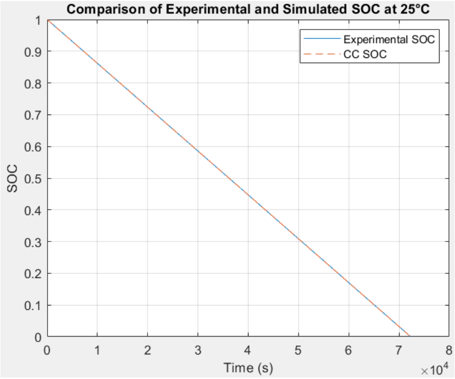

Figure 10. State of Charge Estimation Results Using the Coulomb Counting Method at 25 °C

Figure 10 compares the State of Charge (SoC) estimation results using the Coulomb Counting method at 25 °C. The solid blue line represents the experimental results, while the dashed orange line represents the Coulomb Counting simulation results. Both curves align perfectly throughout the test period, indicating excellent agreement between the estimated and actual SOC values.

Evaluation metrics show ideal results, with an MSE of 0, RMSE of 0, and R^2 of 1, demonstrating that the Coulomb Counting method achieves perfect accuracy in estimating battery SOC at 25 °C. These results confirm that there are no significant deviations between simulation and experimental data under ideal simulation conditions.

However, it is important to note that these results may be influenced by stable and controlled simulation conditions, where external factors such as current measurement noise, battery degradation, and undetected small current fluctuations are not considered. In real-world applications, these factors could affect the accuracy of the Coulomb Counting method.

Figure 11 compares the State of Charge (SoC) estimation results using the OCV-SOC method at 25 °C. The solid blue line represents the experimental results, while the dashed orange line represents the OCV-SOC simulation results. Initially, the two curves align well, but significant deviations occur over time, especially at medium to low SOC levels.

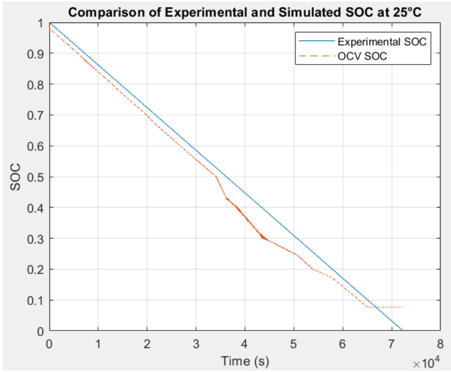

Figure 11. State of Charge Estimation Results Using the OCV-SOC Method at 25 °C

Evaluation metrics show that the OCV-SOC method has an MSE of 0.002, RMSE of 0.045, and R^2 of 0.9757. While the R^2 value indicates a strong correlation between simulation and experimental results, the higher MSE and RMSE compared to the Coulomb Counting method reflect greater deviations. These significant deviations at medium to low SOC levels suggest that the OCV-SOC method struggles to predict SOC accurately when battery voltage becomes unstable or non-linear.

Table 5. Performance Comparison of Coulomb Counting and OCV-SOC at Tbat = 25 °C

Method	Parameter	25 °C
Coulomb Counting	MSE	0
	RMSE	0
	R^2	1
OCV-SOC	MSE	0.002
	RMSE	0.045
	R^2	0.9757

Based on the table 5 results, at a temperature of 25 °C, the Coulomb Counting method remains superior to the OCV-SOC method in terms of lower errors and better prediction accuracy. This demonstrates that the Coulomb Counting method is more reliable for use at room temperature, providing consistent and stable performance.

3.4 State of Charge Estimation Using Coulomb Counting and OCV-SOC Method at Tbat = 45 °C

The graph below illustrates the comparison between the estimated State of Charge (SOC) of the battery using the Coulomb Counting (CC SOC) method and the experimental results at a temperature of 45 °C.

Figure 12 compares the State of Charge (SoC) estimation results using the Coulomb Counting method at 45 °C. The solid blue line represents experimental results, while

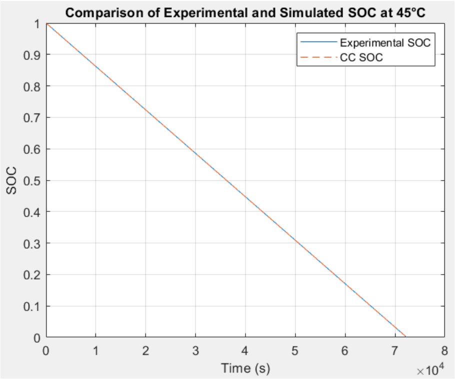

Figure 12. State of Charge Estimation Results Using the Coulomb Counting Method at 45 °C

the dashed orange line represents estimates from the Coulomb Counting method. Both lines align perfectly throughout the test, indicating extremely high accuracy.

