

## Article

# Online Measured Impedance-Assisted State-of-Charge Estimation for Lithium-Ion Batteries Under Low Excitation Conditions via Fractional-Order Modeling

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## Abstract

Accurate online parameter identification and state-of-charge (SOC) estimation are essential for lithium-ion battery management systems. However, under constant or quasi-constant current operating conditions, the system excitation is inherently weak, leading to poor parameter identifiability when conventional model-based estimation methods are used. This issue is particularly critical in grid-connected battery energy storage systems, where current dynamics are limited. To address this problem, this paper proposes an online measured impedance-assisted SOC estimation framework that integrates online electrochemical impedance measurements with a fractional-order battery model and an extended Kalman filter. Online impedance data are utilized to update the model parameters in real time through a geometric-based fitting algorithm, thereby enhancing model adaptability under low excitation conditions. Experimental results obtained from lithium-ion cells with different aging states demonstrate that the proposed method enables stable and accurate online parameter identification and SOC estimation under the tested low-excitation conditions, where conventional time-domain approaches tend to degrade or diverge. Robustness under highly dynamic operating conditions remains to be further validated.

**Keywords:** lithium-ion batteries; state-of-charge estimation; fractional-order model; electrochemical impedance; energy storage systems



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## 1. Introduction

Lithium-ion batteries are widely deployed in electric vehicles (EVs) and grid-side energy storage systems due to their high energy density, long cycle life, and operational flexibility [1,2]. To ensure safety, performance, and longevity, battery management systems (BMSs) rely critically on an accurate state-of-charge (SOC) estimation, which remains a fundamental challenge under practical operating conditions.

Existing SOC estimation methods can be mainly divided into the ampere-hour counting method (AHC), the data-driven method, and the model-based method. The AHC method is easy to implement but requires an accurate initial SOC, and the SOC errors caused by sensor errors can accumulate over time [3]. Open-circuit voltage is used to initialize the battery SOC but requires a long standing time, which is difficult to meet in

practical conditions. Data-driven SOC estimation methods use artificial intelligence techniques, such as neural networks (NN) [4,5] and support vector machines (SVM) [6], which offer strong adaptability but usually require large datasets and extensive training, which limits their generalization capability and online applicability [7]. By contrast, model-based methods provide a favorable balance between accuracy and computational efficiency, and are therefore most widely adopted in practical BMSs. Commonly used battery models include electrochemical models (EMs) and equivalent circuit models (ECMs). EMs are often complex and have a large number of parameters, making them difficult to apply online [8]. Methods based on ECMs can achieve both high accuracy and low computational complexity [9], making them suitable for on-board applications. Combined with ECMs, various Bayesian filters are used to estimate the battery SOC, including the extended Kalman filter (EKF) [10], the unscented Kalman filter (UKF) [9,11], the particle filter (PF) [12,13], and so on.

The performance of a model-based SOC estimation strongly depends on both model structure and parameter accuracy. Conventional integer-order models (IOMs), such as first-order and second-order RC models, are favored for their simplicity but lack the ability to accurately capture distributed electrochemical processes over a wide operating range. Fractional-order models (FOMs) have therefore been introduced by replacing ideal capacitors with constant phase elements (CPEs), enabling a more accurate representation of battery dynamics [14,15]. However, battery parameters evolve with aging, temperature, and operating conditions, and fixed parameters obtained via offline identification often lead to degraded estimation performance in practical applications [16]. To address this issue, various online parameter identification methods have been developed, including genetic algorithms (GA), particle swarm optimization (PSO), Kalman filtering, and least-squares (LS)-based techniques [17–20]. Despite their fast convergence, most time-domain identification algorithms require persistent excitation to ensure parameter identifiability. This requirement poses a critical challenge for grid-side battery energy storage systems (BESSs), which often operate under constant or quasi-constant current profiles, as shown in Figure 1b [21–24]. Under such low-excitation operating conditions, time-domain voltage responses contain limited dynamic information, leading to poor parameter convergence and unreliable SOC estimation. Moreover, although FOMs offer superior modeling accuracy, their online identification remains difficult, and most existing studies still rely on offline optimization methods, limiting their adaptability in real applications [25–28].

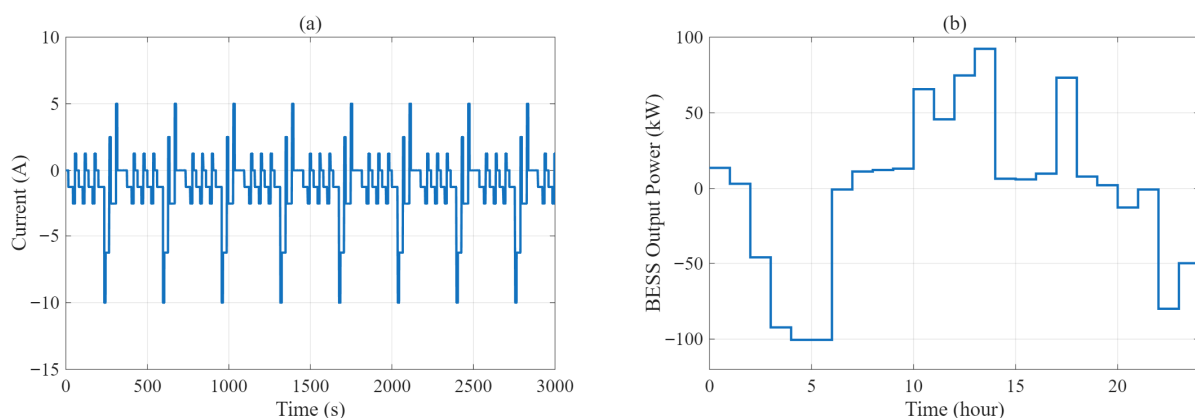


**Figure 1.** (a) Current profile of dynamic stress test in EVs; (b) Output power profile of a peak-shaving BESS.

These limitations indicate that relying solely on time-domain information is insufficient for online parameter identification under low-excitation conditions. Electrochemical

impedance spectroscopy (EIS) provides the frequency-domain characteristics of batteries by injecting small-amplitude alternating current perturbations and measuring the resulting voltage response. A close relationship exists between EIS and FOMs, as impedance features across different frequency bands correspond to internal electrochemical processes and can be directly associated with FOM parameters [28–31].

In recent years, significant progress in onboard EIS measurement technologies has enabled impedance acquisition during normal operation through converters, balancing circuits, or reconfigurable battery systems (RBSs) [32–36]. Although online EIS data have been shown to effectively fit FOMs [37], the identified parameters have not yet been systematically integrated into SOC estimation frameworks. Some recent studies have attempted to directly correlate impedance features with the SOC [38,39]; however, battery impedance is also strongly affected by temperature and aging, leading to limited robustness.

In summary, the existing impedance-based SOC estimation methods generally rely on directly mapping impedance features to the SOC, which may suffer from limited robustness under temperature variation and battery aging. In addition, although online impedance measurement has been applied to battery modeling and parameter fitting, the identified parameters have not been systematically incorporated into a closed-loop SOC estimation framework. Moreover, under constant-current or quasi-static operating conditions, conventional time-domain online parameter identification methods often become ineffective due to insufficient excitation. Therefore, a systematic framework is still needed to use online measured impedance for model updating and SOC estimation under low-excitation conditions.

To address the above challenges, this paper proposes an online-measured impedance-assisted SOC estimation method with the following main contributions:

- An impedance-assisted online parameter identification framework that integrates online EIS measurements with a fractional-order battery model, effectively enhancing parameter identifiability under weak current excitation.
- A closed-loop SOC estimation scheme that fuses frequency-domain impedance information with time-domain state estimation via an extended Kalman filter.
- Experimental validation on lithium-ion cells with different aging levels, demonstrating improved SOC estimation accuracy and robustness in low excitation scenarios.

To illustrate the proposed method, this paper is organized as follows. Section 2 provides a brief introduction to fractional-order differential operations, explains the relationship between EIS and FOMs, and presents the state space equation of FOMs. Section 3 describes the proposed improved SOC estimation scheme based on online EIS. In Section 4, the effectiveness of the proposed method is validated using two 18650 lithium-ion batteries with different aging levels. Finally, the conclusions are summarized in Section 5.

## 2. Impedance Spectroscopy Analysis and Modeling

Due to the introduction of fractional-order elements in the FOM, this section first provides a brief introduction to the mathematical foundations of fractional calculus, which are utilized for the subsequent modeling. Subsequently, the battery's FOM is interpreted through EIS, and the model is simplified to reduce computational burden while retaining the main dynamic characteristics. Finally, the state space equations for the adopted FOM are presented.

### 2.1. Introduction of Fractional-Order Calculus

Fractional calculus is a natural extension of integer-order calculus and is first mentioned in the correspondence between Leibnitz and L'Hôpital in 1697. By allowing differentiation and integration of arbitrary order, fractional calculus significantly enhances

modeling capabilities and applicability. There are three definitions of fractional calculus: the Riemann–Liouville (R–L) definition, the Caputo definition, and the Grünwald–Letnikov (G–L) definition [40]. Due to its ability to discretize continuous fractional-order equations succinctly, the G–L definition is adopted for computations in this paper. This paper does not involve fractional integration operations. The definition of the G–L fractional derivative is as follows:

$$D^\alpha f(t) = \lim_{T_s \rightarrow 0} \frac{1}{T_s^\alpha} \sum_{j=0}^{\lfloor t/T_s \rfloor} (-1)^j \binom{\alpha}{j} f(t - jT_s). \quad (1)$$

where  $D^\alpha$  represents the fractional-order differential operator,  $\alpha > 0$  denotes the order of the differential operation, and  $T_s$  stands for the sampling period. In this paper,  $T_s = 1$  s.  $\binom{\alpha}{j}$  denotes the Newtonian binomial coefficient, which is expressed as follows:

$$\binom{\alpha}{j} = \begin{cases} 1 & j = 0 \\ \frac{\alpha!}{j!(\alpha-j)!} = \frac{\Gamma(\alpha+1)}{\Gamma(j+1)\Gamma(\alpha-j+1)} & j > 0 \end{cases} \quad (2)$$

where  $\Gamma(\cdot)$  is the Gamma function defined by the following:

$$\Gamma(\alpha) = \int_0^\infty t^{\alpha-1} e^{-t} dt. \quad (3)$$

It can be observed from Equation (1) that the fractional-order derivative is a non-local operator, requiring the involvement of all historical data. This reflects the long memory property inherent in fractional-order derivatives, which significantly increases the computational burden of algorithms. To alleviate computational complexity, the short-memory principle proposed by Podlubny [41] is adopted, which considers only the most recent  $L$  data points in state propagation. Consequently, Equation (1) can be approximated as follows:

$$D^\alpha f(t) \approx \lim_{T_s \rightarrow 0} \frac{1}{T_s^\alpha} \sum_{j=0}^L (-1)^j \binom{\alpha}{j} f(t - jT_s). \quad (4)$$

Figure 2 shows that, as the value of  $L$  increases, the error of fitting the battery terminal voltage using the FOM decreases. However, when  $L$  exceeds 150, the fitting error almost stabilizes with no further noticeable changes. Therefore, the value of  $L$  should be chosen based on a balance between model accuracy and computational complexity requirements. In this study,  $L$  is set to 100.

