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Robust SOC estimation for lithium-ion batteries under faulty charging scenarios using sliding mode observer techniques

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ABSTRACT

With the growing demand for electric vehicles, embedded electronics, and renewable energy applications, lithium-ion batteries have become an essential component in modern energy storage systems. Accurate state of charge (SOC) estimation is crucial for ensuring battery reliability, longevity, and safety, particularly under faulty charging conditions—a challenge where many conventional estimation techniques fall short due to model limitations or lack of robustness. In this study, we propose an advanced SOC estimation approach based on a sliding mode observer (SMO) integrated with a third-order equivalent circuit model (ECM). Unlike conventional methods, which either focus on SOC estimation without considering battery voltage or apply SMO techniques only to second-order models, our approach enhances estimation accuracy by incorporating a higher-order model that better captures the complex battery dynamics. The proposed methodology is tested under both normal and faulty charging conditions, demonstrating superior performance in estimating both SOC and terminal voltage over extended periods. The simulation results confirm the robustness of the method, with accurate SOC tracking even in the presence of charging current faults, making it a viable solution for real-world applications in battery management systems (BMS). This work contributes to improving fault-tolerant SOC estimation strategies, advancing the development of safer and more efficient energy storage technologies.

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1. INTRODUCTION

Environmental pollution remains a critical global issue, largely due to emissions from conventional electricity generation and thermal transportation systems [1], [2]. In response, there is growing interest in renewable energy and electric vehicles, which depend on advanced energy storage technologies [3], [4]. Lithium-ion batteries, known for their efficiency, recyclability, and suitability across various applications, are central to this transition [5], [6]. However, a single cell cannot meet electric vehicle energy demands, necessitating battery packs and robust battery management systems (BMS) [7]-[9].

A key function of the BMS is estimating the state of charge (SOC), which cannot be directly measured and thus requires estimation algorithms [10], [11]. These are categorized into four main types: open-loop, equivalent circuit model-based, data-driven, and bookkeeping estimation methods [12], [13]. Data-driven methods such as neural networks and support vector machines offer high accuracy but require significant offline training [14]-[16]. Bookkeeping methods, like coulomb counting, estimate SOC using charge/discharge currents [17], [18]. Open-loop methods, such as the open-circuit voltage (OCV) technique, are simple but unsuitable for real-time applications [19]. Equivalent circuit model (ECM)-based methods, which offer high accuracy, model battery dynamics through relationships among voltage, current, and OCV [20]-[22]. The algorithms using equivalent circuit models include the trace-free Kalman filter [23]. However, this filter can produce significant linear errors and instability due to the reliance on a first-order Taylor expansion for nonlinear functions. To mitigate these issues, the trace-free Kalman filter employs a trace-free transform [6], which enhances estimation accuracy but incurs higher computational costs.

Upon reviewing the literature, we identified a significant gap in accurately estimating the SOC of Li-ion batteries under both normal operating conditions and fault scenarios, particularly faults related to current anomalies. Most existing studies predominantly rely on second-order equivalent circuit models, which constrain both the accuracy and general applicability of SOC estimation methods. To address the aforementioned challenges, various studies have employed sliding mode observers (SMO), which have demonstrated effectiveness in enhancing SOC estimation. However, their performance is highly dependent on the appropriate selection of switching gains. To improve both accuracy and robustness, researchers have proposed SMO with adaptive gain mechanisms and temperature-sensitive battery models [24], [25]. Despite these advancements, many existing approaches are still limited by the use of lower-order battery models and cannot reliably operate under charging anomalies. Additionally, the computational complexity of some methods hampers real-time deployment in embedded systems [26]-[29]. In response, this study proposes an efficient sliding mode observer with adaptive gain, integrated into a third-order ECM to capture battery dynamics and diffusion effects. Designed for robustness under current-level faults, it maintains SOC estimation accuracy over time. A fault scenario was simulated to validate its error detection and mitigation capabilities in SOC estimation.

The paper includes into several sections following the introduction: Section 2 on the sliding mode observer design, section 3 on results under normal and fault conditions, section 4 comparing with previous studies, and section 5 concluding with contributions and future work.

2. COMPAREHENSIVE THEORETICAL BASIS

Accurate battery modeling is essential for predicting lithium-ion performance in EVs and energy storage systems. Among various methods, ECM is preferred in BMS for their balance of accuracy and simplicity. This study uses a third-order ECM with multiple RC branches to capture diffusion effects.

2.1. Battery modeling

This study uses a (3-RC) model for SOC estimation, which better captures battery dynamics and transient behavior than the simpler 2-RC model. Despite its complexity, it improves accuracy under fault conditions and supports real-time fault detection in BMS.

2.1.1. Model description: when the battery is operating normally

Battery models vary in complexity and are typically classified into four types: empirical, equivalent circuit, electrochemical, and data-driven models (Figure 1) [29]. The electrochemical model describes internal reactions and underpins other models. The ECM simplifies these reactions using circuit elements, sharing parameters with the electrochemical model to effectively represent battery behavior [30].

