

Article

State-of-Charge Estimation of Lithium-Ion Batteries Under Low-Temperature Conditions

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Abstract

Low-temperature operation intensifies polarization, causes model-parameter mismatch, and changes the time scale of the dynamic response in lithium-ion batteries. These effects reduce the accuracy of state-of-charge (SOC) estimation. To address this problem, an offline estimation method based on improved forgetting factor recursive least squares and three-dimensional (3D) bridge compensation is proposed. A 25 °C open-circuit voltage (OCV)-SOC curve is used as a unified reference. Under a first-order resistor-capacitor (RC) model, SOC segmentation and a variable forgetting factor are introduced for parameter identification. A genetic algorithm and an extended Kalman filter are then combined to construct the 3D bridge compensation. The results show that the proposed method effectively reduces SOC estimation errors and improves terminal-voltage reconstruction. Under the calibration conditions, the average root mean square error (RMSE) and mean absolute error (MAE) of SOC estimation, evaluated against the Coulomb-counting reference SOC trajectories, decreased from 0.0895 and 0.0834 to 0.0031 and 0.0021, respectively. The RMSE and MAE of terminal-voltage reconstruction, evaluated against the measured terminal voltage, decreased from 0.1623 V and 0.1113 V to 0.0325 V and 0.022 V, respectively. The proposed method provides an improved solution for offline SOC estimation of lithium-ion batteries at low temperatures. It also shows a degree of cross-cycle applicability for the same cell within the calibrated temperature range and provides a reference for correcting the state-estimation accuracy of fixed-reference models.

Keywords: state-of-charge estimation; low temperature; equivalent voltage-bias compensation term; equivalent resistance scaling factor; equivalent time-constant scaling factor



Academic Editor: Nikolaos Koukoulas

Received: 29 June 2026

Revised: 28 July 2026

Accepted: 30 July 2026

Published: 1 August 2026

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1. Introduction

With the rapid development of new-energy vehicles and energy-storage systems, lithium-ion batteries have become a key technology for power and energy-storage batteries because of their high energy density, long cycle life, and low self-discharge rate. As one of the core functions of a battery management system (BMS), the accuracy of SOC estimation directly affects the safety, energy-management performance, and service life of battery systems [1,2]. Since SOC cannot be measured directly by sensors, it is usually estimated indirectly from measurable signals such as current, voltage, and temperature [3]. Its accuracy is therefore readily affected by the battery model, parameter-identification accuracy, and operating-condition variations [4,5]. Temperature is an important factor affecting internal electrochemical reactions and dynamic-response characteristics. Low

temperatures alter the dynamic response of batteries, increase the difficulty of modeling and parameter identification, and reduce SOC-estimation accuracy [6]. Electric vehicles and energy-storage equipment often operate in low-temperature environments in extremely cold regions, high-latitude regions, or during winter. Therefore, accurate SOC estimation under low-temperature conditions is of practical importance [7].

Existing low-temperature SOC-estimation methods can be broadly divided into two categories. One category focuses on temperature-induced changes in static characteristics, whereas the other focuses on changes in battery-model structure and parameter responses under dynamic operating conditions. The former mainly considers changes in the OCV-SOC relationship and model-parameter baselines at different temperatures. For example, Fan et al. [8] proposed an OCV-SOC curve identification method based on a multi-output Gaussian process to address the difficulty of rapidly obtaining temperature-dependent OCV-SOC curves. By integrating OCV-SOC curve data at different temperatures, the method enables rapid construction of an OCV curve at a given temperature. Shen et al. [9] established a temperature-compensated electrical model over a wide temperature range and conducted experiments from $-20\text{ }^{\circ}\text{C}$ to $60\text{ }^{\circ}\text{C}$. A genetic algorithm was used to identify temperature-dependent model parameters, and a square-root cubature Kalman filter was used for SOC estimation. Such methods focus on the temperature-parameter mapping or static-baseline correction, while paying insufficient attention to changes in polarization-response amplitude and time-scale mismatch under dynamic operating conditions. When a battery operates under low-temperature dynamic charge–discharge conditions, static temperature-dependent parameter correction alone cannot fully account for delayed terminal-voltage responses, enhanced polarization, and accumulated errors in recursive SOC estimation.