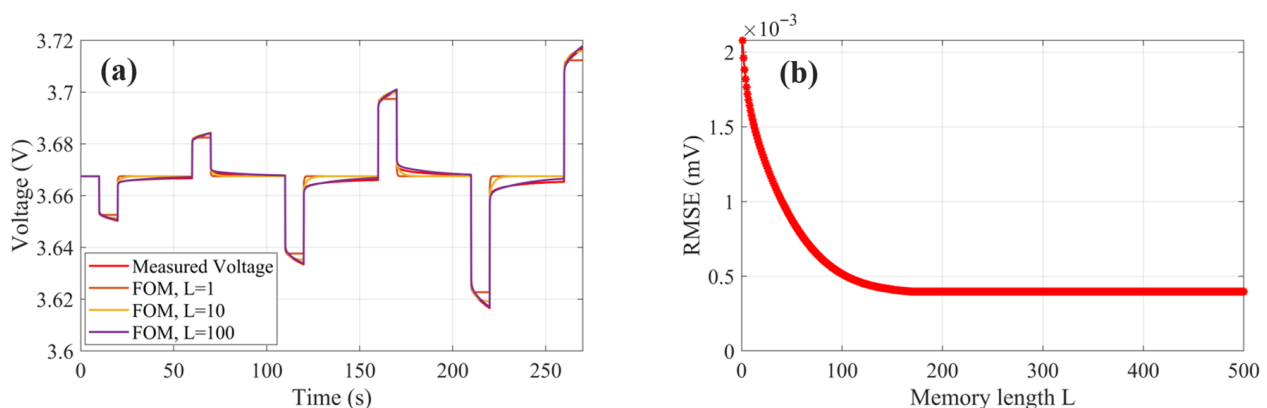


**Figure 2.** Predicted terminal voltages with different  $L$  of the FOM under the hybrid pulse power characterization (HPPC) profile: (a) terminal voltages and (b) RMSE of terminal voltages.

## 2.2. Derivation of the FOM from EIS

EIS is a technique used to characterize the internal dynamics of electrochemical systems, such as batteries and supercapacitors. During EIS measurements, the system is injected into AC excitation with different frequencies, and its response is measured to calculate the impedance. The impedance spectrum of a battery, for instance, reflects various electrode processes within different frequency ranges. Major electrode processes in batteries include charge transfer reactions during lithium-ion intercalation and deintercalation, ohmic resistance, double-layer capacitance, mass transport, and diffusion processes.

Figure 3a illustrates the typical impedance spectrum of an 18650 lithium-ion battery within the frequency range of 1 mHz to 10 kHz, obtained using a commercial electrochemical workstation, Squidstat Plus, manufactured by Admiral Instruments (Tempe, AZ, USA). The impedance spectrum can be divided into four frequency ranges: ultra-high frequency ( $>1.25$  kHz), high frequency (63 Hz–1.25 kHz), medium frequency (0.12 Hz–63 Hz), and low frequency ( $<0.12$  Hz). In the high-frequency range, intersections of the impedance spectrum with the real axis represent the ohmic resistance, while impedance characteristics below the real axis are primarily determined by the parasitic inductance of the current collector and lead. The impedance in the low-frequency range mainly reflects the battery's diffusion processes, approximated by a straight line with a fixed angle, thus represented by a Warburg element. Its impedance expression is given by the following equation:

$$Z_W(j\omega) = \frac{1}{C_w(j\omega)^{\alpha_W}} \quad (5)$$

where  $C_W$  and  $\alpha_W$  represent the capacitance-like parameter and the fractional order of the Warburg element, respectively ( $0 \leq \alpha_W \leq 1$ ). It should be noted that the value of  $C_W$  depends on the adopted parameterization, and should be interpreted within the context of the model rather than as a directly measurable conventional capacitance. When  $\alpha_W = 0$ , the fractional-order element is equivalent to an ideal resistor; when  $\alpha_W = 1$ , it is equivalent to an ideal capacitor.

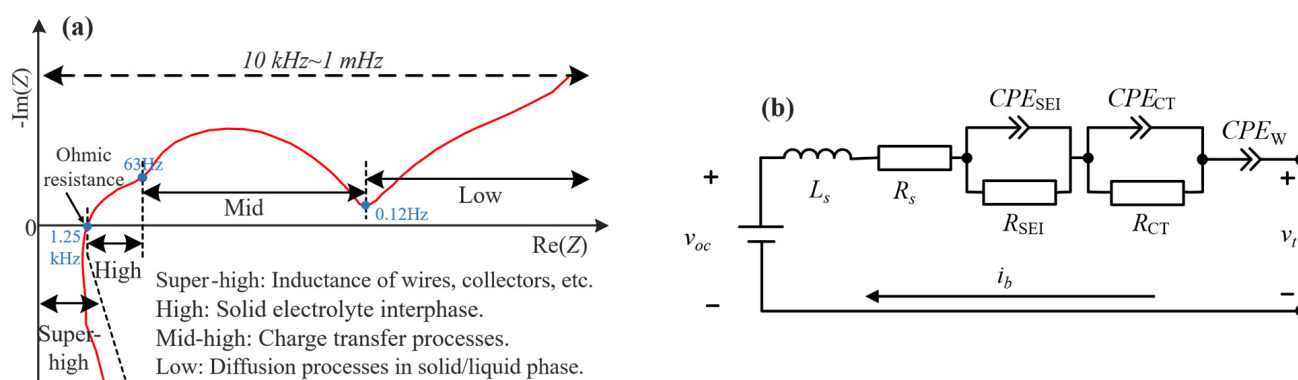


**Figure 3.** (a) A practical 18650 Li-ion battery EIS Nyquist plot; (b) Fractional order battery model.

The EIS curve of lithium batteries forms a semi-ellipse in the high-frequency and mid-frequency ranges, respectively. Each semi-ellipse can be equivalent to a CPE component and an ideal resistor in parallel. In this context, the impedance characteristics in the high-frequency range are attributed to the formation of the solid electrolyte interface (SEI), while those in the mid-frequency range depend on the charge transfer process within the battery

and electrochemical double-layer reactions. The impedance of the CPE components in the high-frequency and mid-frequency ranges are as follows:

$$Z_{CPE_{SEI}}(j\omega) = \frac{1}{C_{SEI}(j\omega)^{\alpha_{SEI}}}, \quad (6)$$

$$Z_{CPE_{CT}}(j\omega) = \frac{1}{C_{CT}(j\omega)^{\alpha_{CT}}}. \quad (7)$$

where  $C_{SEI}$  and  $C_{CT}$  are the capacitance-like parameters of the SEI and charge transfer CPEs, respectively, and  $\alpha_{SEI}$  and  $\alpha_{CT}$  are the fractional orders of the SEI and charge transfer CPEs to describe the dispersion effect, respectively ( $0 \leq \alpha_{SEI}, \alpha_{CT} \leq 1$ ). Based on the above analysis, the complete structure of the battery FOM is depicted in Figure 3b. There are many circuit elements and their associated parameters within the FOM, leading to high computational complexity in parameter identification and estimation algorithms. Therefore, a certain level of simplification has been applied to the model while retaining the primary internal dynamics of the battery. Firstly, the influence of parasitic inductance, which is typically small and irrelevant to the internal dynamics of the battery, has been disregarded. Additionally, since the SEI is predominantly significant only under low-state of health (SOH) and low-temperature conditions, impedance elements corresponding to SEI have also been omitted. Consequently, the simplified FOM adopted in this study is illustrated in Figure 4. In Figure 4,  $v_{oc}$  denotes the open-circuit voltage source of the battery,  $i_b$  is the battery current, defined as positive during discharge, and  $v_t$  is the terminal voltage of the battery. In addition,  $v_{CT}$  represents the voltage across the charge-transfer branch, which consists of  $R_{CT}$  and  $CPE_{CT}$ , while  $v_W$  denotes the voltage across the diffusion branch represented by  $CPE_W$ .

