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State-augmented adaptive sliding-mode observer for estimation of state of charge and measurement fault in lithium-ion batteries

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ABSTRACT

Estimating the state of charge (SoC) in lithium-ion batteries (LiB) encounters challenges due to model uncertainties and sensor measurement errors. To solve this issue, this study introduces an estimator based on an innovative adaptive augmented sliding mode approach. This approach incorporates measurement faults as additional state variables to minimize the impacts of uncertainties effectively. Furthermore, based on the sliding mode framework, the design of this estimator addresses resistance to model uncertainties. However, sliding estimators commonly face the chattering issue. To counteract this, the paper suggests employing adaptive dynamics to determine the estimator's gain. This adaptive approach allows the gain calculation to minimize estimation errors across all time steps, effectively reducing chattering and enhancing estimation accuracy. The performance of the proposed method is validated through simulations using two practical data sets. Results demonstrate superior accuracy compared to conventional sliding methods, with improvements in SoC and terminal voltage estimation.

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1. INTRODUCTION

The growing interest in renewable energy systems has led to a surge in research around energy storage solutions. Among these, batteries are crucial components that are used in almost all energy storage systems. The emergence of lithium-ion batteries (LiB) has revolutionized energy storage. LiBs offer several advantages, including higher charge density, compact size, reduced weight, and stable output voltage. As a result, their use has increased in various applications, including renewable energy systems (RES) and electric vehicles (EVs) [1], [2]. However, the utilization and supervision of LiBs present significant challenges, the primary challenges include accurately estimating parameters like state of charge (SoC), internal resistances, and detecting faults during current and terminal voltage measurements [3]-[5].

Researchers have proposed diverse methods for estimating battery parameters and detecting measurement faults, categorized as signal-based, model-based, or electrochemical concepts. Among these, model-based approaches are widely adopted for their effectiveness in both parameter estimation and fault detection [6]. However, the successful implementation of model-based methods hinges on selecting an appropriate model for LiBs. Various modeling approaches exist, with electrical methods being one prominent option. In this approach, a circuit model is formulated for the battery, from which a state space model is derived. Subsequently, utilizing this state space model, researchers develop tailored estimators to determine battery parameters [7], [8]. There are various types of estimators, with Kalman filters constituting the first category. These filters operate on recursive mathematical relationships, offering solutions for both linear and nonlinear dynamics affected by measurement and process noise. For linear dynamics, conventional filter types suffice, while non-linear dynamics necessitate specialized variants like the extended Kalman filter. However, the extended Kalman filter suffers from linearization errors, diminishing estimation accuracy. To mitigate this, researchers turn to alternatives like the unscented Kalman filter, which requires more computational power, it avoids linearization. Despite its complexity, unscented Kalman filters have superior accuracy compared to their extended counterpart. Establishing process and measurement noise covariance matrices poses a significant challenge in Kalman filter design, often addressed through adaptive approaches [9], [10]. Researchers employ techniques such as fuzzy systems or neural networks to adaptively determine covariance matrices, enhancing estimation accuracy. Nonetheless, a crucial drawback of Kalman filters lies in their dependence on accurate battery models. Errors in model identification engender uncertainty, undermining the filter's precision [11]-[13].

To address model uncertainties, researchers employ robust estimation techniques for estimating the battery's SoC. These methods incorporate a range of uncertainty into their models and adapt the estimator accordingly [14]. Sliding estimators are prominent among these robust techniques [15]. However, they often encounter chattering issues during estimation. To minimize this, some researchers employ adaptive variations that adjust battery parameter estimation [16], [17]. This adaptation can involve making the estimator gain adaptive through techniques like fuzzy systems or neural networks [18], [19], or by introducing specialized dynamics to minimize chattering. Another robust estimator, the H-infinity estimator, tackles model uncertainty by accounting for it in its design, providing accurate estimates even in uncertain conditions. Nonetheless, these estimators suffer from heavy computational requirements and complex practical implementations [20], [21].

In recent years, alongside model-based approaches, learning-based methods have gained significant traction for estimating battery parameters. Notably, techniques such as machine learning, deep learning, and reinforcement learning have emerged as prominent choices in this domain. The primary advantage of these methods lies in their independence from battery modeling, enabling parameter estimation without explicit model knowledge. Nevertheless, a major challenge with these approaches is the necessity for a comprehensive and dependable dataset for learning [22], [23]. Additionally, alternative methods like signal-based approaches utilizing ultrasonic sensors have been proposed for parameter estimation. However, these methods are hindered by the requirement for a fully equipped laboratory setup. Furthermore, techniques such as ampere-hours or impedance measurements offer simplicity and sensitivity to laboratory conditions, albeit at the cost of lower accuracy [24].