Evaluation metrics confirm this, with an MSE of 0, RMSE of 0, and R^2 of 1, demonstrating that Coulomb Counting replicates experimental results with perfect accuracy. At 45 °C, the method proves to be highly stable and effective in estimating battery SOC. However, it is important to note that this measurement uses experimental data, which likely contributes to its high accuracy.

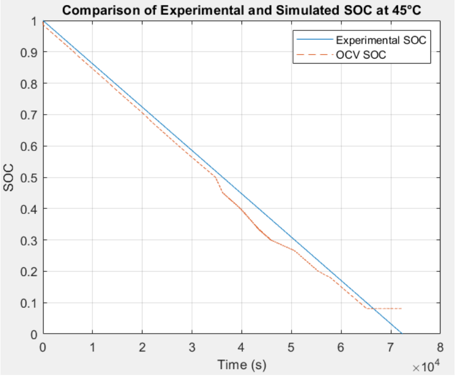

Figure 13. State of Charge Estimation Results Using the OCV-SOC Method at 45 °C

Figure 13 compares the State of Charge (SoC) estimation results using the OCV-SOC method at 45 °C. The solid blue line represents experimental results, while the dashed orange line represents OCV-SOC simulation results. Initially, the curves align well, but noticeable deviations occur over time, especially at medium to low SOC levels.

Evaluation metrics show an MSE of 0.0011, RMSE of 0.0336, and R^2 of 0.9864, indicating a strong correlation between simulation and experimental results. However, the non-zero MSE and RMSE reflect prediction errors, with more significant deviations at medium to low SOC levels. This highlights the limitations of the OCV-SOC method in handling non-linear voltage-SOC relationships, particularly when battery voltage drops at lower SOC levels.

Table 6. Performance Comparison of Coulomb Counting and OCV-SOC at Tbat = 45 °C

Method	Parameter	45 °C
Coulomb Counting	MSE	0
	RMSE	0
	R^2	1
OCV-SOC	MSE	0.0011
	RMSE	0.0336
	R^2	0.9864

Based on table 6 results , at a temperature of 45 °C, the Coulomb Counting method once again outperforms the OCV-SOC method. This confirms that Coulomb Counting is more stable and accurate in predicting battery conditions across various temperature ranges, including high temperatures.

3.5 Statistical Validation Using t-test: Paired two sample for means between Coulomb Counting and OCV-SOC Method

To evaluate the consistency between the State of Charge (SOC) estimation results obtained

from the Coulomb Counting (CC) method and the Open Circuit Voltage (OCV) method, a statistical analysis was conducted using the paired t-test in Microsoft Excel. This test was used to determine whether a statistically significant difference exists between the SOC values estimated by both methods under various temperature conditions, namely 0 °C, 25 °C, and 45 °C.

Table 7 below shows the paired t-test output comparing Coulomb Counting and OCV-SOC method at Tbat = 0 °C. It includes descriptive statistics (mean, variance), the correlation coefficient, t-statistic, and p-values.

Based on table 7, which presents the t-test results between the Coulomb Counting and OCV-SOC methods, shows a very high correlation between the SOC estimates from the Coulomb Counting and Open Circuit Voltage methods ($r = 0.9988$). However, the t-test also indicates that the difference in their mean values is statistically significant ($t = 408.48$, $p < 0.05$), with the OCV method tending to produce lower SOC values compared to the Coulomb Counting method.

Table 8 below shows the paired t-test output comparing Coulomb Counting and OCV-SOC method at Tbat = 25 °C. It includes descriptive statistics (mean, variance), the correlation coefficient, t-statistic, and p-values.

Based on table 8, the paired t-test results between the Coulomb Counting and OCV-SOC methods at a temperature of 25 °C. The SOC estimates from both methods exhibit a very strong correlation ($r = 0.9945$). However, based on the results of the paired two-sample t-test, the difference between the two methods is statistically significant ($t = 295.35$, $p < 0.05$), with the average SOC value from the OCV method being lower than that of the Coulomb Counting method.