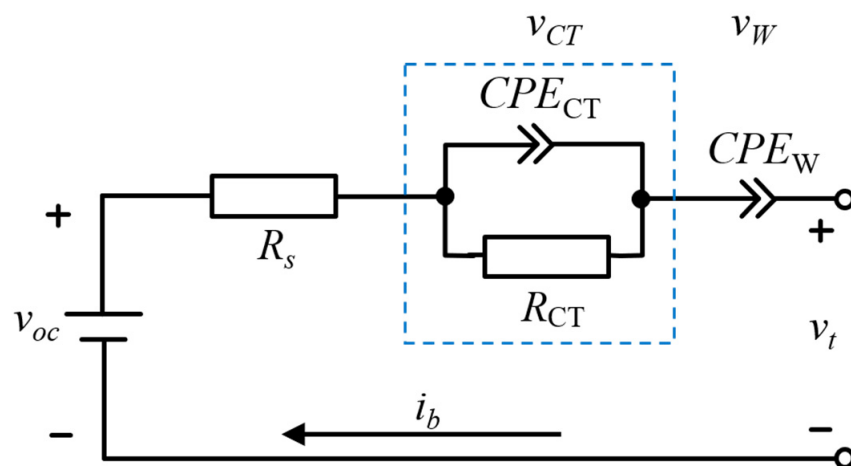


**Figure 4.** Simplified fractional order battery model.

### 2.3. State Space Function of the FOM

Based on the simplified FOM, depicted in Figure 4 and the analysis above, combined with circuit theory, the following equations can be derived:

$$\begin{cases} D^1 z(t) = -\frac{\eta \cdot i_b(t)}{3600 \cdot C_n} \\ D^{\alpha_{CT}} v_{CT}(t) = -\frac{1}{R_{CT} C_{CT}} \cdot v_{CT}(t) + \frac{1}{C_{CT}} \cdot i_b(t) \\ D^{\alpha_{CT}} v_W(t) = \frac{i_b(t)}{C_W} \\ v_t(t) = v_{oc}(t) - v_{CT}(t) - v_W(t) - R_s \cdot i_b(t) \end{cases} \quad (8)$$

where  $z$  represents the SOC and  $\eta$  denotes the coulombic efficiency of the battery. For lithium-ion batteries,  $\eta$  can be approximated as 1 [42], and  $C_n$  represents the rated capacity of the battery under the corresponding operating conditions. Substituting Equation (8) yields the following discrete state equation:

$$\begin{cases} D^N \mathbf{x}_{k+1} = \mathbf{A} \mathbf{x}_k + \mathbf{B} \mathbf{I}_k \\ \mathbf{y}_k = g(\mathbf{x}_k) + \mathbf{D} \mathbf{I}_k \end{cases} \quad (9)$$

where bold symbols in the equations denote matrices and the values are defined as follows:

$$\begin{aligned} \mathbf{N} &= \begin{bmatrix} 1 \\ \alpha_{CT} \\ \alpha_W \end{bmatrix}, \quad \mathbf{x}_k = \begin{bmatrix} z(k) \\ v_{CT}(k) \\ v_W(k) \end{bmatrix}, \quad \mathbf{A} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -\frac{1}{R_{CT}C_{CT}} & 0 \\ 0 & 0 & 0 \end{bmatrix}, \\ \mathbf{B} &= \begin{bmatrix} -1/(3600C_n) & 1/C_{CT} & 1/C_W \end{bmatrix}^T, \quad \mathbf{D} = -R_s, \\ g(\mathbf{x}_k) &= v_{oc}(z(k)) - v_{CT}(k) - v_W(k). \end{aligned} \quad (10)$$

Substitute Equation (4) into Equation (9) and combine with the noise [14] to obtain the following equation:

$$\begin{cases} \mathbf{x}_{k+1} = T_s^N \mathbf{A} \mathbf{x}_k + T_s^N \mathbf{B} \mathbf{I}_k + \boldsymbol{\omega}_k - \sum_{j=1}^L \gamma_j \mathbf{x}_{k+1-j}, \\ \mathbf{y}_k = g(\mathbf{x}_k) + \mathbf{D} \mathbf{I}_k + \mathbf{v}_k \\ T_s^N = \text{diag} \left\{ T_s, T_s^{\alpha_{CT}}, T_s^{\alpha_W} \right\}, \\ \gamma_j = (-1)^j \binom{N}{j} = (-1)^j \cdot \text{diag} \left\{ \begin{pmatrix} 1 \\ j \end{pmatrix}, \begin{pmatrix} \alpha_{CT} \\ j \end{pmatrix}, \begin{pmatrix} \alpha_W \\ j \end{pmatrix} \right\}. \end{cases} \quad (11)$$

where  $\boldsymbol{\omega}_k \in R^3$  represents the process noise and  $\mathbf{v}_k \in R$  denotes the measurement noise. They are assumed to be independent zero-mean Gaussian noise processes, with covariance matrices  $\mathbf{Q}$  and  $\mathbf{R}$ , respectively.

### 3. Impedance-Assisted SOC Estimation Framework

As discussed in the previous sections, under low-current or quasi-static operating conditions, battery systems often suffer from insufficient excitation, which degrades the time-domain parameter identification and, consequently, the SOC estimation performance. This issue is particularly relevant for stationary energy storage applications where current variations are limited. To improve parameter identifiability under weak excitation, this study incorporates online impedance information, which provides the complementary frequency-domain characteristics of the battery. Importantly, the proposed framework requires only the availability of the online impedance data and is not tied to any specific online impedance measurement technique. In this work, the impedance data are obtained online using an RBS-based measurement scheme, as proposed in [33], as an implementation example for experimental verification. The subsequent parameter identification and SOC estimation procedures are independent of the impedance acquisition method and can be extended to other online impedance measurement approaches.

The proposed SOC estimation framework is illustrated in Figure 5. It consists of four main components: the OCV–SOC model, online impedance measurement (implemented in this study using an RBS), impedance-based FOM parameter identification, and a fractional-order EKF for SOC estimation. The OCV–SOC models at different temperatures are obtained through offline calibration, as described in Section 4.2. The online impedance

measurement, parameter identification, and SOC estimation procedures are detailed in the following subsections.

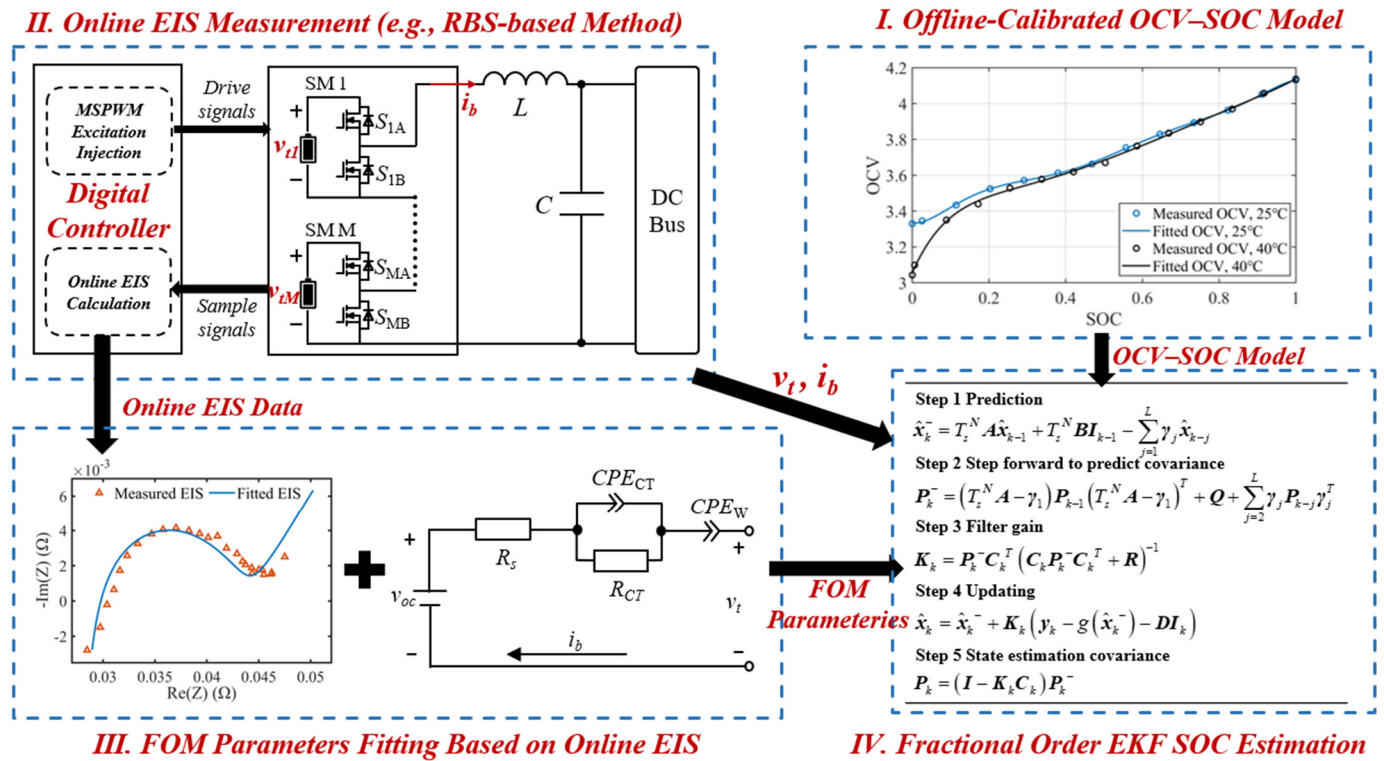


**Figure 5.** The proposed impedance-assisted SOC estimation framework.

### 3.1. Online EIS Measurement

As discussed above, the proposed impedance-assisted SOC estimation framework is not restricted to a particular impedance measurement method. In general, the onboard impedance information can be obtained through different techniques, such as current injection, voltage perturbation, or power electronic excitation, provided that the resulting disturbance remains within acceptable limits for system operation. In this work, the impedance data are obtained online using an RBS-based measurement scheme proposed in [33], which is employed as an implementation example for experimental verification. It should be noted that the RBS is not introduced solely for impedance measurement or for implementing the proposed SOC estimation framework. In practical battery systems, an RBS can also support additional functions, such as balancing control, fault-tolerant operation, redundancy management, and flexible cell reconfiguration. Moreover, the use of the RBS-based measurement scheme in this work is mainly motivated by the authors' previous research platform. In principle, the proposed framework can also be combined with other online impedance acquisition approaches, including lower-cost solutions such as integrated impedance measurement chips and related embedded circuits, provided that the acquired impedance information is sufficiently reliable for model updating. The basic concept of the RBS is that individual battery cells are interfaced with additional power switches, allowing cells to be dynamically inserted into or bypassed from the system during operation, as shown in Figure 6. A battery cell together with its associated power switches forms a submodule (SM), enabling flexible control of cell connection states. During the impedance measurement process, the system output current is assumed to remain approximately constant. By appropriately controlling the insertion and bypassing of a selected cell, small current excitation is introduced, and the corresponding voltage response of the test cell is measured. Based on the injected excitation and measured

voltage response, impedance information over a specified frequency range can be obtained. Detailed modulation and control strategies for the RBS-based impedance measurement can be found in [33], and are therefore not repeated here. It should be clarified that the low-excitation scenario addressed in this paper refers to the insufficient excitation provided by normal operating conditions for time-domain identification. The proposed framework does not aim to eliminate excitation entirely, but rather to avoid reliance on sustained or high-amplitude excitation. The small and controlled probing signals used for impedance acquisition are introduced solely as an auxiliary information source and do not contradict the low-excitation operating premise.