Another category places greater emphasis on changes in dynamic response under low-temperature conditions and seeks to improve estimation by enhancing the ability of the model to track dynamic processes. Xiong et al. [10] noted that changes in polarization characteristics at low temperatures may cause part of the polarization voltage to be erroneously incorporated into the OCV, thereby affecting SOC estimation based on the OCV-SOC mapping. On this basis, they proposed an SOC estimation method that considers low-temperature polarization characteristics. To address the limited adaptability of equivalent circuit models at low temperatures, Mao et al. [11] proposed an ECM-RVM fusion model that combines an equivalent circuit model with a data-driven model and improves the robustness of SOC estimation under varying-temperature conditions through Bayesian fusion. For low-temperature conditions at $-20\text{ }^{\circ}\text{C}$, $-7\text{ }^{\circ}\text{C}$, and $0\text{ }^{\circ}\text{C}$, Gong et al. [12] proposed an SOC estimation method that combines a CNN-Transformer with a square-root unscented Kalman filter. The method extracts nonlinear sequence features under low-temperature conditions and performs state correction. These studies focus on the dynamic response itself but pay insufficient attention to changes in the low-temperature static baseline. Consequently, they may achieve good local voltage fitting but may not provide stable long-term support for SOC estimation.

In summary, existing studies have advanced low-temperature SOC estimation through both static temperature-characteristic correction and dynamic-response modeling. However, these two aspects remain largely separated in most studies. The proposed method combines them but does not simply stack forgetting factor recursive least squares (FFRLS), the extended Kalman filter (EKF), and the genetic algorithm (GA). Instead, it establishes a complete procedure around a fixed $25\text{ }^{\circ}\text{C}$ OCV-SOC reference: local parameter tracking, 3D residual bridge compensation, and cross-cycle parameter application. First, the effective SOC range is segmented. Independent FFRLS parameters and covariance matrices are maintained for each interval, and a soft-gated forgetting factor is jointly driven by voltage

error and current excitation. Second, the residual mismatch of the first-order RC fixed-reference model is decomposed into three complementary components: voltage-reference deviation, resistive-response amplitude, and polarization time scale. These components are jointly corrected using U_s , k_R and s_τ . Finally, the bridge parameters are calibrated offline using the Urban Dynamometer Driving Schedule (UDDS) cycle. They are then directly applied to the Highway Fuel Economy Test (HWFET) and Los Angeles 92 (LA92) driving cycles without rerunning the GA. This design distinguishes in-sample calibration performance from independent cross-cycle validation performance.

Unlike methods that construct OCV curves over the full temperature range, use high-order electrochemical models, or adopt end-to-end data-driven models, this study retains a low-dimensional first-order RC structure. The focus is to examine whether residual output mismatch can be corrected over a limited temperature range under a unified reference relationship. Therefore, the conclusions should be interpreted as offline calibration results for the same cell, the same state of health, and the tested temperature range. They do not demonstrate universal applicability across different chemistries, capacity ratings, or aging stages.

The remainder of this paper is organized as follows. Section 2 analyzes the sources of error under low-temperature conditions and describes the method design. Section 3 presents the improved method for low-temperature offline SOC estimation. Section 4 presents and analyzes the experimental results. Section 5 concludes the paper.

2. Design of an SOC Estimation Method Under Low-Temperature Conditions

Recent studies have shown that temperature variations affect not only the OCV-SOC relationship of batteries but also equivalent circuit parameters, polarization characteristics, and the applicability of state-estimation algorithms [13,14]. Consequently, low-temperature SOC estimation has become an important topic in battery management system research.