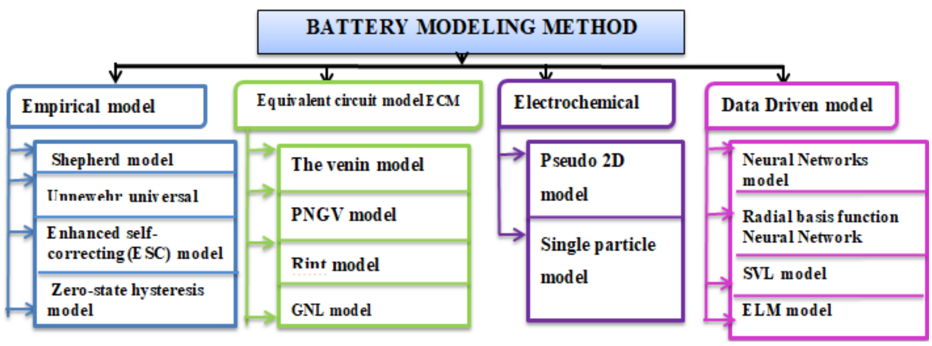


Figure 1. The classifications of battery modelling methods

Among various models, the ECM is widely used in BMS due to its simplicity and low computational cost. This study employs a third-order ECM [31]. Figure 2 for SOC estimation and dynamic analysis. The model consists of an OCV source dependent on SOC, an ohmic resistance (R_0) representing internal losses, and three RC pairs (R_1C_1, R_2C_2, R_3C_3) to capture transient and diffusion effects. The battery current (I_bat) flows through the circuit, influencing the terminal voltage (Vbat), which is measured at the output. This configuration improves accuracy in modeling the battery's nonlinear.

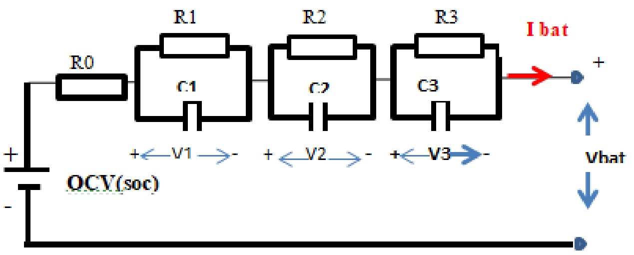


Figure 2. Equivalent circuit model of Li-ion battery

The internal states of the Li-ion battery are described by (1)-(3). These equations define the battery's internal behavior.

$$\frac{dv_1}{dt} = \frac{v_1}{R_1.C_1} - \frac{I_{bat}}{C_1} \tag{1}$$

$$\frac{dv_2}{dt} = \frac{v_2}{R_2.C_2} - \frac{I_{bat}}{C_2} \tag{2}$$

$$\frac{dv_3}{dt} = \frac{v_3}{R_3.C_3} - \frac{I_{bat}}{C_3} \tag{3}$$

The derivative of the SOC of a battery with respect to time can be expressed in (4), where QC represents the cell's charge capacity in (Ah).

$$s\dot{o}c = \frac{-I_{bat}}{Q_c .3600} \tag{4}$$

According to electrical circuit theory, the voltage at the battery terminals can be expressed by (5) and (6).

$$V_{bat} = OCV(soc) - I_{bat}R_0 - v_1 - v_2 - v_3 \tag{5}$$

$$I_{bat} = \frac{V_{bat} - OCV(soc) + v_1 + v_2 + v_3}{R_0} \tag{6}$$

2.1.2. Model description: with current fault

Any unexpected behavior in a controlled process is considered a fault. In batteries, faults can occur in the cell, sensors, or internal components. As shown in Figure 3, faults are classified by their time-varying behavior as sudden, intermittent, or gradual. Effective battery monitoring is essential for detecting and managing such faults [32].

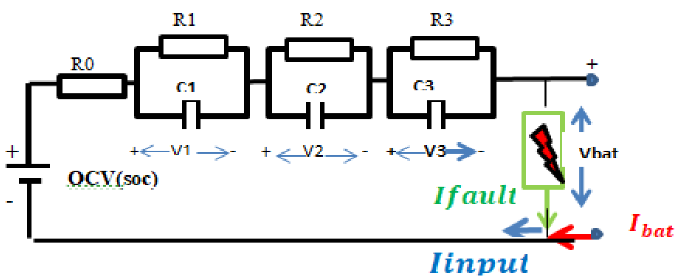


Figure 3. Equivalent circuit model of a Li-ion battery with fault current

The model in Figure 3 consists of R_0, the three pairs RC, the open circuit voltage OCV, V_1, V_2, V_3, and V_{bat}, which we have already defined; Iba is the known input current of the battery. Its reference direction refers to the discharge process (+) and the charging process (-). I_{Fault} is the fault current, which is unidirectional and is actually unknown because it is due to several reasons (sensor error, short circuit, wrong charger selection to speed up the charging process). Iinput is the input current of the battery and is determined by Kirchhoff's circuit law. In the case of fault, as shown in (7).

$$I_{input} = I_{bat} + I_{fault} \tag{7}$$

But when the battery is operating normally, $I_{fault} = 0$ and thus $I_{input} = I_{bat}$.

3. METHOD

This study adopts a structured experimental approach, using a third-order ECM and SMO with algorithmic justification for robust SOC estimation. Coulomb counting is applied for tracking SOC, while the third-order model ensures higher dynamic accuracy than second-order models. To assess the robustness of the SOC estimation method, sensor bias and current drift faults were simulated over 11 hours. This long-term test highlights the SMO observer's stability under undetected faults. Future work will test performance using standard charging profiles like CCCV and CPCV.