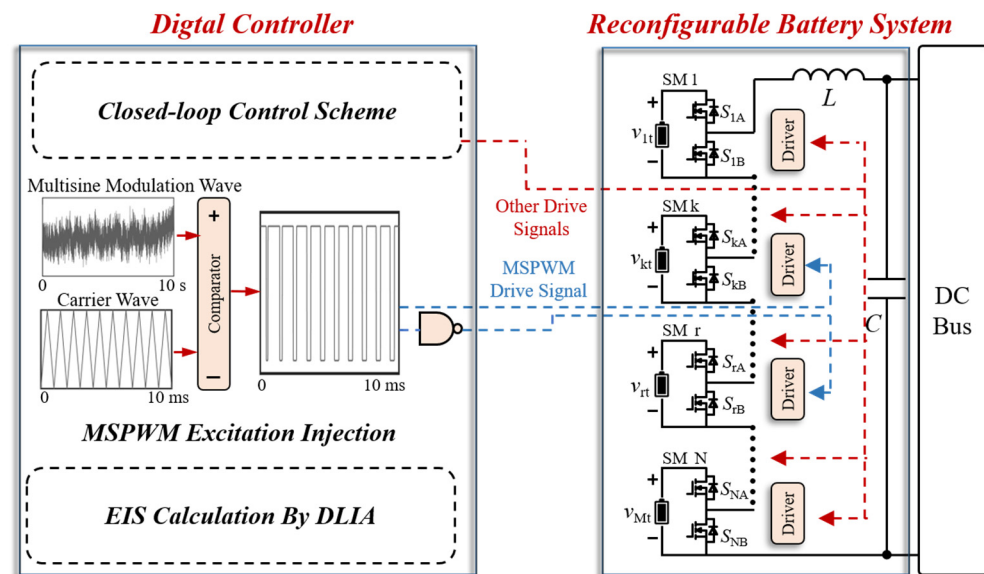


**Figure 6.** Schematic diagram of the online EIS measurement method by the RBS in [33].

The EIS measurement should cover broadband frequency. According to Figure 2a, the chosen EIS measurement frequency range in this paper is 0.1 Hz to 2 kHz. To fit the FOM parameters, six test frequency points are determined for each decade based on a quasi-logarithmic distribution [43]. The EIS measurement of cells in the RBS is conducted alternately, and the time required for each cell to complete one EIS measurement is three times the period corresponding to the lowest measurement frequency, including two cycles of stabilization time and one cycle of measurement time [33]. Thus, for the measurement frequency range set in this paper, completing an EIS measurement for one cell requires 30 s, and for an RBS containing N cells, the time required to complete one round of EIS testing for all cells is 30 N s. The test result is used to fit and update the cell's FOM parameters after each cell completes the online EIS measurement, improving the accuracy of the SOC estimation.

### 3.2. Impedance-Based Parameter Identification of the FOM

The online EIS is utilized for fitting the battery FOM parameters. However, traditional fitting algorithms, such as complex nonlinear least squares (CNLS) [44], although effective, require high computational ability, making them challenging to implement for onboard applications. Jussi Sihvo et al. [31] proposed an FOM parameter fitting algorithm based on the geometric shape of the EIS curve, achieving fast and accurate FOM parameter fitting with low computational overhead. The FOM utilized by this fitting algorithm is depicted in Figure 7, which retains the inductance component compared to the FOM used in this paper, as shown in Figure 4. In this study, the geometric fitting algorithm is first employed to identify the FOM parameters in Figure 7 from the online EIS data, which helps capture

the measured high-frequency impedance behavior. In the subsequent SOC estimation algorithm, the inductance component is omitted because it mainly appears in the high-frequency region and has limited influence on the low-frequency voltage dynamics relevant to SOC evolution. This simplification reduces the complexity of the online estimator, but it also introduces a slight mismatch between the impedance identification model and the SOC-estimation model. The total impedance of the FOM in Figure 7 can be expressed as follows:

$$Z_{FOM} = j\omega L_s + R_s + Z_{CT} + Z_W. \quad (12)$$

where  $Z_{CT}$  and  $Z_W$  represent the impedances of the charge-transfer region and the diffusion region, respectively, and can be expressed as follows:

$$Z_{CT} = \frac{1}{\frac{1}{R_{CT}} + (j\omega)^{\alpha_{CT}} C_{CT}}, \quad (13)$$

$$Z_W = \frac{1}{(j\omega)^{\alpha_W} C_W} = \frac{\cos(\frac{\pi\alpha_W}{2})}{\omega^{\alpha_W} C_W} - \frac{j \sin(\frac{\pi\alpha_W}{2})}{\omega^{\alpha_W} C_W}. \quad (14)$$

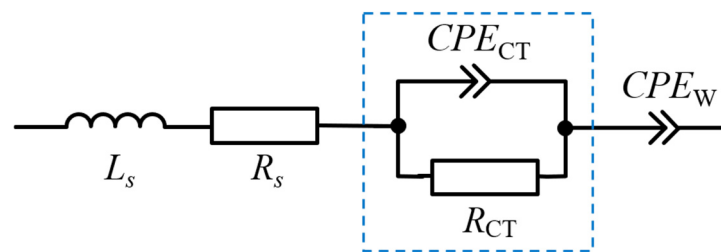


Figure 7. The FOM used for the parameter fitting in [31].

For ease of subsequent model parameterization, the real and imaginary parts of  $Z_{CT}$  are separated, and their expressions are as follows:

$$Z_{CT-re} = \frac{R_{CT} + \cos(\frac{\pi\alpha_{CT}}{2}) R_{CT}^2 C_{CT} \omega^{\alpha_{CT}}}{1 + 2 \cos(\frac{\pi\alpha_{CT}}{2}) R_{CT} C_{CT} \omega^{\alpha_{CT}} + \omega^{2\alpha_{CT}} R_{CT}^2 C_{CT}^2}, \quad (15)$$

$$Z_{CT-im} = \frac{-j \sin(\frac{\pi\alpha_{CT}}{2}) R_{CT}^2 C_{CT} \omega^{\alpha_{CT}}}{1 + 2 \cos(\frac{\pi\alpha_{CT}}{2}) R_{CT} C_{CT} \omega^{\alpha_{CT}} + \omega^{2\alpha_{CT}} R_{CT}^2 C_{CT}^2}. \quad (16)$$

Figure 8 presents an example of online measured EIS by the RBS. According to the fitting algorithm in [31], there are several key characteristic points in the impedance data of the battery used for the parameterization of the FOM, which can be defined as follows:

- Minimum real-part point (MIN), which is the data point with the smallest real part in the impedance data.
- Top of the semi-ellipse point (TSC), which is the vertex of the semi-ellipse curve corresponding to the charge-transfer region, where the derivative is 0.
- End of the diffusion point (EOD), which is the point of intersection between the charge-transfer region and the diffusion region, where the derivative is also 0.

Figure 8 annotates the positions of MIN, TSC, and EOD points in the measured impedance data. Based on the geometric shape, the algorithm utilizes the impedance data of these three characteristic points, as well as the property of the derivative being 0 at the TSC and EOD points, to parameterize the FOM. This paper mostly adopts this fitting algorithm, with only one modification: to fit the order  $\alpha_W$  of the Warburg element, the geometric fitting algorithm requires selecting two data points for calculation in the diffusion region of the EIS curve and far from the EOD point. However, since the diffusion region

corresponds to a very low-frequency range, the set EIS measurement frequency range cannot guarantee the collection of enough data points in the diffusion region. Reducing the test frequency even further would result in a substantial increase in the time needed for EIS measurements, which would undermine the real-time nature of the parameter updates. According to the existing literature [14,45,46], the impedance curve of the lithium battery diffusion region can be approximated as a line with a slope of  $\pi/4$ , corresponding to a Warburg element order of 0.5. Therefore, this paper fixes  $\alpha_W$  to 0.5, while keeping the other fitting steps detailed in [31] unchanged.

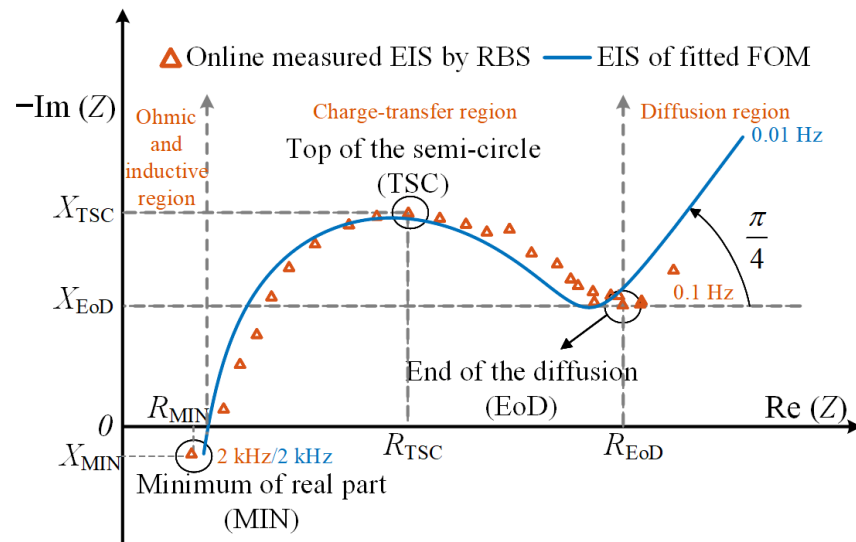


**Figure 8.** An example of the online measured EIS by the RBS and its fitting results.

Table 1 presents the FOM parameters fitted based on the measured impedance data in Figure 8, and the fitted EIS curve corresponding to the FOM is also plotted in Figure 8, with the lower frequency band extended to 0.01 Hz to demonstrate the impedance characteristics of the diffusion region. The fitting accuracy is evaluated through the normalized root mean square error (NRMSE), and is defined as follows:

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{l} \sum_{i=1}^l \left(1 - \frac{\|Z_{\text{fit}}(i)\|}{\|Z_{\text{mea}}(i)\|}\right)^2}}{\max(\|Z_{\text{mea}}\|) - \min(\|Z_{\text{mea}}\|)}. \quad (17)$$

where  $Z_{\text{fit}}(i)$  and  $Z_{\text{mea}}(i)$  denote the fitted and measured impedance at the  $i$ -th frequency point, respectively,  $l$  is the total number of frequency points, and  $\|\cdot\|$  denotes the modulus of the complex impedance. In addition,  $\max(\|Z_{\text{mea}}\|)$  and  $\min(\|Z_{\text{mea}}\|)$  represent the maximum and minimum modulus values of the measured impedance over all frequency points. As shown in Table 1, the NRMSE of the fitting result is only 1.5%, demonstrating the effectiveness of the fitting algorithm.

