

IMPROVED TERMINAL SLIDING MODE OBSERVER FOR INTERNAL SHORT-CIRCUIT FAULT DIAGNOSIS IN LITHIUM-ION BATTERY PACKS

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ABSTRACT. *With the rapid development of the lithium battery industry driven by the rise of new energy vehicles, safety issues associated with lithium batteries have emerged as a critical concern that remains to be fully addressed. Accordingly, this paper proposes a method for diagnosing internal short-circuit faults in lithium batteries based on an improved terminal sliding mode observer. The second-order RC equivalent circuit model was first established. Based on the equivalent circuit model, the model parameters were identified using Forgetting Factor Recursive Least Squares (FFRLS). An improved terminal sliding mode observer (ITSMO) was employed for state estimation, achieving a state of charge (SOC) estimation accuracy within 1%, which verifies the tracking performance of the proposed observer and ensures reliability for fault diagnosis. Internal short-circuit faults were simulated by connecting an external parallel resistor. The proposed observer was then used to monitor the system, and by comparing the estimated values with pre-defined thresholds, the triggering of fault signals could be controlled, thereby enabling the diagnosis of internal short-circuit faults in lithium-ion battery packs.*

Keywords: Lithium-ion battery, Sliding mode observer, State estimation, SOC, Fault diagnosis

1. Introduction. In the past decade, new energy vehicles have experienced rapid growth. Lithium-ion batteries, owing to their long cycle life and high energy density, have emerged as the preferred power source for these vehicles, thereby driving the swift expansion of the lithium battery industry [1-3]. However, battery safety issues have become increasingly prominent, characterized by rapid fault propagation, short escape times, and a high risk of fire [4]. These problems not only jeopardize the safety of life and property but also undermine public confidence in new energy vehicles, posing a challenge that cannot be ignored. Therefore, the rapid and accurate prediction and diagnosis of lithium-ion battery faults have become crucial measures to enhance the safety and reliability of electric vehicles, making battery fault diagnosis a research hotspot [5]. Against the backdrop of the fast development of new energy vehicles, improving the diagnostic capabilities for lithium-ion battery faults is of great significance for promoting the sustainable development of the industry.

At present, mainstream lithium-ion battery fault diagnosis algorithms can be mainly categorized into knowledge-based, data-driven, and model-based approaches. Knowledge-based fault diagnosis algorithms primarily include expert systems [6], fault decision trees [7], and fuzzy logic methods [8]. These methods utilize expert experience, historical data, and system modeling knowledge to perform lithium-ion battery fault diagnosis through logical reasoning or rule matching, and they generally achieve high accuracy. Nevertheless, they are limited in addressing complex scenarios such as battery aging and sudden changes in operating conditions, and it is difficult for them to accurately identify unknown faults that fall outside the established rule base. Data-driven fault diagnosis methods are mainly divided into signal processing methods [9,10], statistical analysis methods [11], and machine learning methods [12-14]. These approaches extract features directly from large volumes of offline and online operational data of lithium-ion batteries for fault diagnosis, eliminating the need for accurate physical models. However, they place high demands on data quality and typically require advanced electronic hardware for computation. In contrast, model-based fault diagnosis algorithms establish mathematical models of lithium-ion batteries to predict battery parameters [15]. By comparing residuals against a threshold, the deviation between actual values and model predictions is analyzed, and faults can be diagnosed [16]. This approach offers high real-time performance and does not require large amounts of data, making it widely applied in practice.

Model-based fault diagnosis algorithms rely heavily on the accuracy of the modeling process. Therefore, selecting appropriate modeling methods and estimation algorithms is particularly important for effective fault diagnosis [17]. In [18], a combination of finite memory multiple innovation least squares and adaptive Kalman filter algorithms was proposed, which effectively improves convergence speed and tracking capability, although the algorithm is relatively complex. [19] proposed an online internal short-circuit detection method for lithium-ion batteries based on transfer functions. By collecting real-time current and voltage data, a discrete-time regression model is constructed to dynamically update the electrical parameters, thus enabling rapid fault diagnosis; however, the stability of this method requires further improvement. In [20], an electrochemical-thermal-internal short-circuit coupled mechanism model for ternary lithium batteries was established and combined with deep learning algorithms to accomplish internal short-circuit fault diagnosis. Nevertheless, the accuracy of this approach is difficult to validate.

In recent years, sliding mode observers have been repeatedly applied to the fault diagnosis of lithium batteries. [21] employs a sliding mode observer to estimate the terminal voltage and SOC of the battery pack. It diagnoses sensor failures in lithium batteries, but this study does not account for the most common internal short-circuit fault. In [22], a model-based diagnostic scheme is presented that uses SMOs designed based on the electrical and thermal dynamics of the battery. Based on the above analysis of lithium-ion battery fault diagnosis methods and the challenges associated with certain existing approaches, this study proposes a lithium-ion battery fault diagnosis method utilizing an improved terminal sliding mode observer, leveraging the strong robustness, high accuracy, and stability inherent to sliding mode observers [23]. Specifically, by monitoring the state variables of lithium-ion batteries, the following methodology is proposed. Firstly, a second-order RC equivalent circuit model is constructed, and model parameters are identified using a least squares method with a forgetting factor. Subsequently, the ITSMO is designed by innovatively introducing a double-layer sliding surface and incorporating an integral term to enhance the observer's tracking capability; in addition, adaptive gain is implemented to improve convergence speed and reduce chattering. Finally, internal short-circuit faults are simulated by connecting an external short-circuit resistor. The observer

is utilized to estimate battery states, and fault diagnosis is achieved by comparing selected state variables against predefined thresholds to control the triggering of fault signals.