Addressing measurement faults alongside battery parameter estimation is crucial, particularly in high-current applications. Currently, limited methods are available for detecting and estimating measurement errors in batteries. Furthermore, the uncertainty inherent in battery models can significantly impact parameter estimation accuracy. This article proposes an extension method for sliding estimators to tackle these challenges. This approach treats measurement faults as an additional state variable, estimating them alongside SoC using an adaptive sliding estimator. As a result, both SoC and sensor faults can be accurately and easily estimated. The estimator employs a specially designed dynamic process to adaptively extract filter gain, reducing chattering during estimation. The remaining part of this paper is structured as follows: Section 2 mentions the state space model of LiB. Section 3 introduces the proposed state-augmented adaptive sliding-mode observer for estimation of soc and measurement fault. Section 4 shows the estimation results of SoC and measurement fault using practical data. Finally, section 5 contains some conclusions.

2. STATE SPACE MODEL OF LIB

Several approaches to modeling LiBs have been proposed. These include electrochemical models, equivalent circuit models, and experimental models. Among these, the equivalent circuit models have garnered significant attention from engineers and designers due to their ability to strike a balance between precision and simplicity, making them particularly appealing for design purposes. To describe more accurately the dynamics of LiB, in this research, the second order of LiB is used [25], [26].

As depicted in Figure 1, this paper employs a second-order equivalent circuit model to characterize the LiB. The circuit model encompasses various components: resistor R_0 representing the internal resistance of the battery, two resistor/capacitor loops R_1, C_1, and R_2, C_2 to emulate the battery's transient behavior over both long and short terms, SoC dependent voltage source $OCV(\varsigma)$ to incorporate the nonlinear relationship between open circuit voltage and SoC of the battery, resistor R_b to illustrate self-discharge, and capacitor C_b to signify the total battery capacity. By utilizing Kirchhoff's laws, the terminal voltage can be expressed by (1).

$$V_b = OCV(\varsigma) - V_1 - V_2 - I_b R_0 \quad (1)$$

In which, ς is the SoC of LiB; V_1 and V_2 are the voltages across the two resistor/capacitor loops respectively. The dynamical equations of the SoC, V_1, and V_2 by (2), (3), and (4), respectively.

$$\frac{d\varsigma}{dt} = -\frac{\varsigma}{R_b C_b} - \frac{I_b}{C_b} \quad (2)$$

$$\frac{dV_1}{dt} = -\frac{V_1}{R_1 C_1} + \frac{I_b}{C_1} \quad (3)$$

$$\frac{dV_2}{dt} = -\frac{V_2}{R_2 C_2} + \frac{I_b}{C_2} \quad (4)$$

By considering $\frac{dI_b}{dt} = 0$ and using (1) and (2), the dynamical equation of the terminal voltage V_b is formulated as (5).

$$\frac{dV_b}{dt} = \frac{\partial OCV(\varsigma)}{\partial \varsigma}\frac{d\varsigma}{dt} - \frac{dV_1}{dt} - \frac{dV_2}{dt} \quad (5)$$

The state vector is considered as $z = [\varsigma, V_1, V_2, V_b]^T$, I_b is the input u and V_b is the output y of the battery model. The state space model of the battery by using (2), (3), (4), and (5), can be written as (6).

$$\begin{cases} \frac{dz}{dt} = f(z,u) + \rho \\ y = Cz + n, \end{cases} \quad , \quad C = [0 \quad 0 \quad 0 \quad 1] \quad (6)$$

The terms ρ and n, with zero mean, represent noises related to process and measurement. The nonlinear function vector $f(z,u)$ can be expressed as (7).

$$f(z,u) = \begin{bmatrix} -\frac{\varsigma}{R_b C_b} - \frac{I_b}{C_b} \\ -\frac{V_1}{R_1 C_1} + \frac{I_b}{C_1} \\ -\frac{V_2}{R_2 C_2} + \frac{I_b}{C_2} \\ \frac{\partial OCV(\varsigma)}{\partial \varsigma}\frac{d\varsigma}{dt} + \frac{V_1}{R_1 C_1} + \frac{V_2}{R_2 C_2} - \left(\frac{C_1 + C_2}{C_1 C_2}\right) I_b \end{bmatrix} \quad (7)$$

The (7) describes the dynamics of LiB, in which the parameters of this model will be identified from experimental data sets, one of the effective parameter identification methods is the authors' method in the document [27]. In order to confirm the accuracy of a battery model, it is crucial to simulate it in a software environment and compare the terminal voltage with the voltage measured during practical tests. If the simulated voltage closely matches the measured voltage within a predefined threshold, it confirms the successful identification of the battery.