Coulomb counting is widely used for SOC estimation but suffers from error accumulation due to sensor inaccuracies and voltage fluctuations, especially over time or under abnormal conditions. More robust alternatives, like the SMO with an ECM, better handle dynamic behaviors and reduce long-term estimation errors. The SMO is selected due to its robustness against measurement noise and parameter variations. Table 1 represents Information about the used battery.

Table 1. Information about the used battery

Li-ion battery	Variable	Value	Parameter
	Maximum voltage	4.5	V
	Nominal voltage	3.7	V
	battery current	10	A
	R_0	0.0014	Ω
	R_1	0.0024	Ω
	C_1	24000	F
	R_2	0.0030	Ω
	C_2	26000	F
	R_3	0.0040	Ω
	C_3	27000	F

3.1. Sliding mode observer

The SMO is a state monitoring technique valued for its simplicity and low computational demand, as it does not require a complex mathematical model of the controlled system and is insensitive to parameter variations. This makes it an effective strategy for designing monitoring systems that can accurately measure and efficiently track the states of nonlinear systems. The monitor is also resistant to external disturbances and noise, demonstrating excellent performance in real-world applications. When calculating the SOC of a Li-ion battery, factors such as computational complexity, flexibility, and convergence speed must be considered. Its high resistance to interference indicates exceptional robustness, allowing it to maintain performance even in the presence of battery-level disturbances. To estimate the SOC using the adaptive sliding mode observer, it is essential to establish a mathematical model of the Li-ion battery system and derive the state-space equations. Following this, the design of the relevant SMO is implemented to monitor the battery's state variables for SOC estimation [33]-[35].

The state equations of the battery system can be derived through a systematic process. This process is outlined in (8)–(12).

$$\dot{v}_{bat} = a_1 v_{bat} + a_2 ocv(soc) - a_3 v_1 - a_4 v_2 - a_5 v_3 - \frac{\alpha}{Q_c.3600}.I_{bat} + \Delta_{f1} \tag{8}$$

$$s\dot{o}c = \frac{1}{Q_c.3600} V_t - a_6 ocv(soc) - a_6.v_1 - \frac{1}{Q_c.3600}.v_2 - \frac{1}{Q_c.3600}.v_3 + \Delta_{f2} \tag{9}$$

$$\dot{v}_1 = \frac{1}{R_1 C_2}.v_1 - \frac{\alpha}{Q_c.3600}.I_{bat} + \Delta_{f3} \tag{10}$$

$$\dot{v}_2 = \frac{1}{R_2 C_2}.v_1 - \frac{1}{C_1}.I_{bat} + \Delta_{f4} \tag{11}$$

$$\dot{v}_3 = \frac{1}{R_3C_3}.v_3 - \frac{1}{C_2}.I_{bat} + \Delta_{f5} \quad (12)$$

$a_1 = (C_3C_2+R_1C_1C_3+C_1C_2)/(R_1C_2C_3)$; $a_2 = (C_3C_2+C_1C_3+C_1C_2)/(C_1C_2C_3)$;
$a_3 = (C_3C_2+R_1C_2C_3+C_3R_1+R_1C_2)/(R_1C_2C_3)$; $a_4 = (R_2C_3+R_2C_2+C_1C_3+R_2C_2C_3)/(R_2C_2C_3)$;
$a_5 = (C_3C_2+R_3C_3+C_3RC_1+C_2R_2C_1)/(R_3C_3C_1)^2$.

The state equation can be expressed concisely in terms of matrices, as shown in (13)-(15).

$$\begin{cases} \dot{X(t)} = Ax(t) + Bu(t) + \Delta f \\ y(t) = Cx(t) \end{cases} \quad (13)$$

$$\begin{bmatrix} \dot{v_{bat}} \\ \dot{soc} \\ \dot{v_1} \\ \dot{v_2} \\ \dot{v_3} \end{bmatrix} = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \\ a_6 & a_6 & a_6 & a_6 & a_6 \\ 0 & 0 & a_7 & 0 & 0 \\ 0 & 0 & 0 & a_8 & 0 \\ 0 & 0 & 0 & 0 & a_9 \end{bmatrix} . \begin{bmatrix} v_{bat} \\ ocv \\ v_1 \\ v_2 \\ v_3 \end{bmatrix} - \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} I_{bat} + \Delta f \quad (14)$$

$$v_{bat} = [1 \ 0 \ 0 \ 0 \ 0 \ ].[\, v_{bat} \ ocv \ v_1 \ v_2 \ v_3 \ ]^T \quad (15)$$

The inputs and outputs of the circle model were defined as U(t) = I_{bat} and y(t) = V_{bat} in row, system condition variables are chosen as V_{bat}, SOC, V_1, V_2, V_3. The OCV of the electrical circuit is expressed as a function of the state of charge (SOC) using the piecewise linear approximation method, as shown in (16).

$$ocv(soc) = \alpha soc + \beta \quad (16)$$

The OCV derivative of the electrical circuit is expressed as a function of the state of charge (SOC) using the piecewise linear approximation method, as shown in (17).

$$\dot{ocv}(soc) = -\alpha \frac{I_{bat}}{3600.Q} \quad (17)$$

Where α and β are constant values in every 10% of SOC, which allow us to represent the time derivative of Uoc in each 10% of SOC.