The rest of this article is organized as follows. In Section 2, a second-order RC model of the lithium-ion battery is constructed and parameter identification is performed. In Section 3, an improved terminal sliding mode observer is proposed based on the lithium-ion battery model, and its stability is proven. Section 4 introduces the internal short-circuit fault diagnosis method, and Section 5 verifies the effectiveness of the proposed method through simulation validation of both the observer and the fault diagnosis method. Finally, Section 6 presents several conclusions drawn from this study.

2. Lithium-Ion Battery Modeling.

2.1. Equivalent circuit model. The selection of a suitable equivalent circuit model is a fundamental prerequisite for accurately estimating lithium-ion battery parameters. In this study, the second-order RC model is adopted as the equivalent circuit model, and its structure is illustrated in Figure 1.

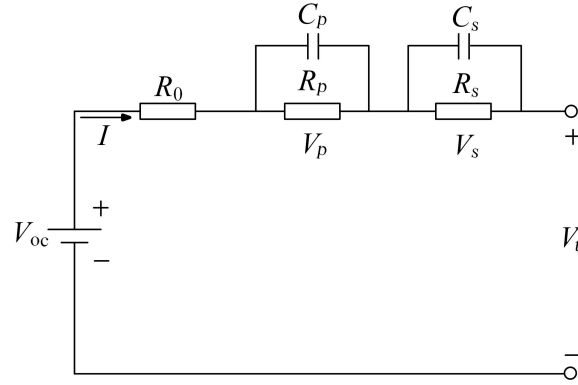


FIGURE 1. Second-order RC equivalent circuit model

In Figure 1, V_{oc} represents the open-circuit voltage; R_0 is the ohmic resistance; R_s and C_s correspond to the electrochemical polarization resistance and electrochemical polarization capacitance, respectively; R_p and C_p represent the concentration polarization resistance and concentration polarization capacitance; V_s and V_p are the voltages across R_s and R_p ; V_t denotes the battery output voltage; I represents the operating current.

According to Figure 1, based on Kirchhoff's laws, we can obtain

$$V_t = V_{oc} - V_p - V_s - IR_0 \quad (1)$$

$$\dot{V}_p = -\frac{V_p}{R_p C_p} + \frac{I}{C_p} \quad (2)$$

$$\dot{V}_s = -\frac{V_s}{R_s C_s} + \frac{I}{C_s} \quad (3)$$

Based on the small-signal modeling approach, the relationship between OCV and SOC can be expressed as a piecewise-linear function:

$$V_{oc} = V_{oc}(\text{SOC}) = k\text{SOC} + b \quad (4)$$

where k and b represent undetermined parameters corresponding to different SOC ranges. For every 10% change in SOC, there is a set of corresponding values for k and b .

Per the ampere-hour integration method, provided the initial SOC value is known, the SOC at time t_1 can be obtained by integrating the current over the time interval from t_0 to t_1 , as follows:

$$\text{SOC}(t_1) = \text{SOC}(t_0) - \frac{\eta}{Q_n} \int_{t_0}^{t_1} I(t) dt \quad (5)$$

where $\text{SOC}(t_1)$ denotes the SOC value at time t_1 ; η represents the coulombic efficiency of the battery; and Q_n is the nominal capacity of the battery.

Perform the derivative operation on Equation (1) and bring Equation (2)-Equation (4) into the differentiated equation (1), and simplify the resulting expression to obtain

$$\dot{V}_t = V_d - b_1 I \quad (6)$$

where $V_d = \frac{V_p}{R_p C_p} + \frac{V_s}{R_s C_s}$, $b_1 = \frac{k}{Q_n} + \frac{1}{C_p} + \frac{1}{C_s}$.

Further organizing Equation (1)-Equation (6), the equation of state of the battery equivalent circuit is obtained as

$$\begin{cases} \dot{V}_t = V_d - b_1 I + \Delta\omega_1 \\ \dot{V}_d = -a_{22}V_d + a_{23}V_s + b_2 I + \Delta\omega_2 \\ \dot{V}_s = -a_{31}V_t - a_{32}V_d + a_{33}V_s - a_{34}V_{oc}(\text{SOC}) + \Delta\omega_3 \\ \dot{\text{SOC}} = a_{41}V_t + a_{42}V_d + a_{43}V_s - a_{44}V_{oc}(\text{SOC}) + \Delta\omega_4 \end{cases} \quad (7)$$