Table 7. Paired t-test between Coulomb Counting and OCV-SOC method at Tbat = 0 °C

Method	*CC_SOC0*	*OCV_SOC0*
Mean	0.534423101	0.500313126
Variance	0.072254248	0.081615174
Observations	67152	67152
Pearson Correlation	0.99880693	
Hypothesized Mean Difference	0	
df	67151	
t Stat	408.4831364	
P(T<=t) one-tail	0	
t Critical one-tail	1.644876319	
P(T<=t) two-tail	0	
t Critical two-tail	1.959999313	

Table 8. Paired t-test between Coulomb Counting and OCV-SOC method at Tbat = 25 °C

Method	*CC_SOC25*	*OCV_SOC25*
Mean	0.500152769	0.466836366
Variance	0.083329573	0.082968891
Observations	72314	72314
Pearson Correlation	0.99446912	
Hypothesized Mean Difference	0	
df	72313	
t Stat	295.3494959	
P(T<=t) one-tail	0	
t Critical one-tail	1.644874699	
P(T<=t) two-tail	0	
t Critical two-tail	1.959996791	

Table 9 below shows the paired t-test output comparing Coulomb Counting and OCV-SOC method at Tbat = 45 °C. It includes descriptive statistics (mean, variance), the correlation coefficient, t-statistic, and p-values.

Based on table 9, shows the t-test results between the Coulomb Counting and OCV-SOC methods at a battery temperature of 45 °C. The SOC estimates from both methods demonstrate a very high correlation ($r = 0.9963$). However, the t-test indicates that the mean values of the two methods differ significantly ($t = 241.69$, $p < 0.05$), with the OCV method tending to produce lower SOC values compared to the Coulomb Counting method.

The conclusion from the statistical analysis indicates that although SOC estimation using the OCV-SOC method shows a very high correlation with the Coulomb Counting method, the OCV method consistently yields lower SOC values. This discrepancy may be attributed to the sensitivity of the OCV method to temperature

Table 9. Paired t-test between Coulomb Counting and OCV-SOC method at Tbat = 45 °C

Method	*CC_SOC45*	*OCV_SOC45*
Mean	0.499940902	0.477468691
Variance	0.083338441	0.081926728
Observations	72343	72343
Pearson Correlation	0.996252049	
Hypothesized Mean Difference	0	
df	72342	
t Stat	241.6911284	
P(T<=t) one-tail	0	
t Critical one-tail	1.644874691	
P(T<=t) two-tail	0	
t Critical two-tail	1.959996778	

variations and the voltage relaxation phenomenon, which is not directly accounted for in the estimation process.

4. Conclusion

Based on the accuracy analysis of State of Charge (SOC) estimation using Coulomb Counting and Open Circuit Voltage-State of Charge (OCV-SOC) methods at three different temperatures (0 °C, 25 °C, and 45 °C), the findings are as follows: The 1RC model demonstrated the lowest error compared to 2RC and 3RC models at 0 °C, 25 °C, and 45 °C; therefore, the 1RC equivalent circuit model was selected as the battery model for SOC estimation using both Coulomb Counting and OCV-SOC methods. Coulomb Counting outperformed OCV-SOC, achieving an R^2 value of 1 at all temperatures, although this near-perfect accuracy likely resulted from ideal simulation data that ignored external factors such as current leakage and sensor measurement fluctuations. The OCV-SOC method performed reasonably well across the temperatures but showed higher errors than Coulomb Counting, particularly at 25 °C and low SOC levels (0–10%), likely due to reduced voltage estimation accuracy in this range.

Although this study uses real experimental data under controlled conditions, real-world implementation of SOC estimation methods faces several additional challenges. Sensor noise, for instance, can significantly affect the accuracy of current measurements in the Coulomb Counting method, leading to accumulated errors over time. Similarly, capacity fade caused by battery aging can alter the relationship between voltage and SOC, reducing the reliability of the OCV-SOC method if not properly accounted for. Leakage currents and thermal variations can also introduce inaccuracies, especially in long-term operation. Addressing these issues requires robust filtering techniques, periodic recalibration, or adaptive models that can compensate for such non-idealities in real-world applications.

Future work may focus on implementing SOC estimation under dynamic load profiles to better reflect operational conditions in electric vehicles and energy storage systems. Additionally, incorporating model aging effects and exploring advanced estimation techniques such as Kalman Filters or machine learning-based methods could further improve accuracy and adaptability in long-term battery management applications.

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