To accurately estimate the state of charge, SMO equations are proposed. These equations are shown in (18)–(22).

$$\dot{\widehat{v_{bat}}} = a_1 v_{bat} + a_2 ocv(soc) - b_1.I_{bat} + L_1 sgn(e_{v_{bat}}) \quad (18)$$

$$\dot{\widehat{soc}} = a_3 V_{bat} - a_3 ocv(soc) + a_3.v_1 + a_3.v_2 + a_3.v_3 + L_2 sgn(e_{soc}) \quad (19)$$

$$\dot{\widehat{v_1}} = a_4.v_1 - b_2.I_{bat} + \Delta_{f3} + L_3 sgn(e_{v_1}) \quad (20)$$

$$\dot{\widehat{v_2}} = a_5.v_1 - b_3.I_{bat} + \Delta_{f4} + L_4 sgn(e_{v_2}) \quad (21)$$

$$\dot{\widehat{v_3}} = a_6.v_3 - b_4.I_{bat} + \Delta_{f5} + L_5 sgn(e_{v_3}) \quad (22)$$

Where $sgn(e) \begin{cases} +1, & e > 0 \\ -1, & e < 0 \end{cases}$. The state error is shown in (23).

$$\begin{cases} e_{v_{bat}} = v_{bat} - \widehat{v_{bat}} \\ e_{ocv} = ocv - \widehat{ocv} = ke_{soc} \\ e_{v_1} = v_1 - \widehat{v_1} \\ e_{v_2} = v_2 - \widehat{v_2} \\ e_{v_3} = v_3 - \widehat{v_3} \end{cases} \quad (23)$$

By subtracting (20)-(24) from (10)-(14), we obtain the error dynamics ebat, esoc, ev1, ev2, ev3, as shown in (24)-(28).

$$\dot{e_{v_{bat}}} = a_1 e_{v_{bat}} + a_2 e_{ocv} + \Delta_{f1} - L_1 sgn(e_{v_{bat}}) \quad (24)$$

$$\dot{e_{soc}} = a_3 e_{v_{bat}} - a_3 k e_{soc} + a_3 . e_{v_1} + a_3 . e_{v_2} + a_3 . e_{v_3} + \Delta_{f2} - L_2 sgn(e_{soc}) \quad (25)$$

$$\dot{e_{v_1}} = a_4 . e_{v_1} + \Delta_{f2} - L_3 sgn(e_{v_1}) \quad (26)$$

$$\dot{e_{v_2}} = a_5 . e_{v_2} + \Delta_{f2} - L_4 sgn(e_{v_2}) \quad (27)$$

$$\dot{e_{v_3}} = a_6 . e_{v_3} + \Delta_{f2} - L_5 sgn(e_{v_3}) \quad (28)$$

Based on Lyapunov's stability theory, the asymptotic convergence of the terminal voltage error can be proven by choosing a candidate Lyapunov function, as shown in (29).

$$\begin{cases} V_{v_{bat}} = \frac{1}{2} {e_{v_{bat}}}^2 \\ \dot{V_{v_{bat}}} = e_{v_{bat}} - \dot{e_{v_{bat}}} \end{cases} \quad (29)$$

The time derivative of a Lyapunov function filter must be negative to ensure a sliding regime, and after developing the expressions of (V_(v_bat))˙, L1>> $\Delta f1$ is the value of L1 that ensures (V_(v_bat))˙<0. All symbols that have been used in the equations should be defined in the following text.

4. RESULTS AND DISCUSSION

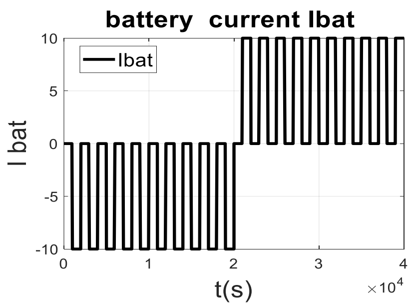
The proposed method improves SOC estimation accuracy and battery safety under fault conditions. An SMO was tested on a third-generation Li-ion battery using both normal and fault currents to estimate system states (Vbat, SOC, V1, V2, and V3). Future work will focus on real-time implementation and adaptive gain optimization. Polarization voltages (V1, V2, V3) were validated by comparing SMO estimates to benchmark ECM values. RMSE analysis confirmed the method's accuracy under both normal and fault conditions.

This study aims to improve the accuracy and robustness of (SOC) and terminal voltage estimation under both normal and faulty conditions. Unlike previous works that use second-order models or short simulation durations [32], [36], it employs a third-order ECM combined with an adaptive SMO. This approach enhances dynamic performance, extends operational time up to 40,000 seconds far surpassing the durations handled by models in [36]-[38], which are limited to less than 14,000, 1,800, and 900 seconds respectively, and simultaneously estimates SOC, voltage, and polarization potentials (V_1, V_2, V_3), offering a more comprehensive and fault-tolerant solution for battery management systems.

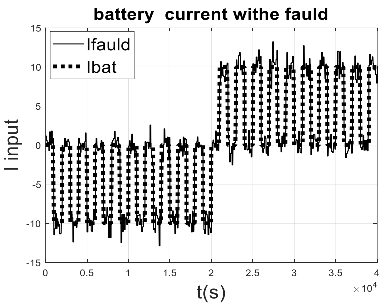
4.1. Battery current analysis

This study simulated common faults like sensor bias and current drift to test the SOC estimation method's robustness. The 11-hour fault analysis assessed the SMO-based observer's performance under long-term fault conditions, reflecting scenarios where a BMS may not act immediately. This extended test highlights the method's long-term accuracy and stability. The 3-RC model enhances SOC estimation accuracy by better capturing voltage fluctuations and transient dynamics under fault conditions. Its added complexity is justified for real-time, fault-tolerant BMS.