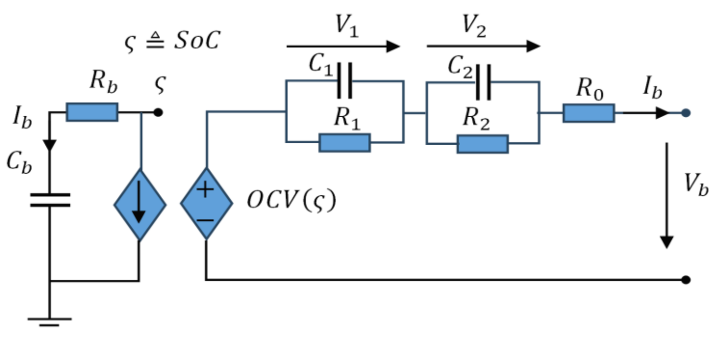

Figure 1. The second-order equivalent circuit model of LiB

3. STATE-AUGMENTED ADAPTIVE SLIDING-MODE OBSERVER FOR ESTIMATION OF SOC AND MEASUREMENT FAULT

To accurately estimate the state variables, such as SoC and measurement sensor fault, it's necessary to rewrite the current variables vector as (8) and (9).

$$z^a = [\,\varsigma, V_1, V_2, V_o, \xi]^T \tag{8}$$

$$f^a(z^a,u) = \begin{bmatrix} -\frac{\varsigma}{R_b C_b} - \frac{I_b}{C_b} \\ -\frac{V_1}{R_1 C_1} + \frac{I_b}{C_1} \\ -\frac{V_2}{R_2 C_2} + \frac{I_b}{C_2} \\ \frac{\partial OCV(\varsigma)}{\partial \varsigma}\frac{d\varsigma}{dt} + \frac{V_1}{R_1 C_1} + \frac{V_2}{R_2 C_2} - \left(\frac{C_1+C_2}{C_1 C_2}\right) I_b \\ 0 \end{bmatrix} \tag{9}$$

We will proceed with developing the observer by introducing the spatial model for the newly developed state. The state dynamics of the adaptive sliding mode estimator can be expressed in (10).

$$\begin{cases} \frac{d\hat{z}^a}{dt} = A^a \hat{z}^a + B^a u + \Gamma(e_\varsigma) + \beta^a \\ \hat{y} = C^a \hat{z}^a \end{cases} \tag{10}$$

In (10), the pole-placement method is used to determine the function vector Γ, while vector β^a represents the switching gains of the observer, which is derived through specific dynamics, $e_\varsigma = \varsigma - \hat{\varsigma}$ is the SoC estimation error, $C^a = [1 \quad 0 \quad 0 \quad 0 \quad 0]$. The dynamics of the estimation error vector $e = z^a - \hat{z}^a$ is calculated as (11).

$$\frac{de}{dt} = \tilde{A}^a e + \lambda \Delta(z) - \beta^a, \quad \tilde{A}^a = (A^a - \Gamma C^a) \tag{11}$$

According to the Lyapunov stability theory, matrix $\tilde{A}^a$ must be satisfied (12).

$$\tilde{A}^a P + P(\tilde{A}^a)^T = -Q, \quad C^a = \lambda^T P \tag{12}$$

Where Q is any given positive definite symmetric matrix and P is unique solution of the Lyapunov equation (12). In order to ensure observer stability, a Lyapunov function based on the error is necessary, it can be formulated as (13).

$$V(e) = \frac{1}{2}\left(e^T P e + \left(\frac{K}{\sigma}\right)^2\right) \tag{13}$$

We use K to denote an assumption for the gain of the proposed observer, which is represented by $K = \hat{K} - K_d$, σ is a constant. In order to proof stability of estimation errors, it is essential that the rate of change of the Lyapunov function is negative. To achieve this, we derive the Lyapunov function as (14).