where $a_{22} = \frac{1}{R_p C_p}$, $a_{23} = \frac{1}{R_p C_p R_s C_s} - \frac{1}{R_s^2 C_s^2}$, $a_{31} = \frac{1}{R_0 C_s}$, $a_{32} = \frac{R_p C_p}{R_0 C_s}$, $a_{33} = -\frac{1}{R_s C_s} - \frac{1}{R_0 C_s} + \frac{R_p C_p}{R_0 R_s C_s^2}$, $a_{34} = -a_{31}$, $a_{41} = \frac{1}{R_0 Q_n}$, $a_{42} = \frac{R_p C_p}{R_0 Q_n}$, $a_{43} = \frac{1}{R_0 Q_n} - \frac{R_p C_p}{R_0 Q_n R_s C_s}$, $a_{44} = a_{41}$; $\Delta\omega_1$, $\Delta\omega_2$, $\Delta\omega_3$ and $\Delta\omega_4$ represent the uncertainty.

2.2. OCV-SOC curve fitting. In practical applications, the relationship between SOC and Open Circuit Voltage (OCV) is typically established using either a lookup table method or curve fitting techniques. In this study, the INR18650-20R cell (2.0 Ah, 3.6 V nominal) is selected as the test specimen and subjected to the Hybrid Pulse Power Characterization (HPPC) procedure, and the OCV and SOC data obtained during the test are shown in Table 1.

TABLE 1. OCV-SOC data table

OCV(V)	SOC	OCV(V)	SOC
4.1758	1	3.6648	0.5050
4.0502	0.9101	3.6261	0.4060
3.9400	0.8020	3.5995	0.3069
3.8400	0.7030	3.5556	0.2079
3.7536	0.6040	3.4677	0.1088

Based on the data in Table 1, the OCV-SOC curve is fitted using the polynomial fitting function of MATLAB's Curve Fitting Toolbox. The Root Mean Square Error (RMSE) is used as the evaluation metric, and its formula is

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (8)$$

where N represents the number of sample points, y_i is the true value, typically obtained from the laboratory, and $\hat{y}_i$ is the estimated value or the fitted value.

The RMSE values for the 4th, 5th, 6th, and 7th-order polynomial fits are 1.25%, 1.17%, 0.78%, and 0.64%, respectively. From these results, it can be observed that the fitting accuracy improves as the polynomial order increases. However, compared to the 6th-order fit, the 7th-order fit involves a significantly higher computational cost while yielding only a marginal improvement in accuracy. Consequently, a 6th-order polynomial is selected

for the purpose of fitting in this study. The 6th-order polynomial fitting equation is as follows:

$$V_{oc} = 20.2288\text{SOC}^6 - 61.7760\text{SOC}^5 + 68.8875\text{SOC}^4 - 32.7556\text{SOC}^3 + 5.6389\text{SOC}^2 + 0.5592\text{SOC} + 3.3843 \quad (9)$$

2.3. Model parameter identification. In lithium-ion battery modeling and state estimation, accurate parameter identification is one of the key steps. In this paper, the FFRLS [24] method is employed for parameter identification, through which the internal parameters of the lithium-ion battery are obtained. First, the second-order RC model is discretized, yielding

$$y(k) = \sigma^T(k)\theta + \varepsilon(k) \quad (10)$$

where $y(k)$ is the measured output, $\sigma^T(k)$ is the regression vector, θ is the parameter vector to be estimated, and $\varepsilon(k)$ is the measurement noise.

Initialize each variable and select the value of the forgetting factor λ . In most of the studies, the range of λ is from 0.95 to 1. An excessively large λ value impairs the algorithm's ability to track new parameters, while an excessively small λ value reduces the algorithm's stability. After comprehensive consideration, λ is set to 0.99 in this study. Then, calculate the gain matrix, update the parameter estimates and the estimation error covariance matrix as follows:

$$K(k) = P(k-1)\sigma(k) [\lambda + \sigma^T(k)P(k-1)\sigma(k)]^{-1} \quad (11)$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k) [y(k) - \sigma^T(k)\hat{\theta}(k-1)] \quad (12)$$

$$P(k) = \frac{1}{\lambda} [P(k-1) - K(k)\sigma^T(k)P(k-1)] \quad (13)$$

Repeat the above steps until the parameters converge or a predetermined number of iterations is reached. The final estimated parameter vector $\hat{\theta}$ is the identified parameter set of the second-order RC equivalent circuit model for the lithium-ion battery.

3. Improved Terminal Sliding Mode Observer. The SMO features a simple structure, fast convergence, and strong robustness, demonstrating outstanding performance in applications such as the estimation and fault diagnosis of lithium-ion batteries. The ITSMO builds upon the conventional TSMO and offers further optimization. While maintaining the aforementioned advantages, it achieves even better performance.