Figure 4 shows battery current under normal and faulty conditions. In Figure 4(a), the healthy battery exhibits a stable and consistent current profile. In contrast, Figure 4(b) shows a faulty battery with fluctuations caused by issues such as sensor errors, short circuits, or improper charger use. These deviations highlight the impact of faults on performance and the need for effective fault detection in BMS.



(a)

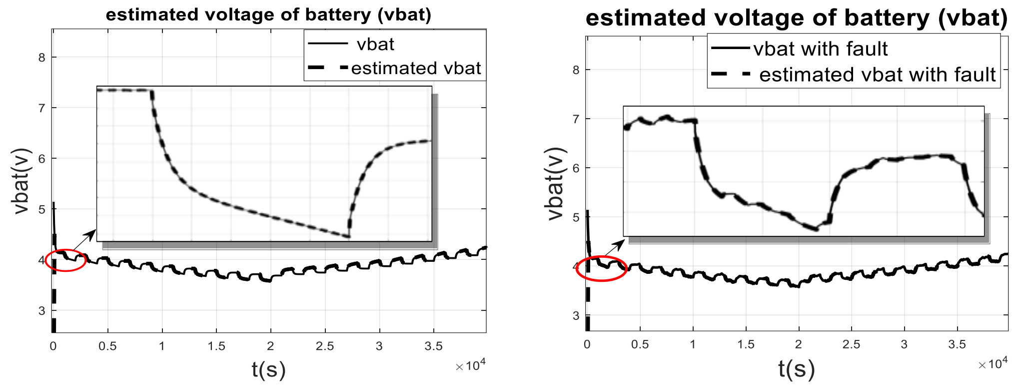


(b)

Figure 4. Battery current: (a) battery current in operating normally and (b) battery current with fault

4.2. Battery voltage estimation

Figure 5 shows the estimation of battery terminal voltage (Vbat) under normal and faulty conditions over 40,000 seconds (approximately 11 hours). The proposed SMO accurately tracks voltage throughout this period, outperforming the method in [36], which remains reliable only up to 14,000 seconds. Figures 5(a) and 5(b) compare estimated and actual Vbat under normal and faulty conditions. While the method in [36] is reliable only up to 14,000 seconds, the SMO-based estimator ensures stable voltage tracking with minor oscillations in normal conditions and clearly detects deviations during faults. These results confirm its robustness for long-term, real-time battery monitoring and fault detection in BMS.

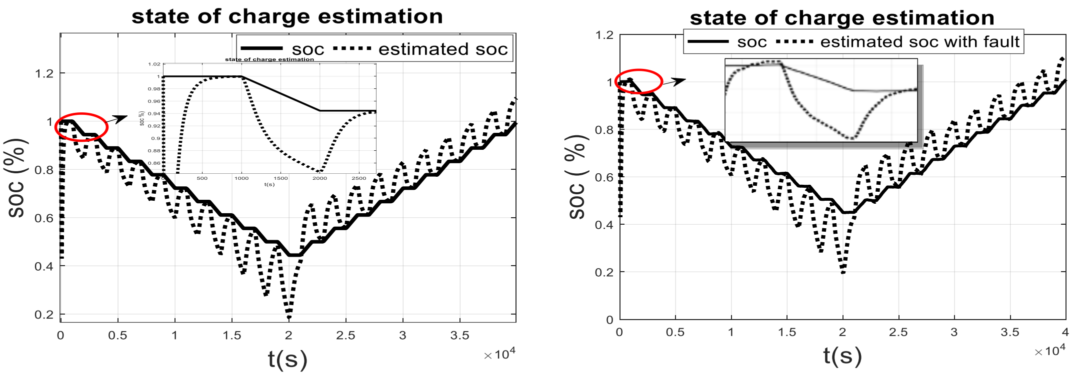


(a) (b)

Figure 5. Battery voltage: (a) battery voltage in operating normally and (b) battery voltage with fault

4.3. State of charge estimation

Figure 6 illustrates SOC estimation under normal and faulty conditions over 40,000 seconds. The proposed SMO method ensures accurate and stable tracking throughout, with minimal deviation in normal operation, as shown in Figure 6(a), and clear fault detection under abnormal conditions, as shown in Figure 6(b). In contrast, methods in [32] and [37] are reliable only up to 1,000 and 1,800 seconds, respectively, highlighting the superior robustness and long-term accuracy of the SMO-based approach.