2.1. Effects of Low Temperatures on the Dynamic Characteristics of Lithium-Ion Batteries

At low temperatures, ion transport in the electrolyte is weakened, charge-transfer processes slow down, and electrode-interfacial impedance increases [15]. During charging and discharging, batteries are more likely to exhibit a faster terminal-voltage drop, reduced available capacity, increased internal resistance, and enhanced polarization [16]. Under dynamic operating conditions, frequent current variations further increase the contribution of the polarization voltage to the terminal voltage. The voltage response therefore exhibits a more pronounced delay and nonlinearity, which directly affects the parameters of the equivalent circuit model. As a result, a single fixed global parameter set can hardly describe an entire dynamic process accurately at low temperatures [17].

2.2. Sources of Error in Conventional SOC Estimation at Low Temperatures

OCV reference mismatch at low temperatures [18]. The OCV-SOC relationship is an important basis for correction in many model-driven SOC estimation methods. However, it is readily affected by temperature, aging, and testing procedures. Under low-temperature dynamic conditions, the polarization voltage superimposed on the terminal voltage weakens the effectiveness of state correction based on the OCV curve [19,20].

Parameter identification is more susceptible to distortion at low temperatures [21]. SOC estimation based on equivalent circuit models depends on accurate identification of model parameters. However, identification accuracy and stability are significantly affected by abrupt operating-condition changes, increased noise, or pronounced time-varying parameters [22]. At low temperatures, an identification process that only minimizes the

overall voltage error may incorrectly attribute part of the polarization voltage to the OCV or RC parameters, resulting in distorted equivalent parameters.

Mismatch in the dynamic-response time scale at low temperatures. A decrease in temperature slows internal diffusion and charge-transfer processes in batteries and makes the terminal-voltage response more prone to delay. If the time constant of a first-order RC model does not adequately match the actual terminal-voltage dynamics, SOC estimation errors may accumulate during continued recursion even when local voltage fitting is good [23].

2.3. Method Design

To mitigate the above error sources under low-temperature conditions, SOC segmentation and a variable forgetting factor are introduced during parameter identification to enhance the adaptability of the model to local-state differences and dynamic-stage variations. During state estimation, three-dimensional bridge compensation is further introduced to jointly correct the residual equivalent voltage bias, equivalent resistance-parameter deviation, and time-scale deviation at low temperatures. This forms a two-stage low-temperature SOC estimation framework with enhanced front-end identification and back-end bridge compensation. Figure 1 shows the residual mismatch of the fixed-reference model at low temperatures, its effects on estimation, and the corresponding correction strategies.

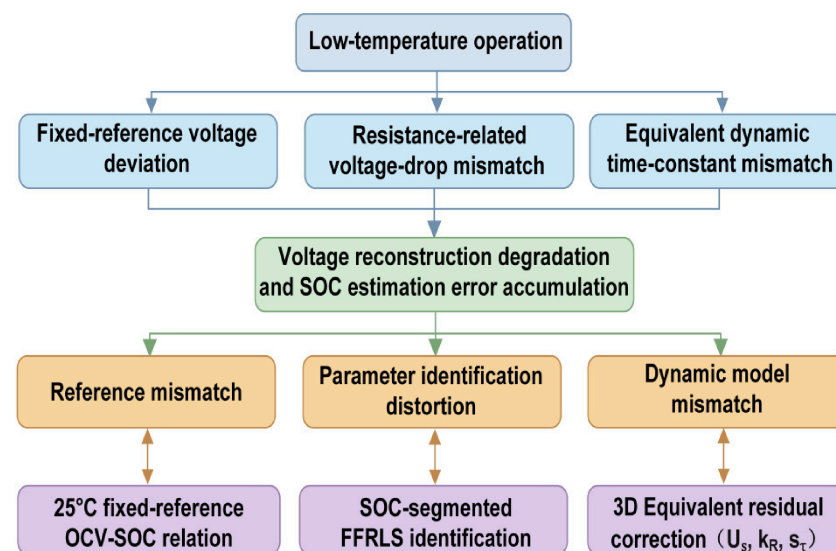


Figure 1. Low-temperature residual mismatch in the fixed-reference model, its effects on estimation, and the corresponding correction strategies.