3.1. Design of the improved terminal sliding mode observer. To further enhance the performance of the observer, a two-layer sliding surface is designed as follows:

$$\begin{cases} S_{i1} = k_i e_i + g_i \int e_i dt \\ S_{i2} = \dot{S}_{i1} + \beta_i S_{i1}^{\frac{q_i}{p_i}} \end{cases} \quad (14)$$

where S_{i1} denotes the first-layer sliding surface and S_{i2} denotes the second-layer sliding surface. The parameters k_i , g_i , and β_i are positive design parameters. p_i and q_i are positive odd integers and satisfy $\frac{1}{2} < \frac{q_i}{p_i} < 1$. e_i denotes the state estimation error. An integral term is introduced into the first-layer sliding surface, allowing the system to rapidly converge to the predetermined sliding mode trajectory within a finite time, thus accelerating the convergence process from the initial stage of the sliding surface and reducing the tracking error. In addition, the integral action mitigates noise caused by current differentiation, effectively suppressing the chattering phenomenon of the sliding mode observer, reducing the steady-state error, and ultimately enhancing the accuracy of state prediction. The

two-layer sliding surface not only ensures system stability and fast response, but also achieves smoother tracking performance, suppresses chattering error, and improves the effectiveness of state prediction.

According to Equation (7), the improved terminal sliding mode observer is designed as follows:

$$\begin{cases} \dot{\hat{V}}_t = \hat{V}_d - b_1 I + \nu_1 \\ \dot{\hat{V}}_d = -a_{22}\hat{V}_d + a_{23}\hat{V}_s + b_2 I + \nu_2 \\ \dot{\hat{V}}_s = -a_{31}\hat{V}_t - a_{32}\hat{V}_d + a_{33}\hat{V}_s - a_{34}V_{oc} \left(\widehat{\text{SOC}} \right) + \nu_3 \\ \dot{\widehat{\text{SOC}}} = a_{41}\hat{V}_t + a_{42}\hat{V}_d + a_{43}\hat{V}_s - a_{44}V_{oc} \left(\widehat{\text{SOC}} \right) + \nu_4 \end{cases} \quad (15)$$

where ν_1 , ν_2 , ν_3 and ν_4 denote the sliding mode control laws of the observer.

By subtracting Equation (15) from Equation (7), the tracking error dynamics are obtained as

$$\begin{cases} \dot{e}_1 = e_2 + \Delta\omega_1 - \nu_1 \\ \dot{e}_2 = -a_{22}e_2 + a_{23}e_3 + \Delta\omega_2 - \nu_2 \\ \dot{e}_3 = -a_{31}e_1 - a_{32}e_2 + a_{33}e_3 - ka_{34}e_4 + \Delta\omega_3 - \nu_3 \\ \dot{e}_4 = a_{41}e_1 + a_{42}e_2 + a_{43}e_3 - ka_{44}e_4 + \Delta\omega_4 - \nu_4 \end{cases} \quad (16)$$

According to Equation (16), the sliding mode control law ν_1 is designed as follows:

$$\begin{cases} \nu_1 = \nu_{11} + \nu_{12} \\ \nu_{11} = \frac{g_1}{k_1}e_1 + \frac{\beta_1}{k_1} \left(k_1 e_1 + g_1 \int_0^t e_1 dt \right)^{\frac{q_1}{p_1}} \\ \nu_{12} = \frac{1}{k_1} \int_0^t \gamma_1 \text{sat}(S_{12}) dt \end{cases} \quad (17)$$

where ν_{11} is the equivalent control term of the sliding mode control law, which ensures that the system converges to the switching surface within a finite time. ν_{12} is the switching control term, which can counteract disturbances and errors when the system is subjected to disturbances, thereby ensuring that the system always remains on the switching surface. γ_1 is the adaptive switching gain, which is designed as follows:

$$\dot{\gamma}_1 = \theta_1 |S_{12}| \quad (18)$$

where θ_1 is a constant greater than zero.

After the sliding mode control law ν_1 is designed, the stability of the proposed observer is proved. The Lyapunov function for the sliding surface S_{12} is defined as follows:

$$V_1 = \frac{1}{2} S_{12}^2 \quad (19)$$

The derivative of the Lyapunov function can be obtained as follows:

$$\begin{aligned} \dot{V}_1 &= S_{12} \dot{S}_{12} = S_{12} [k_1 \dot{e}_2 + k_1 \Delta\dot{\omega}_1 - \gamma_1 \text{sat}(S_{12})] \\ &= k_1 \dot{e}_2 S_{12} + k_1 \Delta\dot{\omega}_1 S_{12} - \gamma_1 \text{sat}(S_{12}) S_{12} \\ &< |k_1 \dot{e}_2| |S_{12}| + |k_1 \Delta\dot{\omega}_1| |S_{12}| - \gamma_1 \text{sat}(|S_{12}|) |S_{12}| \\ &= [|k_1 \dot{e}_2| + |k_1 \Delta\dot{\omega}_1| - \gamma_1 \text{sat}(|S_{12}|)] |S_{12}| \end{aligned} \quad (20)$$