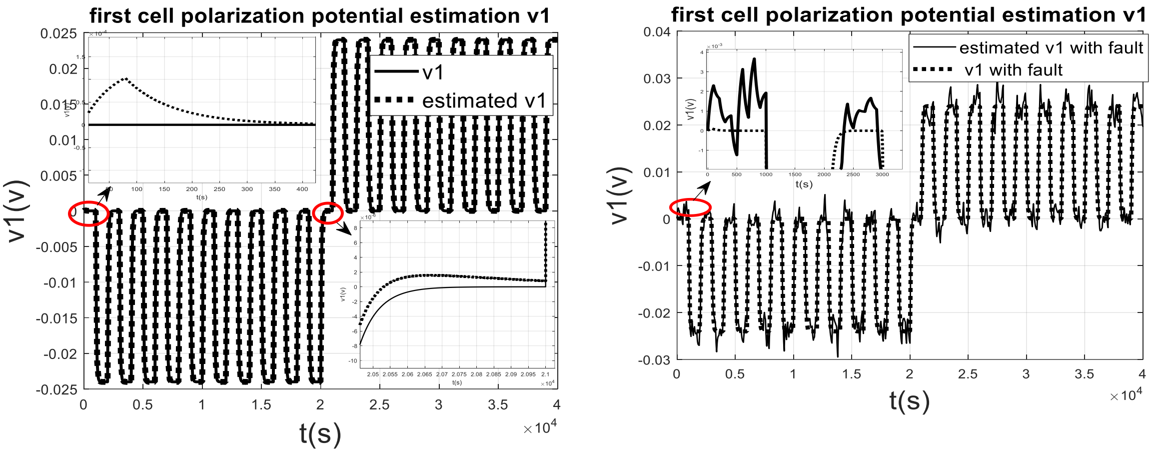


(a) (b)

Figure 6. State of charge estimation: (a) SOC in operating normally and (b) SOC with fault

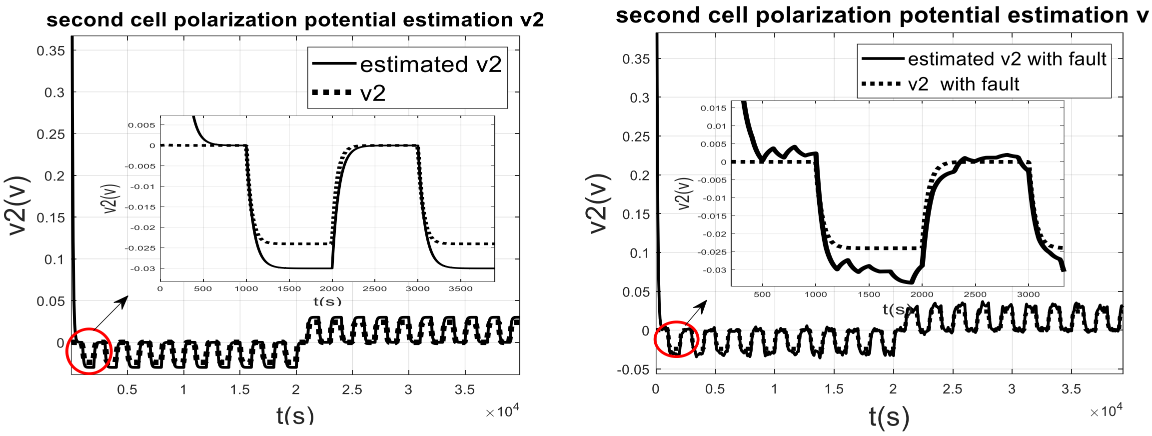
4.4. Cell polarization potential estimation

Figures 7, 8, and 9 show the estimated cell polarization voltages (V_1, V_2, and V_3) under normal and faulty conditions over 40,000 seconds. This extended period enables a thorough evaluation of the proposed controller's ability to track voltage dynamics over time. In contrast, the method in [38] was tested over only 900 seconds, limiting its effectiveness for long-term monitoring. The results highlight the proposed controller's superior stability, reliability, and accuracy even under fault conditions, improving fault detection and overall BMS performance. This demonstrates its robustness for real-world energy storage applications.



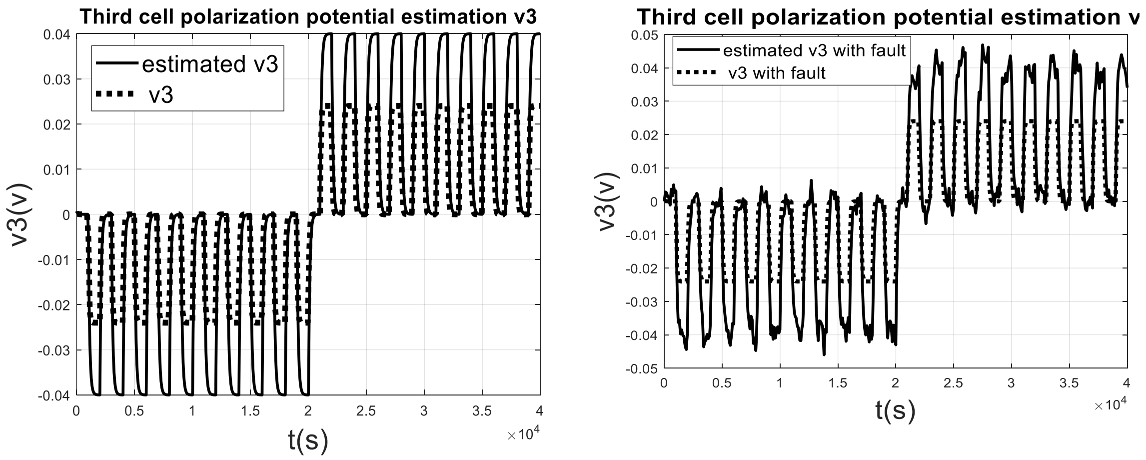
(a) (b)

Figure 7. First cell polarization potential estimation: (a) V_1 operating normally and (b) V_1 with fault



(a) (b)

Figure 8. Second cell polarization potential estimation: (a) V_2 in operating normally and (b) V_2 with fault