**Table 1.** The FOM fitting parameter values from EIS in Figure 7.

| $L_s$ ( $10^{-7}$ H) | $R_s$ (m $\Omega$ ) | $R_{CT}$ (m $\Omega$ ) | $C_{CT}$ (F) | $\alpha_{CT}$ | $C_W$ (F) | NRMSE (%) |
|----------------------|---------------------|------------------------|--------------|---------------|-----------|-----------|
| 3.8                  | 27.2                | 17.1                   | 1.4          | 0.58          | 449.2     | 1.5       |

### 3.3. SOC Estimation with Impedance-Informed Model Updating

The model-based SOC estimation methods typically utilize Kalman filters and their variants, such as the EKF, UKF, and Central Difference Kalman Filter (CDKF), among others. Considering both algorithm accuracy and complexity, this paper adopts the fractional-order

EKF to estimate the battery SOC and utilizes online EIS measurements by the RBS to update the parameters of the FOM, thus improving the SOC estimation accuracy.

Based on the state space function in Equation (11), the steps of the improved SOC estimation method are as follows. In the following EKF-based SOC estimation procedure,  $\hat{x}_k^-$  and  $\hat{x}_k$  denote the prior and posterior state estimates at the  $k$ -th sampling instant, respectively, while  $P_k^-$  and  $P_k$  represent the corresponding prior and posterior error covariance matrices, respectively.  $I_k$  is the load current,  $Q$  is the process noise covariance matrix, and  $R$  is the measurement noise covariance matrix.  $T_s^N A$ ,  $T_s^N B$ , and  $D$  are the discrete-time state-space matrices updated according to the online impedance-identified FOM parameters. In addition,  $\gamma_j$  denotes the fractional-order weighting coefficient and  $L$  is the memory length used in the fractional-order state update.

- (1) Initialization: Given the initial state  $x_0$ ,  $Q$ ,  $R$ , and the state error covariance  $P_0$ .
- (2) Update the FOM parameters based on online EIS: Based on the above analysis, the battery cells within the RBS perform the online EIS measurement in turn. Whenever a test cell completes the EIS measurement and fitting of the FOM parameters, matrices related to the model parameters are updated, including  $T_s^N A$ ,  $T_s^N B$ , and  $D$ .
- (3) Update the prior states estimation as follows:

$$\hat{x}_k^- = T_s^N A \hat{x}_{k-1} + T_s^N B I_{k-1} - \sum_{j=1}^L \gamma_j \hat{x}_{k-j}. \quad (18)$$

- (4) Update the covariance of prior states estimation as follows:

$$P_k^- = \left( T_s^N A - \gamma_1 \right) P_{k-1} \left( T_s^N A - \gamma_1 \right)^T + Q + \sum_{j=2}^L \gamma_j P_{k-j} \gamma_j^T. \quad (19)$$

- (5) Update the Kalman gain as follows:

$$K_k = P_k^- C_k^T \left( C_k P_k^- C_k^T + R \right)^{-1}. \quad (20)$$

where  $K_k$  is the Kalman gain matrix and  $C_k$  is the value of the Jacobian matrix of  $g(x_k)$  at the prior states estimation, and its expression is as follows:

$$C_k = \left[ \frac{\partial v_{oc}}{\partial z}(\hat{z}_k^-) - 1 - 1 \right]. \quad (21)$$

where  $v_{oc}(z)$  denotes the OCV–SOC function and  $z$  is the SOC state variable.

- (6) Updating the posterior states estimation as follows:

$$\hat{x}_k = \hat{x}_k^- + K_k (y_k - g(\hat{x}_k^-) - D I_k). \quad (22)$$

- (7) Updating the covariance of posterior states estimation as follows:

$$P_k = (I - K_k C_k) P_k^-. \quad (23)$$

where  $I$  denotes the identity matrix.

## 4. Experimental Validation

### 4.1. Experimental Setup

To validate the effectiveness of the proposed improved SOC estimation method, experiments are conducted using two LiNiMnCo (NMC) 18650 lithium-ion batteries manufactured by Panasonic (Osaka, Japan) with different degrees of aging, referred to as NMC-New

and NMC-Old, respectively, with their main parameters listed in Table 2. Since the exact full-life usage history of the cells was not fully available, the degradation stage was identified primarily based on the SOH. The new and old batteries had measured SOH values of 96.1% and 81.8%, respectively. Figure 9 illustrates the battery testing platform, comprising a NEWARE CT-4008T battery tester manufactured by NEWARE (Shenzhen, China) for calibrating the OCV–SOC model and performing standard CC–CV charging of the batteries after each experiment, a temperature chamber to control ambient temperature, an RBS with 16 SMs, a programmable electronic load, and a host computer. The voltage and current accuracies of the NEWARE CT-4008T under the operating ranges used in this work are  $\pm 2.5$  mV and  $\pm 1.5$  mA, respectively, and the temperature chamber has a control accuracy of  $\pm 1$  °C. The two test cells are installed in the first and second cell positions of the RBS, as shown in Figure 9a. During the experiment, the RBS is placed inside the temperature chamber and connected to the electronic load. The RBS is controlled by a microprocessor TMS320F28386S manufactured by Texas Instruments (Dallas, TX, USA) integrating four 16-bit ADCs, and the cell voltage, output current, and output voltage are sampled through ADC channels. Since the RBS consists of 16 individual cells, a 16-to-1 multiplexer is employed to sequentially sample the voltage of each cell, while the output current is measured through a 20 m $\Omega$  shunt resistor. The voltage and current sampling accuracies of the RBS are  $\pm 5$  mV and  $\pm 50$  mA, respectively. The sampled data and estimation results are transmitted to the host computer via the RS485 interface for analysis. These accuracy factors mainly influence the SOC estimation through current integration, terminal-voltage correction, OCV–SOC calibration, and impedance-based parameter updating. Therefore, the measurement uncertainties of the experimental platform were taken into account qualitatively in evaluating the reliability of the proposed SOC estimation method.

**Table 2.** Specifications of the two test cells.

| Ref of Cells                        | NMC-New | NMC-Old |
|-------------------------------------|---------|---------|
| Nominal capacity (Ah)               | 3       | 3       |
| Nominal voltage (V)                 | 3.65    | 3.65    |
| Lower and upper cut-off voltage (V) | 2.5~4.2 | 2.5~4.2 |
| SOH                                 | 96.1%   | 81.8%   |

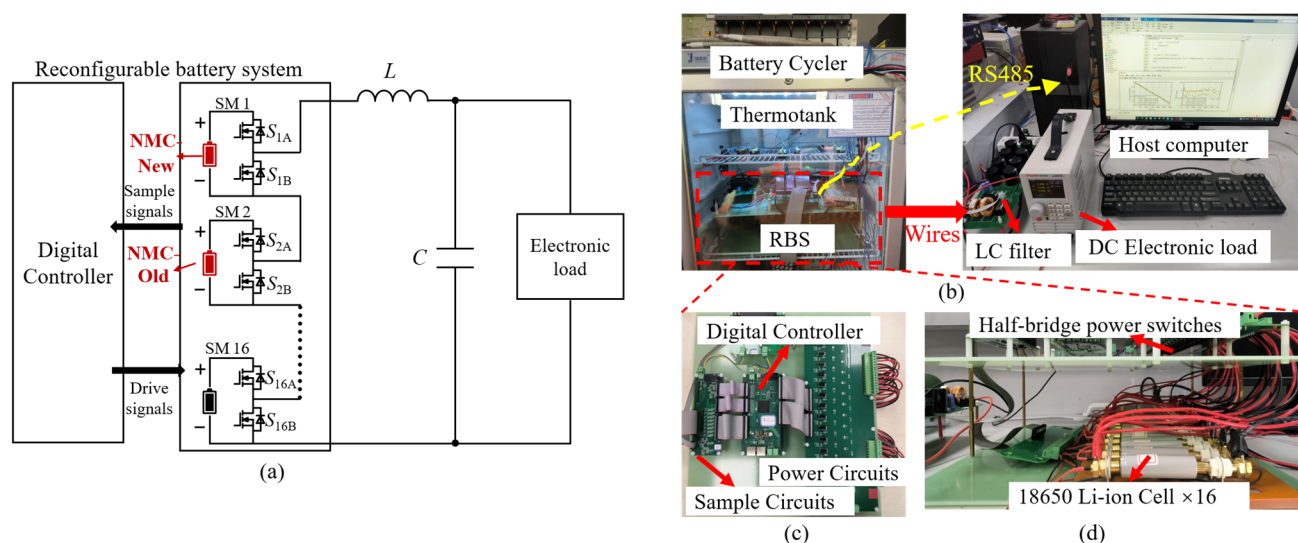


**Figure 9.** Battery test bench: (a) Block diagram; (b) The picture of whole experimental setup; (c) Top view of the RBS; (d) Side view of the RBS.

#### 4.2. OCV–SOC Model

As part of the model, the OCV–SOC model directly influences the accuracy of the estimation results. After a prolonged period of battery rest, the terminal voltage of the battery approximates the OCV, making it suitable for offline calibration of the OCV–SOC relationship. Using a battery tester, the test cells are charged to 100% SOC following the standard CC–CV charging protocol, rested for 2 h, and the terminal voltage is recorded. Subsequently, the cells are discharged at 1 C for 5 min, rested for another 2 h, and the terminal voltage is recorded until reaching the cut-off voltage. Combining the test data, the OCV–SOC relationship is typically modeled using a polynomial function. In this study, a 7th-order polynomial is adopted as a compromise between the fitting accuracy and model complexity based on engineering experience as follows:

$$v_{oc}(z) = K_0 + \sum_{i=1}^7 K_i z^i. \quad (24)$$

where  $z$  represents the SOC. Figure 10 presents the OCV–SOC test data and the fitted model curves for two test cells at temperatures of 25 °C and 40 °C, respectively. The fitting accuracy is evaluated using the root mean square error (RMSE). The RMSE values are 3.51 mV and 5.84 mV for the NMC-New cell at 25 °C and 40 °C, and 2.96 mV and 6.51 mV for the NMC-Old cell at 25 °C and 40 °C, respectively, indicating that the selected polynomial order provides sufficient accuracy for the OCV–SOC model. In this study, the fitted OCV–SOC relationship is used as a simplified static mapping in the model. Therefore, the hysteresis effect between charge and discharge OCV curves is not explicitly considered, which should be further considered in future work.