Therefore, there exists a finite non-negative γ_1 such that $\gamma_1 > \frac{|k_1 \dot{e}_2| + |k_1 \Delta\dot{\omega}_1|}{\text{sat}(|S_{12}|)}$, and $\dot{V}_1 < 0$, which satisfies the Lyapunov stability criterion. Thus, the designed observer is stable. The sliding variable S_{12} will reach the switching surface $S_{12} = 0$ in finite time, and the terminal voltage error e_1 will converge to equilibrium along the switching surface within

a specified time. When the sliding surface enters sliding mode, both the error e_1 and the uncertainty term $\Delta\omega_1$ will asymptotically converge to zero. Thus, we have

$$e_1 = \dot{e}_1 = 0 \quad (21)$$

According to the theory of equivalent control, at this time, e_2 can be derived from Equation (17) as follows:

$$e_2 = \frac{\beta_1}{k_1} \left(g_1 \int_0^t e_1 dt \right)^{\frac{q_1}{p_1}} + \frac{1}{k_1} \int_0^t \gamma_1 \text{sat}(S_{12}) dt \quad (22)$$

Similarly, according to the design method in Equation (17), the sliding mode control laws ν_2 , ν_3 and ν_4 are designed sequentially as follows:

$$\begin{cases} \nu_2 = \nu_{21} + \nu_{22} \\ \nu_{21} = \left(-a_{22} + \frac{g_2}{k_2} \right) e_2 + \frac{\beta_2}{k_2} \left(k_2 e_2 + g_2 \int_0^t e_2 dt \right)^{\frac{q_2}{p_2}} \\ \nu_{22} = \frac{1}{k_1} \int_0^t \gamma_1 \text{sat}(S_{22}) dt \end{cases} \quad (23)$$

$$\begin{cases} \nu_3 = \nu_{31} + \nu_{32} \\ \nu_{31} = -a_{31}e_1 - a_{32}e_2 + \left(a_{33} + \frac{g_3}{k_3} \right) e_3 + \frac{\beta_3}{k_3} \left(k_3 e_3 + g_3 \int_0^t e_3 dt \right)^{\frac{q_3}{p_3}} \\ \nu_{32} = \frac{1}{k_3} \int_0^t \gamma_3 \text{sat}(S_{32}) dt \end{cases} \quad (24)$$

$$\begin{cases} \nu_4 = \nu_{41} + \nu_{42} \\ \nu_{41} = a_{41}e_1 + a_{42}e_2 + a_{43}e_3 + \left(-ka_{44} + \frac{g_4}{k_4} \right) e_4 + \frac{\beta_4}{k_4} \left(k_4 e_4 + g_4 \int_0^t e_4 dt \right)^{\frac{q_4}{p_4}} \\ \nu_{42} = \frac{1}{k_4} \int_0^t \gamma_4 \text{sat}(S_{42}) dt \end{cases} \quad (25)$$

By analogy with the proof procedures of Equations (19) and (20), the sliding surfaces S_{22} , S_{32} and S_{42} all satisfy the Lyapunov stability criterion. V_t , V_d , V_s and SOC are asymptotically stabilized in sequence, and SOC can be estimated by the designed observer.

In subsequent simulation verifications of the observer performance, Mean Absolute Error (MAE) and RMSE are employed as evaluation metrics. The formula for calculating MAE is

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N \left| \text{SOC}_i - \hat{\text{SOC}}_i \right| \quad (26)$$

where N represents the number of samples, SOC_i denotes the true value of SOC, and $\hat{\text{SOC}}_i$ denotes the estimated value of SOC.

According to Equation (8), the RMSE can be rewritten as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\text{SOC}_i - \hat{\text{SOC}}_i \right)^2} \quad (27)$$

3.2. Design of sliding mode observer for SOC variation. Real-time monitoring of the variation in the SOC is a crucial prerequisite for the system to rapidly identify fault signals. Therefore, the SOC variation is defined as follows:

$$\Delta \text{SOC}(t) = \text{SOC}(t) - \text{SOC}(t - n) \quad (28)$$

where $\Delta\text{SOC}(t)$ represents the variation in SOC between time t and time $t - n$; in this study, when n is less than 10, noise interference and irregular variations in operating parameters cause excessive image jitter in $\Delta\text{SOC}(t)$, obscuring its trend. Conversely, when n is excessively large, the proportion of historical data increases, leading to slow tracking speed. Therefore, n is set to 20. Hence, the sliding mode observer is designed as follows:

$$\widehat{\Delta\text{SOC}}(t) = \widehat{\text{SOC}}(t) - \widehat{\text{SOC}}(t - n) + \nu_5 \quad (29)$$

Here, ν_5 denotes the sliding mode control law of the observer. According to Equation (29) and the design method of the aforementioned observer, ν_5 is designed as follows:

$$\begin{cases} \nu_5 = \nu_{51} + \nu_{52} \\ \nu_{51} = a_{41}[e_1(t) - e_1(t - n)] + a_{42}[e_2(t) - e_2(t - n)] + a_{43}[e_3(t) - e_3(t - n)] \\ \quad - a_{44}[e_4(t) - e_4(t - n)] + \left(-ka_{44} + \frac{g_5}{k_5}\right)e_5 + \frac{\beta_5}{k_5} \left(k_5 e_5 + g_5 \int_0^t e_5 dt\right)^{\frac{q_5}{p_5}} \\ \nu_{52} = \frac{1}{k_5} \int_0^t \gamma_5 \text{sat}(S_{52}) dt \end{cases} \quad (30)$$

By analogy with the proof steps of Equations (19) and (20), the sliding surface S_{52} satisfies the Lyapunov stability criterion, which indicates that the designed observer is stable, and the ΔSOC can be estimated using the proposed observer.