$$\begin{aligned} \frac{dV(e)}{dt} &= \frac{1}{2}\left(\left(\frac{de}{dt}\right)^T Pe + e^T P \frac{de}{dt}\right) + \sigma^{-2} K \frac{dK}{dt} \\ &= \frac{1}{2}\left(e^T\left(\tilde{A}^a P + P(\tilde{A}^a)^T\right)e\right) + \frac{1}{2}\left((\lambda^T \Delta^T - (\beta^a)^T)Pe + e^T P(\lambda\Delta - \beta^a)\right) + \sigma^{-2} K \frac{dK}{dt} \\ &= -\frac{1}{2} e^T Q e + \Delta \lambda^T P e - (\beta^a)^T P e + \delta^{-2} K \frac{dK}{dt} \end{aligned} \tag{14}$$

If we select K as $\sigma^2 |e_\varsigma|$, and the β^a is chosen as $K_d \frac{\lambda |e_\varsigma|}{e_\varsigma}$, then we have (15).

$$\frac{dV(e)}{dt} = -\frac{1}{2} e^T Q e + \Delta \lambda^T P e - \hat{K}\frac{|e_\varsigma|}{e_\varsigma}\lambda^T P e \;= -\frac{1}{2} e^T Q e + \left(\Delta - K_d \frac{|e_\varsigma|}{e_\varsigma}\right) \tag{15}$$

If Q is positively symmetric, $-\frac{1}{2} e^T Q e$ will be negative. Moreover, $|\Delta| \leq \gamma$ is less than zero, and $K_d > \gamma$ is always positive, ensuring $\left(\Delta - K_d \frac{|e_\varsigma|}{e_\varsigma}\right)$ is negative. Consequently, the adaptive observer gain β^a is determined through dynamics, while σ, directly influencing convergence time, is computed via the optimization methods. β^a is obtained using (16).

$$\frac{d\hat{\rho}}{dt} = \sigma|e_\varsigma|$$
$$\frac{de}{dt} = \tilde{A}^a e + \lambda\Delta(z) - \beta^a \quad (16)$$

So, the adaptive observer gain β^a is calculated by (17).

$$\beta^a = \begin{cases} \hat{\rho}(e_\varsigma)\Delta sign(e_\varsigma), & e_\varsigma \neq 0 \\ 0, & e_\varsigma = 0 \end{cases} \quad (17)$$

4. ESTIMATION RESULTS OF SOC AND MEASUREMENT FAULT USING PRACTICAL DATA

In order to determine how well the supplementary estimation technique works when evaluating lithium battery faults and charge levels, an implementation system was used. This system configuration, shown in Figure 2, involves discharging the lithium battery in advance with a programmable load. The voltage and current measurements are then utilized for simulations to estimate both the SoC and faults.

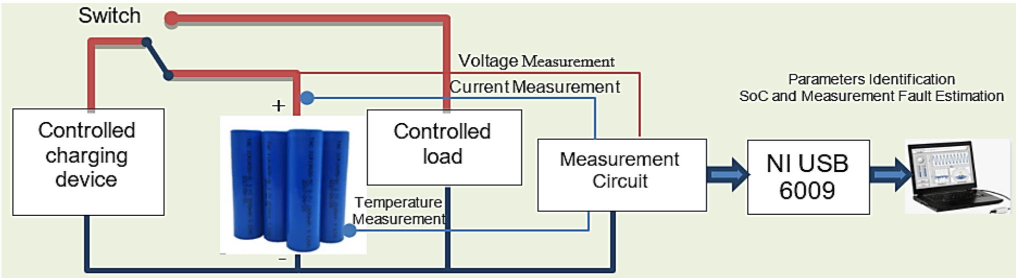

Figure 2. The configuration of the implementation system for parameters identification SoC and measurement fault estimation

After conducting a set of experiments, the dynamic equations for the battery model are derived, and the parameters in the battery state space model are determined. In this study, we use the battery type UL18650, 4.2 V, 3400 mAh, using the identification method of the authors in [27], the parameters (7) are determined as (18).

$$R_b = 1.0714 \times 10^3(\Omega); C_b = 666.667(\mu F);\ R_1 = 454.5455\ (\Omega); C_1 = 20(\mu F)$$
$$R_2 = 0.75\ (\Omega); C_2 = 133(\mu F)$$
$$\frac{\partial OCV(\varsigma)}{\partial\varsigma}\frac{d\varsigma}{dt} \approx -0.3 \times 10^{-4}\varsigma^3 + 0.3 \times 10^{-4}(1 - I_b)\varsigma^2 + 0.31 \times 10^{-4} I_b\varsigma - 0.01(I_b + 1)e^{-39\varsigma} \quad (18)$$

To evaluate the effectiveness of the proposed method, we validate the simulations using two sets of real-world data. These datasets involve altering the frequency of terminal current during discharge to evaluate the efficacy of the estimation method. Figures 3 to 7 show performance results for the first data set, while Figures 8 to 11 show results for the second data set.