Based on the correction strategy in Figure 1, an overall offline low-temperature SOC estimation procedure is further constructed, as shown in Figure 2. The procedure contains four parts: experimental data and reference construction, base-model identification, calibration and application-rule construction for the 3D bridge parameters, and low-temperature recursive estimation with cross-cycle validation. First, a reference OCV-SOC curve is constructed from the 25 °C experimental data, and reference SOC trajectories are generated from the low-temperature dynamic-cycle data. Second, the Thevenin first-order RC equivalent circuit model is discretized and converted into an autoregressive model with exogenous input (ARX). SOC segmentation and a variable forgetting factor are then introduced to improve FFRLS parameter identification. Next, GA-EKF is used to jointly calibrate the equivalent voltage-bias compensation term, equivalent resistance scaling factor, and equivalent time-constant scaling factor. An application rule for the bridge parameters within the limited low-temperature range is then established. Finally, the bridge parameters

are applied under the target cycle to correct the model. The EKF recursively estimates SOC and reconstructs the terminal voltage. Error metrics are used to evaluate the accuracy and cross-cycle applicability of the proposed method.

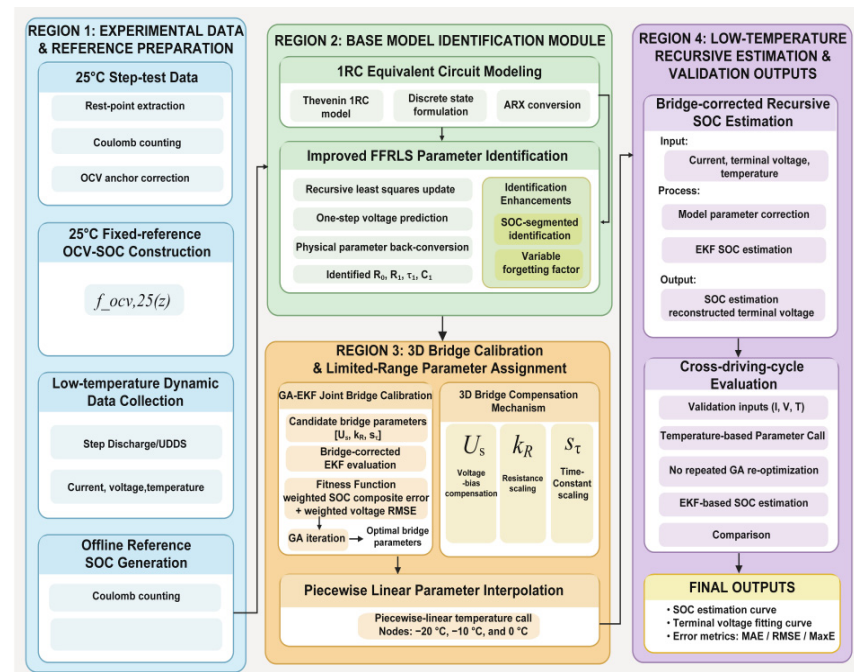


Figure 2. Workflow for low-temperature offline SOC estimation.

3. Low-Temperature Offline SOC Estimation Method Based on Improved FFRLS and Three-Dimensional Bridge Compensation

3.1. Construction of the Fixed-Reference OCV Curve and Reference SOC Trajectory

The test object is an INR18650HG2 lithium-ion cell with a rated capacity of 3000 mAh. The charge and discharge cutoff voltages are 4.2 V and 2.5 V, respectively. The experimental data include step-discharge data and UDDS-cycle data at 25 °C, 0 °C, −10 °C, and −20 °C. The OCV-SOC curve constructed at 25 °C is used as the fixed reference throughout recursive model estimation. This provides a unified reference for different low-temperature conditions and allows the correction of residual mismatch to be evaluated. The fixed-reference OCV-SOC curves are shown in Figure 3. OCV_1 , OCV_2 , and OCV_3 denote the OCV-SOC curves fitted from three sets of rest data. OCV_{ref} is the 25 °C fixed-reference OCV-SOC curve selected in this study.