4. Internal Short-Circuit Fault Diagnosis Method. Multiple lithium-ion cells are connected in series to constitute a lithium-ion battery pack, as shown in Figure 2. A short-circuit resistor is connected in parallel across the terminals of a battery cell to simulate an internal short-circuit fault within the lithium-ion battery pack.

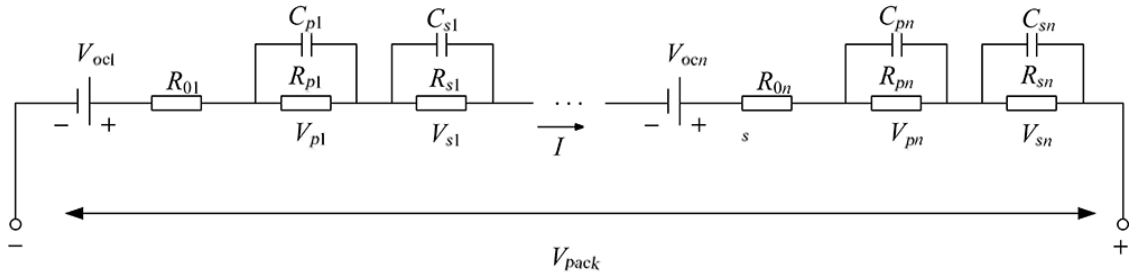


FIGURE 2. Lithium-ion battery pack

The designed observer is utilized to monitor the lithium-ion battery pack experiencing internal short-circuit faults and to obtain estimated SOC values. By comparing the residual between the estimated and actual SOC with a predefined threshold, the presence of a fault can be determined. The threshold calculation method is as follows:

$$J = \mu + k_z \sigma_n^2 \quad (31)$$

where μ is the mean value of the residuals under normal conditions, and k_z is the confidence coefficient. Typically, the confidence coefficient ranges from 3 to 5. A smaller coefficient helps narrow the threshold range and improve diagnostic speed; therefore, in this paper, k_z is set to 3. σ_n^2 is the standard deviation of the residuals under normal conditions.

The fault indicator is defined as follows:

$$F = \begin{cases} 1, & e_r > J \\ 0, & e_r \leq J \end{cases} \quad (32)$$

Here, e_r represents the SOC residual. When the fault indicator equals 1, a fault is detected.

The average value of the SOC estimate over m seconds is calculated as follows:

$$\overline{\Delta SOC} = \frac{\sum_{i=n-m}^n \Delta SOC_i}{m} \quad (33)$$

The average value of the ΔSOC estimate over m seconds is used instead of the residual, and is compared with the threshold to decide whether a fault has taken place.

5. Simulation Experiment Verification.

5.1. Simulation results and analysis under normal operating conditions. To validate the effectiveness of the proposed observer, simulation verification was conducted under the Federal Urban Driving Schedule (FUDS) condition. In this experiment, the initial value of the lithium battery's SOC was set to 0.8, and the sampling frequency was 1 Hz. The working current profile under the FUDS condition is shown in Figure 3, and the estimated output voltage is presented in Figure 4. As can be seen from Figure 4, the error between the estimated output voltage and the actual output voltage remains within 0.05 V, indicating that the established model is capable of high-precision estimation and meets the desired requirements.