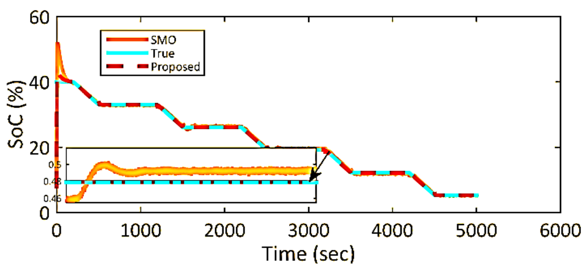

Figure 3. SoC estimation for first data set

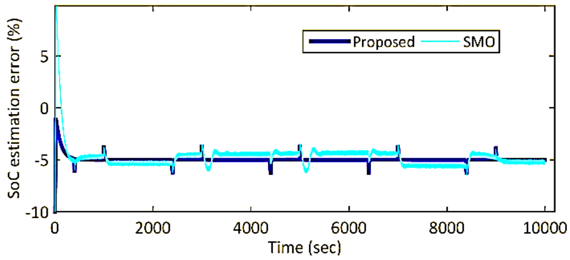

Figure 4. SoC estimation error for the first data set

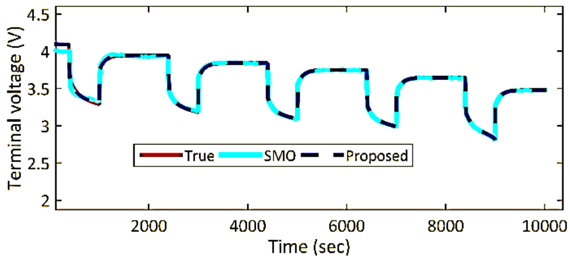

Figure 5. Terminal voltage estimation for the first data set

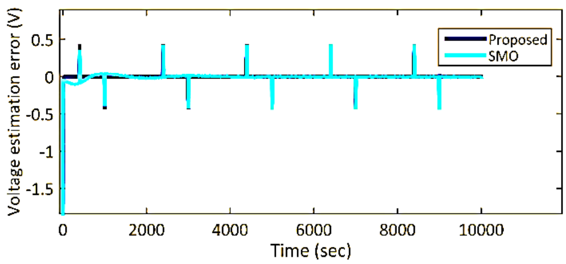

Figure 6. Voltage estimation error for the first data set

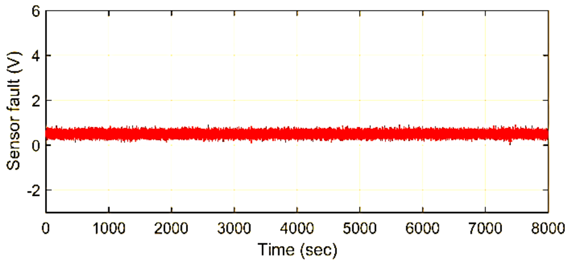

Figure 7. Fault estimation for the first data set

Figure 3 compares the performance of the proposed method for estimating SoC at a lower frequency with that of a conventional sliding mode approach. The adaptive sliding mode method explained in this study shows a 2.95% lower estimation error than the conventional method as plotted in Figure 4. Moreover, the proposed method presents minimal chattering while the conventional approach displays some chattering in its performance. The difference between the two methods can be attributed to the adaptive calculation of the estimator's gain and the use of a genetic algorithm to enhance performance in the proposed method. The unique dynamics employed for adaptively calculating the estimator's gain are designed based on minimizing estimation errors.

Figure 5 compares the proposed method's performance in terminal voltage estimation with that of the conventional sliding method. Figure 6 shows that this comparison reveals that the proposed method achieves a 2 (V) lower voltage estimation error than the conventional method. However, the chattering phenomenon persists in the terminal voltage estimation function using the proposed method. Additionally, the proposed method considers measurement sensor faults as an additional state variable in the estimator's dynamics, enabling it to estimate faults accurately. Figure 7 illustrates the estimation of sensor faults. The conventional sliding method cannot estimate sensor faults, which can negatively impact the accuracy of state variable estimation. This limitation is demonstrated in Figures 8-11, where the absence of sensor fault estimation in the conventional sliding method is evident.