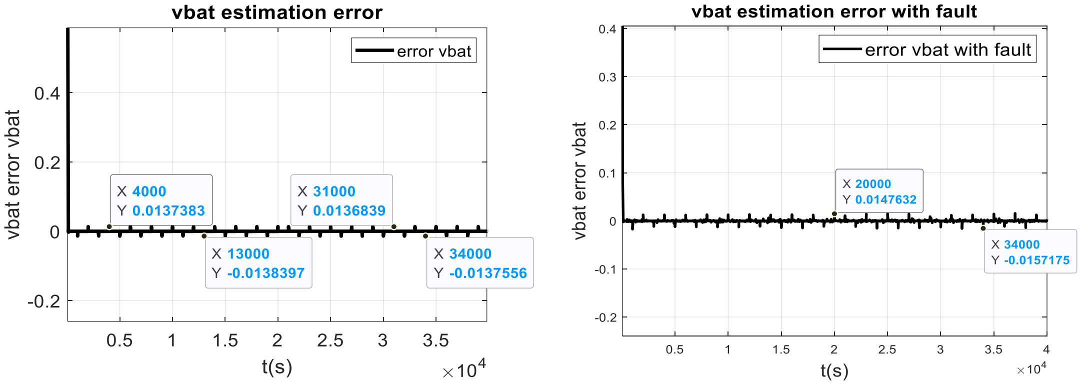


(a) (b)

Figure 9. Third cell polarization potential estimation: (a) V_3 in operating normally and (b) V_3 with fault

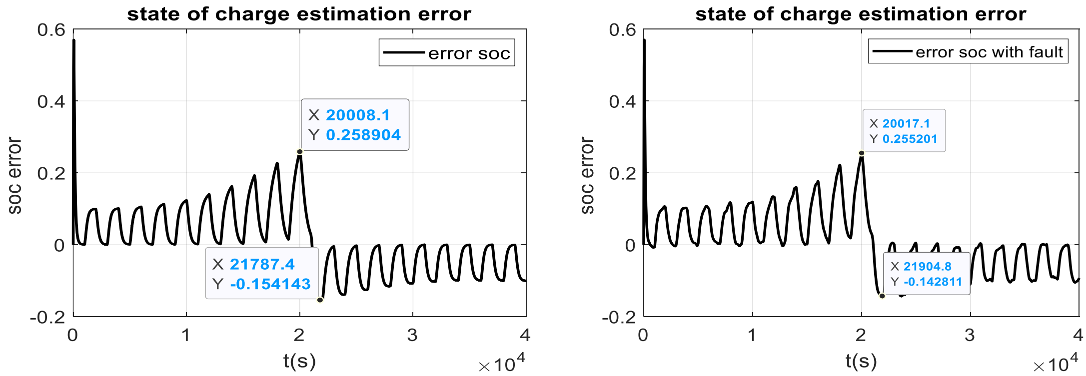
4.5. Estimation error analysis

Figures 10-14 show estimation errors for battery voltage (Vbat), SOC, and polarization voltages (V_1, V_2, V_3) under normal and fault conditions over 40,000 seconds. This duration offers a strong comparison to [39] and [40], which cover only 25,000 and 1,065 seconds, respectively. The near-zero errors demonstrate the proposed method's accuracy and reliability in estimating system states, even during faults. The observer consistently tracks voltage and SOC with high precision, confirming its robustness for real-time, fault-tolerant BMS applications.



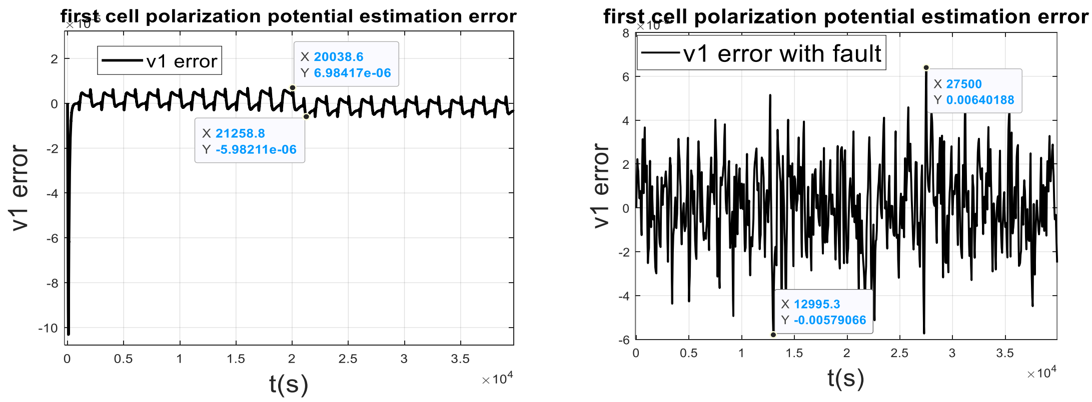
(a) (b)

Figure 10. V_{bat} estimation error: (a) error V_{bat} in operating normally and (b) error V_{bat} with fault