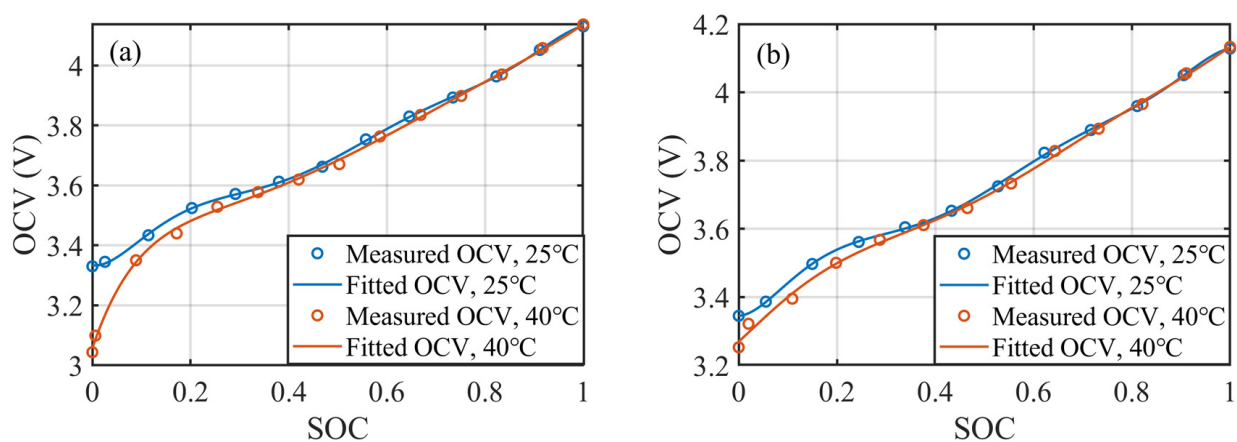


**Figure 10.** OCV–SOC curves of (a) NMC-New and (b) NMC-Old.

The OCV–SOC curves are calibrated separately at 25 °C and 40 °C, as the experiments in this work are conducted under these two constant ambient temperature conditions. Therefore, no interpolation strategy between the temperatures is required in the present study. For practical applications under continuously varying temperatures, temperature-dependent interpolation or coupled OCV–SOC modeling would be necessary.

#### 4.3. SOC Estimation Results Under Low Excitation Level

The step constant current (SCC) test is used to represent a typical low-excitation operating condition, where the nearly constant current provides limited dynamic information for time-domain parameter identification, as illustrated in Figure 11. The test current profile is designed to verify the proposed SOC estimation algorithm, with each constant current

condition lasting 5 min. The verification experiments are conducted at temperatures of 25 °C and 40 °C, respectively.

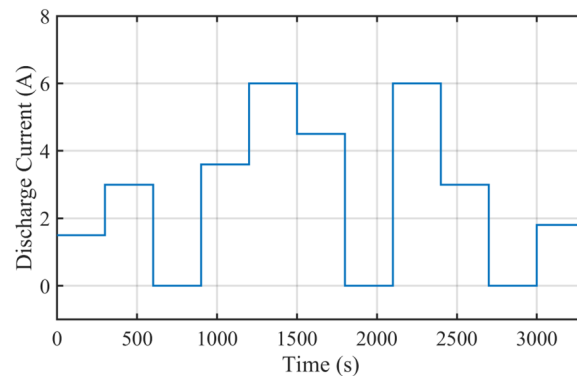


**Figure 11.** Current profile of the designed SCC test condition.

Figure 12 presents the sampled voltage of the test cells and the EIS data measured online by the RBS at an ambient temperature of 25 °C under the SCC conditions. As analyzed in Section 3.1, the online EIS measurement for a single cell in the RBS takes 30 s, and there are a total of 16 cells in the RBS. Thus, during the testing process, online EIS measurements are performed for the test cells every 8 min. It should be noted that the RBS cannot measure EIS when the current is zero [33], resulting in a total of five online EIS measurements during the testing process. After each online EIS measurement, the impedance data are used to fit and update the parameters of the battery's FOM, as shown in Tables 3 and 4. It can be found that the online impedance fitting error is larger for the aged cell in some cases. This is mainly because the simplified FOM used in this work does not explicitly include the impedance element associated with the SEI. As the SOH decreases, the SEI-related impedance becomes more significant, making the simplified FOM less capable of accurately fitting the impedance spectrum of the aged cell. Since the fitted impedance parameters are used to update the FOM parameters in the EKF-based SOC estimator, larger fitting errors may further affect parameter accuracy and contribute to the SOC estimation errors.

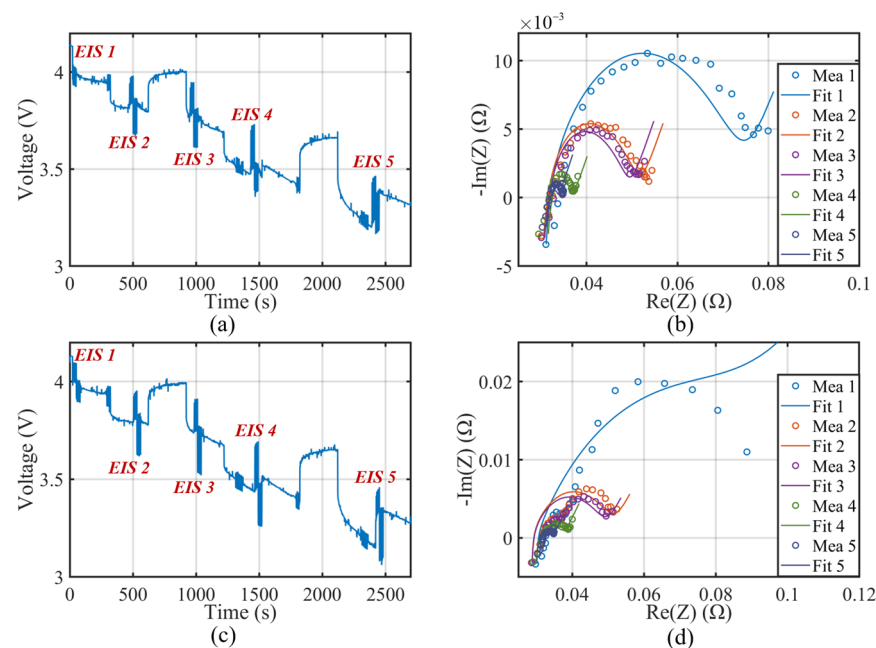


**Figure 12.** Terminal voltage and online EIS of (a,b) NMC-New and (c,d) NMC-Old during the SCC test at 25 °C.

**Table 3.** The fitted FOM parameters of NMC-New using online EIS during the SCC test at 25 °C.

| Test Time              | 1     | 2     | 3     | 4     | 5     |
|------------------------|-------|-------|-------|-------|-------|
| $L_s$ ( $10^{-7}$ H)   | 4.6   | 4.2   | 4.4   | 3.1   | 2.7   |
| $R_s$ (m $\Omega$ )    | 28.8  | 28.0  | 28.0  | 29.3  | 29.2  |
| $R_{CT}$ (m $\Omega$ ) | 45.6  | 23.6  | 21.4  | 7.9   | 4.6   |
| $C_{CT}$ (F)           | 1.72  | 1.29  | 1.16  | 3.85  | 0.68  |
| $\alpha_{CT}$          | 0.54  | 0.56  | 0.56  | 0.45  | 0.64  |
| $C_W$ (F)              | 393.7 | 531.5 | 512.3 | 949.4 | 897.6 |
| NRMSE (%)              | 2.1   | 1.5   | 1.6   | 4.6   | 6.6   |

**Table 4.** The fitted FOM parameters of NMC-Old using online EIS during the SCC test at 25 °C.

| Test Time              | 1     | 2     | 3     | 4     | 5     |
|------------------------|-------|-------|-------|-------|-------|
| $L_s$ ( $10^{-7}$ H)   | 3.0   | 3.0   | 3.0   | 3.5   | 2.0   |
| $R_s$ (m $\Omega$ )    | 29.7  | 28.4  | 28.3  | 27.9  | 30.2  |
| $R_{CT}$ (m $\Omega$ ) | 58.9  | 22.8  | 20.7  | 9.8   | 4.5   |
| $C_{CT}$ (F)           | 8.4   | 5.3   | 5.2   | 4.6   | 13.1  |
| $\alpha_{CT}$          | 0.57  | 0.59  | 0.58  | 0.45  | 0.46  |
| $C_W$ (F)              | 811.0 | 543.8 | 588.5 | 652.4 | 965.7 |
| NRMSE (%)              | 8.7   | 16.5  | 17.4  | 4.3   | 11.6  |

To evaluate the proposed online EIS-updated FOM and SOC estimation method, the 1-RC model with online updated parameters and the FOM with fixed offline identified parameters are taken as benchmarks, while the estimation algorithm remains the same (i.e., EKF). The parameters for the 1-RC model are online identified through the forgetting factor recursive least squares (FFRLS) algorithm. The offline parameter identification for the FOM utilized the HPPC test data of the test cells at 50% SOC, obtained through the GA, which is a commonly used parameter identification method for FOMs in previous studies [27]. The initial SOC is erroneously set to 0.6 to examine the robustness of the SOC estimation, and the estimation results obtained through different methods are illustrated in Figure 13.