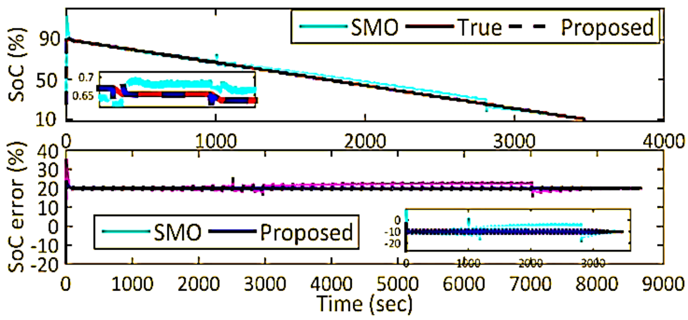

Figure 8. SoC estimation and SoC estimation error for second data set

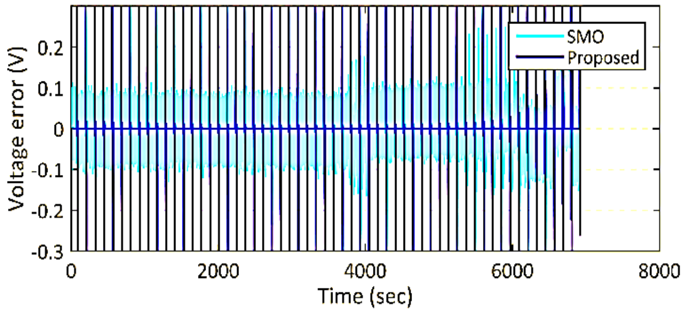

Figure 9. Voltage estimation error for second data set

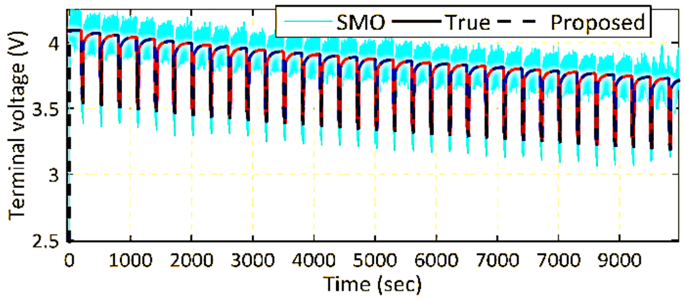

Figure 10. Terminal voltage estimation for second data set

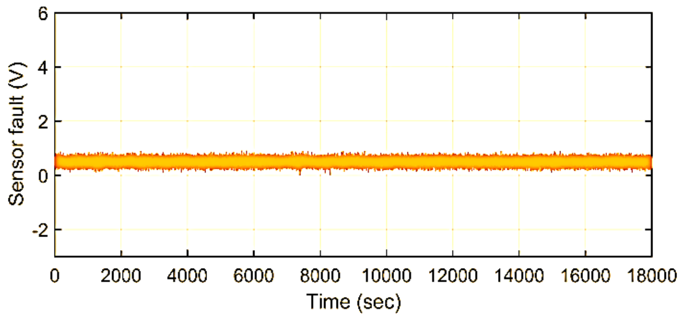

Figure 11. Fault estimation for second data set

5. CONCLUSION

This paper proposed an augmented adaptive sliding mode method to address model uncertainties and measurement sensor errors. The method treats measurement errors as incremental mode variables, effectively combating model uncertainties. The inherent chattering problem associated with sliding estimators is mitigated by adaptively designing the estimator's gain. Our approach reduces the chattering effect by leveraging estimation error and dynamically designed dynamics. This method minimizes estimation error across all time steps by optimizing the gain calculation to eliminate chattering in SoC estimation and enhance accuracy. Through simulation with practical data in two distinct phases, our proposed method demonstrates superior accuracy compared to the conventional sliding method, achieving a better SoC estimation percentage.

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AUTHOR CONTRIBUTIONS STATEMENT

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Thuy Nguyen Vinh		✓	✓		✓	✓		✓	✓	✓				
Chi Nguyen Van	✓	✓	✓			✓			✓	✓	✓			
Vy Nguyen Van		✓	✓	✓						✓	✓			

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 state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author [CNV], upon reasonable request.

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