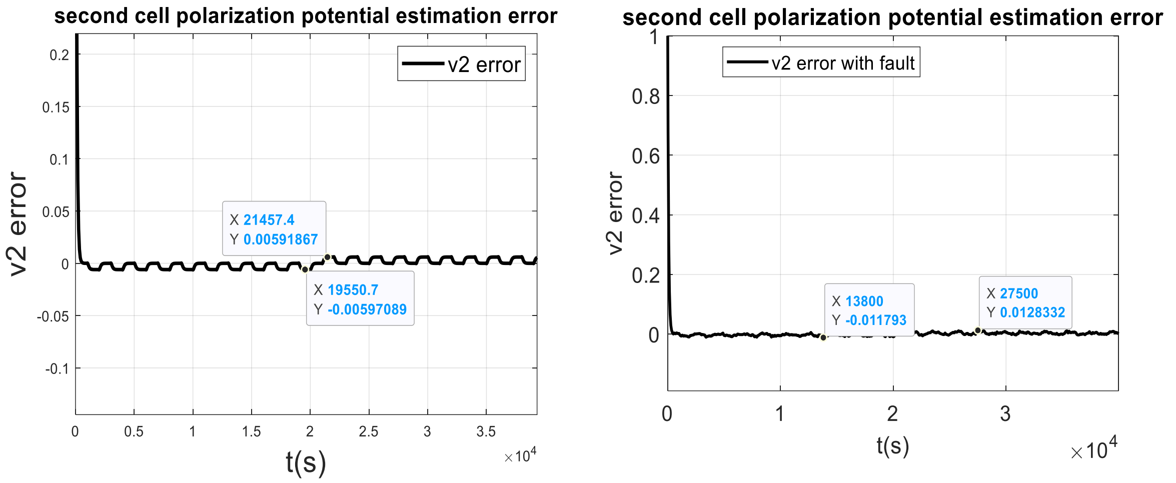
(a) (b)

Figure 11. State of charge estimation error: (a) SOC error in operating normally and (b) SOC error with fault



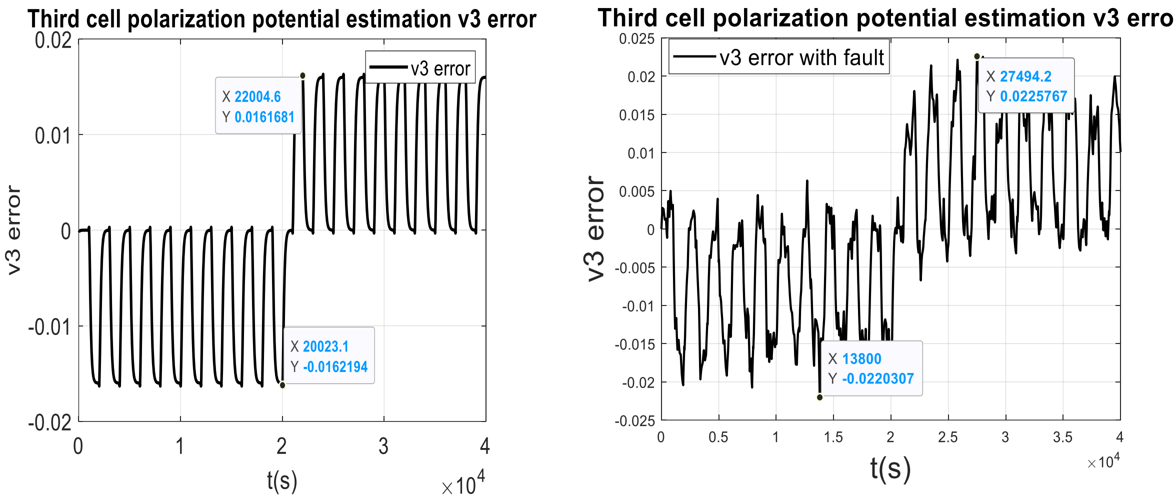
(a) (b)

Figure 12. First cell polarization potential estimation error: (a) V_1 errror in operating normally and (b) V_1 error with fault



(a) (b)

Figure 13. Second cell polarization potential estimation error: (a) V_2 errror in operating normally and (b) V_2 error with fault



(a) (b)

Figure 14. Third cell polarization potential estimation error: (a) V_3 errror in operating normally and (b) V_3 error with fault

5. CONCLUSION

This paper presents a novel SMO designed to accurately estimate the SOC and terminal voltage of Li-ion batteries using a third-order ECM with three resistor–capacitor (RC) networks. The proposed method effectively captures the battery's dynamic behavior, providing precise SOC estimation under both normal and faulty conditions. Simulation results confirm its high accuracy, robustness, and superior performance compared to conventional approaches. The SMO also distinguishes between normal and fault scenarios, making it suitable for real-time BMS.

This study enhances battery reliability, safety, and lifespan, especially for electric vehicles and renewable energy storage applications. This study presents an estimation method based on a 3-RC battery model that balances accuracy and computational efficiency. The method performs reliably even under faulty charging conditions, making it well-suited for practical applications. Future work should focus on real-time validation using experimental testbenches and adaptive gain control to improve robustness. Integrating SMO techniques with machine learning could enhance fault diagnosis and predictive accuracy. Applying the approach to different battery chemistries, such as lithium-ion and solid-state systems, and optimizing computational performance will support its use in low-power embedded and IoT-based energy storage systems. These developments will strengthen the adaptability and efficiency of next-generation battery management technologies.

The adoption of the 3-RC model for SOC estimation represents a well-balanced compromise between accuracy and computational efficiency. While the increased computational load may appear as a limitation, the model's enhanced performance under faulty charging conditions makes it the most suitable choice for this study. Future research may explore further generalizations to n-RC models to further improve accuracy.

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AUTHOR CONTRIBUTIONS STATEMENT

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

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

CONFLICT OF INTEREST STATEMENT

Authors declare that there are no conflicts of interest in this manuscript.

DATA AVAILABILITY

Part of the system data used is included within the manuscript and is available in Table 1.

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