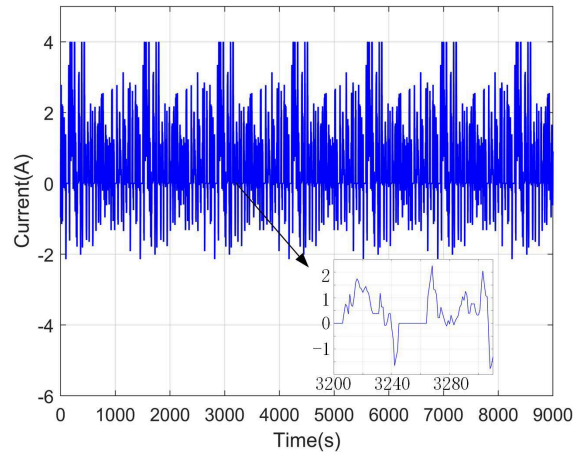


FIGURE 3. Working current under FUDS condition

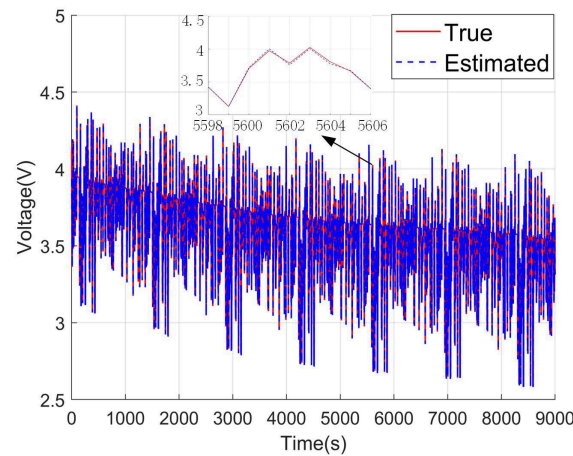


FIGURE 4. Output voltage under FUDS condition

Figure 5 shows the SOC estimation curves of SMO and ITSMO under the FUDS condition, while Figure 6 presents the SOC estimation error curves. Analysis of Figures 5 and 6 indicates that the proposed observer can converge to the true SOC value much faster. According to Figure 6, the maximum SOC estimation error of the proposed observer is only 0.65% with minimal chattering, whereas the maximum error of SMO reaches 1.52% with significant chattering. Based on these two points, the proposed observer exhibits faster tracking speed and higher tracking accuracy. Table 2 compares the RMSE and MAE between the estimated SOC values and the true SOC values for different methods.

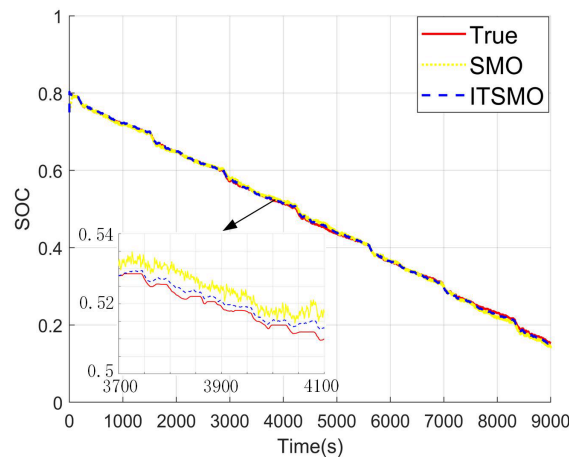


FIGURE 5. SOC estimation curves under FUDS condition

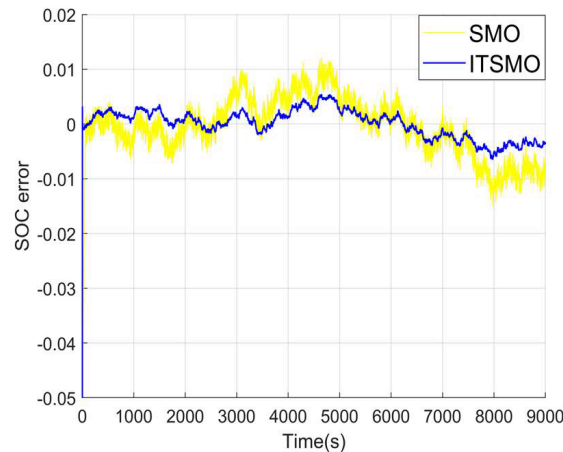


FIGURE 6. SOC estimation error curves

TABLE 2. Comparison of estimation errors of SOC results

	SMO	ITSMO
MAE	0.42%	0.22%
RMSE	0.57%	0.26%

As shown in Table 2, the proposed observer exhibits higher estimation accuracy. Compared with the SMO, the MAE of the proposed observer is reduced by 47.6%, and the RMSE is reduced by 54.4%, demonstrating stronger robustness.

5.2. Simulation results and analysis under fault conditions. A lithium battery pack composed of three series-connected INR 18650-20R cells was selected as the research object, and the proposed observer was used to monitor all three battery cells. Specifically, Cell 1 operated normally under the FUDS condition; Cell 2 experienced an internal short-circuit fault at 3500 seconds with a short-circuit resistance of $1\ \Omega$; and Cell 3 experienced an internal short-circuit fault at 3500 seconds with a short-circuit resistance of $0.2\ \Omega$.

Figure 7 shows the SOC estimation curves of different cells in the lithium battery pack. It can be seen that, when an internal short-circuit fault occurs, the SOC of the faulty cell drops rapidly, and the observer is able to promptly track the change in SOC. Figure 8 depicts the SOC estimation error curves and fault signals of different battery cells, respectively. By analyzing Figure 8, it is evident that when a fault occurs, the residual estimated by the SOC exceeds the preset threshold and continues to increase, triggering the fault signal. The fault signal for Cell 2 is triggered at 23 seconds, while for Cell 3, it takes only 9 seconds. These results demonstrate that the proposed method enables rapid and accurate detection of internal short-circuit faults within lithium-ion battery packs, and that the diagnosis time decreases with the reduction in short-circuit resistance.