It is worth noting that the estimator handoff during the RBS-based online EIS measurement is a limitation of the present implementation. During the RBS-based EIS measurement, a high-frequency square-wave excitation is injected into the cell, and the switching frequency of the corresponding half-bridge is significantly higher than the voltage sampling frequency. Therefore, the sampled voltage data are dominated by the excitation response and cannot be directly used for the normal EKF voltage update. As a result, the battery SOC is temporarily updated using the coulomb counting method during the online EIS measurement period. After the EIS measurement is completed, the original SOC estimation algorithm is restored. However, because the internal polarization states are not fully reconstructed when the EKF resumes, the SOC estimation results may exhibit short transient jumps followed by reconvergence, leading to the peaks observed in Figure 13.

This discontinuity is mainly caused by the adopted RBS-based impedance measurement scheme rather than the proposed impedance-assisted SOC estimation framework itself. The proposed framework is not restricted to a specific online impedance measurement technique. If other methods, such as small-amplitude AC perturbation, are used, the voltage response may still be incorporated into the SOC estimator after appropriate signal processing, and the switch to coulomb counting may be avoided. Future work will investigate state-reset, polarization-state warm-start, and smoothing strategies to improve the SOC estimation continuity during online impedance measurement.

The performance of different SOC estimation algorithms is evaluated using mean absolute error (MAE) and root mean square error (RMSE); the results are shown in Figure 14. From the experimental results, it can be observed that the 1-RC model with online identified

parameters outperforms the FOM with offline identified parameters for SOC estimation. This is because the FOM parameters vary a lot during the SCC test, as shown in Figure 12. Contrarily, the proposed online EIS method can accurately capture battery dynamics by updating the FOM parameters regularly, which remarkably enhances the model accuracy. Therefore, the FOM-EKF with online EIS-updated parameters shows more superiority over the FFRLS-based 1-RC model owing to its improved model structure. The findings indicate that an FOM may not always perform better in an SOC estimation than an IOM if the parameters of the FOM cannot be online identified.

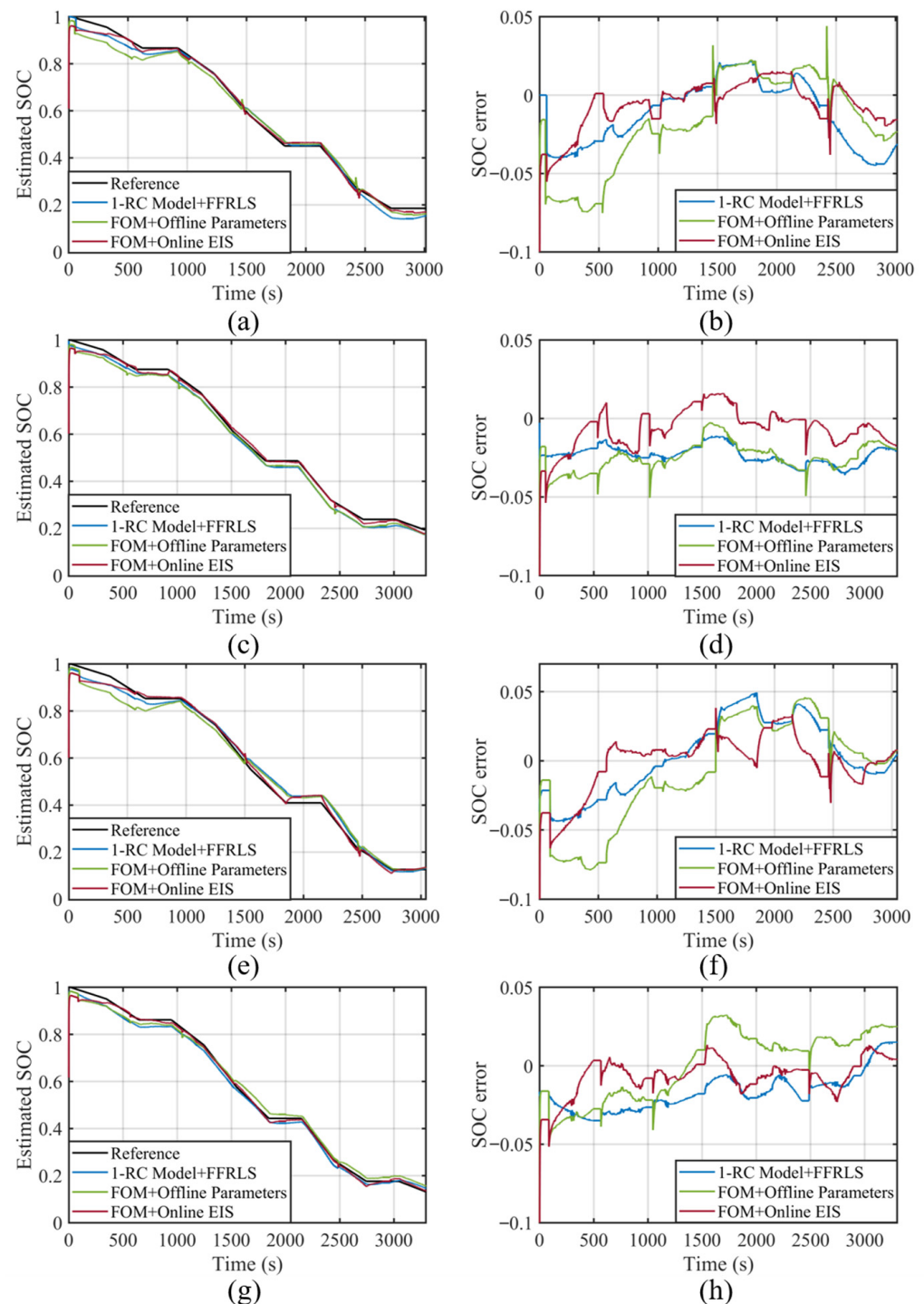


**Figure 13.** SOC Estimation results and errors during the SCC test: (a,b) NMC-New, 25 °C; (c,d) NMC-New, 40 °C; (e,f) NMC-Old, 25 °C; (g,h) NMC-Old, 40 °C.

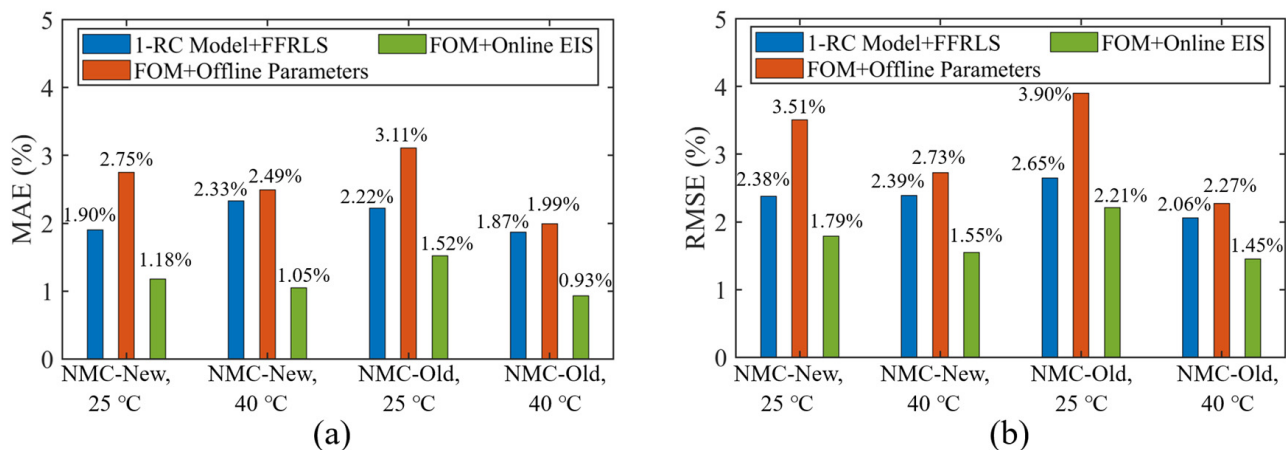


**Figure 14.** Estimation of (a) MAEs and (b) RMSEs with different SOC estimation methods.

#### 4.4. Dependence of Embedded Execution Time on Memory Length $L$

To further evaluate the real-time feasibility of the proposed method, the execution time of one online SOC estimation update was measured on the TMS320F28386S microcontroller for different memory lengths  $L$ , as summarized in Table 5. The measured results indicate that the execution time exhibits an approximately linear dependence on  $L$ . This trend is expected because the conventional EKF correction step has a fixed computational cost, whereas the dominant variable computational burden of the proposed FOM-EKF comes from the short-memory summation of historical state and covariance terms, both of which scale with the memory length. As a result, when  $L$  increases, the number of operations required in each online estimation update increases almost proportionally. For the value used in this study,  $L = 100$ , the measured execution time is still far below the adopted sampling interval of 1 s, demonstrating the real-time implementation of the proposed method on the TMS320F28386S. Therefore, the choice of  $L$  should consider not only the improvement in model accuracy, but the corresponding increase in execution time and computational burden.

**Table 5.** Dependence of embedded execution time on memory length  $L$ .

| Memory Length $L$         | 20  | 50  | 100 | 200 |
|---------------------------|-----|-----|-----|-----|
| Execution Time ( $\mu$ s) | 107 | 258 | 492 | 938 |

#### 4.5. Sensitivity Analysis of the Warburg Fractional Order

To further justify the fixed Warburg fractional order used in the proposed FOM-based SOC estimation framework, a sensitivity analysis of  $\alpha_W$  was conducted using the NCM-Old cell at 25 °C. In this analysis,  $\alpha_W$  was fixed at 0.3, 0.4, 0.5, 0.6, and 0.7, respectively. For each fixed  $\alpha_W$ , the corresponding FOM parameters were reidentified from the online EIS fitting results and then incorporated into the online EIS-assisted FOM-EKF estimator. Therefore, the comparison reflects the influence of different fixed  $\alpha_W$  values on the SOC estimation performance while considering the coupled variation of the other FOM parameters.

The obtained results are shown in Figure 15. It can be observed that the SOC estimation accuracy is affected by the selection of  $\alpha_W$ . Table 6 shows that, among all tested values,  $\alpha_W = 0.5$  gives the best estimation performance, with the lowest MAE and RMSE of 1.52% and 2.21%, respectively. When  $\alpha_W$  deviates from 0.5, both error metrics increase.