Figure 9 shows the Δ SOC estimation curves of different battery cells in the lithium battery pack. From the analysis of Figure 9, it can be seen that under normal FUDS conditions, Δ SOC fluctuates within a certain range, and when a fault occurs, Δ SOC

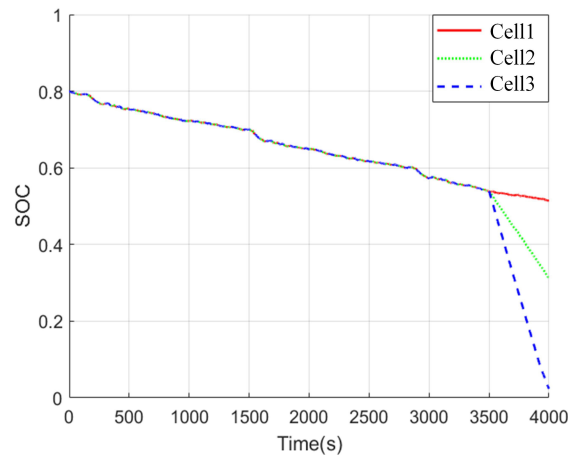


FIGURE 7. SOC estimation curves of different battery cells

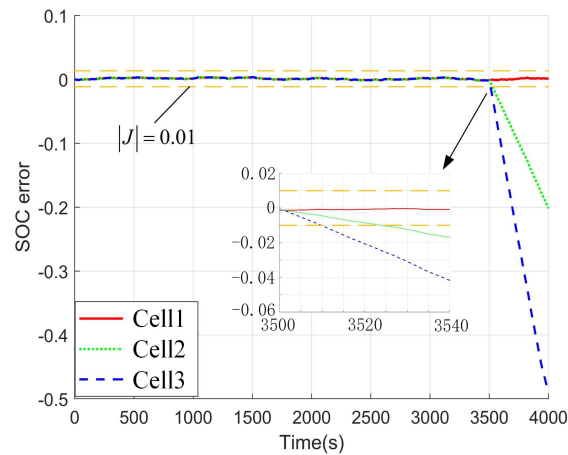


FIGURE 8. SOC estimation error curves of different battery cells

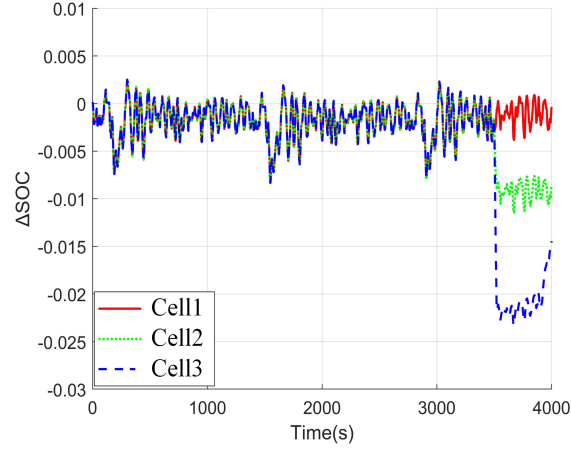
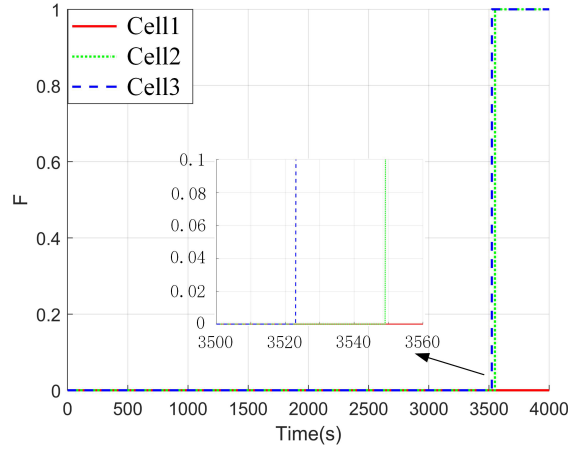
FIGURE 9. ΔSOC estimation curves of different battery cells

FIGURE 10. Fault signal of different battery cells

drops rapidly. When a fault occurs, $\overline{\Delta\text{SOC}}$ gradually exceeds the preset threshold, and the fault signal is triggered. As shown in Figure 10, the fault signals of Cells 2 and 3 are triggered at 23 seconds and 49 seconds, respectively. This method addresses the problem of ineffective fault diagnosis when the initial value of SOC cannot be accurately determined, and validates the effectiveness of the proposed method.

6. Conclusions. Based on a comprehensive review of state-of-the-art domestic and international methods for lithium-ion battery SOC estimation and battery pack fault diagnosis, this study selects the INR 18650-20R ternary lithium battery as the research subject. Taking the second-order RC equivalent circuit as the foundation, we propose an internal short-circuit fault diagnosis method based on an improved terminal sliding mode observer. This method introduces the concept of double-layer sliding mode and constructs a novel sliding mode surface with an added integral term to reduce steady-state error. At the same time, an adaptive gain is designed to shorten convergence time and mitigate the adverse effects of gain tuning. On the premise of accurate SOC estimation, a fault diagnosis approach is put forward that identifies internal short-circuit faults by monitoring changes in SOC. This effectively addresses the issues of missed or false diagnosis arising from the inability to acquire accurate initial SOC values. Simulation results indicate that,

compared to the SMO, the proposed ITSMO achieves faster convergence, higher estimation accuracy, and significantly reduced chattering, thereby meeting the requirements of rapidity, accuracy and robustness.

In future research, we will further apply the proposed ITSMO to battery management systems, diagnose various types of faults within these systems, and conduct corresponding simulations and experimental validations.

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