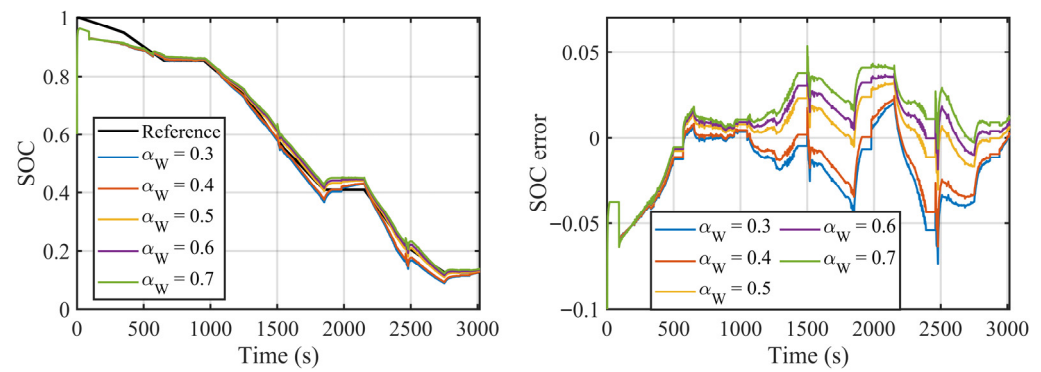


**Figure 15.** SOC estimation results and errors of NCM-Old at 25 °C with different  $\alpha_W$ .

**Table 6.** SOC estimation MAEs and RMSEs of NCM-Old at 25 °C with different  $\alpha_W$ .

| $\alpha_W$ | 0.3  | 0.4  | 0.5  | 0.6  | 0.7  |
|------------|------|------|------|------|------|
| MAE (%)    | 2.10 | 1.79 | 1.52 | 1.82 | 2.26 |
| RMSE (%)   | 2.78 | 2.49 | 2.21 | 2.42 | 2.71 |

These results demonstrate that the fixed  $\alpha_W = 0.5$  assumption is not arbitrary for the tested NCM-Old cell at 25 °C, but is supported by the sensitivity analysis. Nevertheless, the underlying physical mechanism behind the optimal performance at  $\alpha_W = 0.5$  may be related to the diffusion dynamics represented by the Warburg element and its coupling with the other identified FOM parameters. A more detailed investigation of this mechanism will be considered in future work.

#### 4.6. Experimental Results Discussion

The experimental results indicate that the proposed method consistently outperforms conventional time-domain SOC estimation approaches, particularly under low-excitation operating conditions, such as the SCC test. In these scenarios, the nearly constant current provides insufficient information for reliable online parameter identification, leading to parameter drift and accumulated SOC errors in traditional methods.

These results can also be discussed in relation to the limitations summarized in the Introduction. First, unlike existing impedance-based SOC estimation methods that directly map impedance features to the SOC, the proposed method uses online measured impedance only for updating the fractional-order model parameters, while the SOC is estimated through the EKF-based model framework. This helps improve robustness under different temperatures and aging states. Second, unlike previous studies that mainly use online impedance for battery modeling or parameter fitting, this work incorporates the updated parameters into a closed-loop FOM-EKF SOC estimation framework for the first time. Third, the SCC test results verify that the proposed method is effective under constant-current or quasi-static operating conditions, where conventional time-domain online identification methods often become ineffective due to insufficient excitation.

Impedance measurement errors caused by noise, or temperature drift may affect the identified model parameters and thereby indirectly influence the SOC estimation accuracy. In this study, the experiments were conducted under controlled thermal conditions to reduce such effects. A more systematic robustness analysis with respect to impedance measurement uncertainty will be addressed in future work.

It should be noted that the effectiveness of the proposed method under highly dynamic operating conditions has not been fully validated in this study. This limitation mainly arises from the adopted RBS-based online impedance measurement scheme, which

currently cannot acquire reliable impedance information under highly dynamic operating conditions. In addition, although the experiments were conducted at 25 °C and 40 °C, these two cases correspond to separate controlled-temperature conditions, rather than continuously varying thermal environments. Therefore, the present study verifies the proposed impedance-assisted SOC estimation framework mainly under quasi-static and weakly dynamic operating conditions at fixed temperatures, where online impedance measurements can be performed in a stable and controlled manner.

Moreover, the present validation is based on two representative NMC cells with different health conditions, namely NMC-New and NMC-Old. Although the results support the feasibility of the proposed method, the limited sample size is insufficient for statistically strong conclusions regarding robustness across broader cell-to-cell variations, aging levels, production variations, and operating conditions.

Future work will focus on extending the proposed framework to fast dynamic and dynamically varying thermal conditions using advanced online impedance measurement techniques. Larger-scale experimental validation involving more cells, broader aging states, production variations, and wider operating scenarios will also be conducted to further assess the generality and robustness of the proposed method.

## 5. Conclusions

This paper addresses the challenge of SOC estimation for lithium-ion batteries operating under low-excitation conditions, where conventional time-domain online identification suffers from insufficient excitation and poor parameter identifiability. To overcome this issue, an impedance-assisted SOC estimation framework is proposed by integrating online EIS data with FOMs.

By exploiting complementary frequency-domain information from online EIS measurements, the proposed method enhances parameter identifiability under weak excitation and enables reliable online updating of the FOM parameters. An extended Kalman filter based on the impedance-informed FOM is then employed to estimate the SOC, forming a closed-loop framework that integrates frequency-domain measurements with time-domain state estimation.

Experimental validation on two 18650 lithium-ion batteries with different aging levels under low excitation conditions demonstrates that the proposed approach achieves a more accurate and stable SOC estimation than methods relying solely on time-domain identification or fixed offline models. The results confirm that introducing online EIS effectively improves the SOC estimation robustness when current excitation is insufficient. Overall, the proposed framework provides a practical solution for quasi-constant battery applications, such as BESSs.

Future work will focus on improving the efficiency of online impedance acquisition, extending the proposed framework to fast dynamic and dynamically varying thermal conditions, and validating its performance through larger-scale experiments involving more cells, broader aging states, production variations, and wider operating scenarios, so as to further enhance its practical applicability in BESSs.

**Author Contributions:** Z.C.: conceptualization, methodology, writing—original draft, writing—review and editing.; Y.L.: supervision, writing—review and editing.; C.L.: software.; Y.W.: writing—review and editing.; L.W.: writing—review and editing.; Y.Y.: supervision, funding acquisition, conceptualization.; J.L.: supervision, project administration, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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## Abbreviations

The following abbreviations are used in this manuscript:

|       |                                        |
|-------|----------------------------------------|
| SOC   | State of Charge                        |
| EIS   | Electrochemical Impedance Spectroscopy |
| FOM   | Fractional-Order Model                 |
| HPPC  | Hybrid Pulse Power Characterization    |
| RMSE  | Root Mean Square Error                 |
| OCV   | Open-Circuit Voltage                   |
| CPE   | Constant Phase Element                 |
| SEI   | Solid Electrolyte Interphase           |
| SOH   | State of Health                        |
| RBS   | Reconfigurable Battery System          |
| CNLS  | Complex Nonlinear Least Squares        |
| TSC   | Top of the Semi-Ellipse Point          |
| EOD   | End of Diffusion Point                 |
| NRMSE | Normalized Root Mean Square Error      |
| EKF   | Extended Kalman Filter                 |
| SM    | Submodule                              |
| SCC   | Step Constant Current                  |

## Nomenclature

|                 |                                                                          |
|-----------------|--------------------------------------------------------------------------|
| $D^\alpha$      | Fractional-order differential operator                                   |
| $\alpha$        | Fractional order                                                         |
| $T_s$           | Sampling period                                                          |
| $\Gamma(\cdot)$ | Gamma function                                                           |
| $L$             | Memory length in the short-memory principle                              |
| $Z_W$           | Warburg impedance                                                        |
| $C_W$           | Capacitance-like parameter of the Warburg element                        |
| $\alpha_W$      | Fractional order of the Warburg element                                  |
| $Z_{CPE_{SEI}}$ | Impedance of the SEI constant phase element                              |
| $C_{SEI}$       | Capacitance-like parameter of the SEI constant phase element             |
| $\alpha_{SEI}$  | Fractional order of SEI constant phase element                           |
| $Z_{CPE_{CT}}$  | Impedance of the charge-transfer constant phase element                  |
| $C_{CT}$        | Capacitance-like parameter of the charge-transfer constant phase element |
| $\alpha_{CT}$   | Fractional order of the charge-transfer constant phase element           |
| $Z_{FOM}$       | Total impedance of the fractional-order model                            |
| $R_s$           | Ohmic resistance                                                         |
| $R_{CT}$        | Charge-transfer resistance                                               |
| $z$             | State of charge                                                          |
| $\eta$          | Coulombic efficiency                                                     |
| $C_n$           | Nominal capacity of the battery                                          |
| $i_b(t)$        | Battery current                                                          |
| $v_t(t)$        | Terminal voltage of the battery                                          |
| $v_{oc}(z)$     | Open-circuit voltage as a function of SOC                                |
| $v_{CT}(t)$     | Voltage across the charge-transfer impedance                             |

|              |                                                   |
|--------------|---------------------------------------------------|
| $v_W(t)$     | Voltage across the Warburg impedance              |
| $x_k$        | State vector at time step $k$                     |
| $\omega_k$   | Process noise                                     |
| $v_k$        | Measurement noise                                 |
| $\gamma_j$   | Fractional-order weighting coefficient            |
| $P_k^-$      | Prior error covariance matrix                     |
| $P_k$        | Posterior error covariance matrix                 |
| $Q$          | Process noise covariance matrix                   |
| $R$          | Measurement noise covariance matrix               |
| $K_k$        | Kalman gain matrix                                |
| $C_k$        | Jacobian matrix of the measurement function       |
| $y_k$        | Measured output at time step $k$                  |
| $I_k$        | Input current at time step $k$                    |
| $Z_{CT}$     | Charge-transfer impedance                         |
| $Z_{CT-re}$  | Real part of the charge-transfer impedance        |
| $Z_{CT-im}$  | Imaginary part of the charge-transfer impedance   |
| $Z_{fit}(i)$ | Fitted impedance at the $i$ -th frequency point   |
| $Z_{mea}(i)$ | Measured impedance at the $i$ -th frequency point |

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