Because the actual available capacity at low temperatures may be lower than the rated capacity, the effective capacity at each temperature is determined by integrating the current over a complete discharge test. The reference SOC trajectory is then constructed using Coulomb counting [24]:

$$Q_T = \frac{1}{3600} \sum_{k=1}^N I_k \Delta t \quad (1)$$

where Q_T is the measured effective capacity at temperature T . At 0 °C, for example, the complete step-discharge data with a sampling interval of 11 s yield an effective capacity of 2.7434 Ah. This value is the charge released under the specified discharge profile until the 2.5 V cutoff voltage is reached. The reference SOC is then updated as follows:

$$SOC_{ref,k+1} = SOC_{ref,k} - \frac{\eta_T I_k \Delta t}{3600 Q_T} \quad (2)$$

where I_k is the discharge current, Δt is the sampling interval, and η_T is the Coulombic efficiency. Because this study focuses on discharge conditions, η_T is set to 1. The initial SOC is set to 1. Reference SOC trajectories at the other temperatures are calculated in the same manner using the corresponding measured effective capacities.

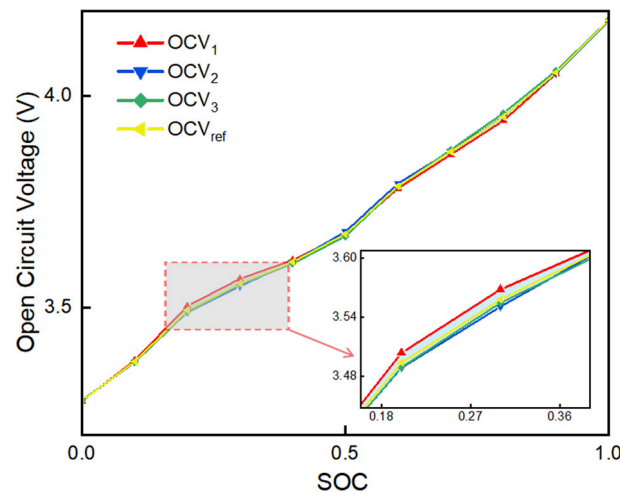


Figure 3. Fixed-reference OCV-SOC curve.

3.2. FFRLS Parameter Identification Based on SOC Segmentation and a Variable Forgetting Factor

3.2.1. First-Order RC Equivalent Circuit Model

A first-order RC equivalent circuit model is adopted, as shown in Figure 4. Compared with higher-order models, this low-dimensional structure is selected according to the objective of this study. First, the model contains only SOC and one polarization-branch state. After discretization, it yields a low-dimensional ARX regression that can be updated stably by segmented FFRLS. Second, the voltage bias, resistive-response amplitude, and single dominant time constant correspond directly to the three subsequent bridge variables. This avoids the reduced interpretability that may result from parameter coupling in higher-order models [25,26]. The first-order RC model also has limitations. It cannot distinguish multiple polarization time scales and does not explicitly describe hysteresis, temperature gradients, or electrochemical reaction mechanisms. Residual transient terminal-voltage errors may therefore remain during rapid current switching or long relaxation periods. In addition, state of health (SOH) and aging parameters are not included. R_0 , R_1 and C_1 only represent equivalent quantities for the current cell at its current SOH. If substantial capacity loss, internal-resistance growth, or OCV-curve drift occurs, the capacity and OCV relationship must be measured again, and the bridge parameters must be recalibrated. The current parameters should not be reused directly.

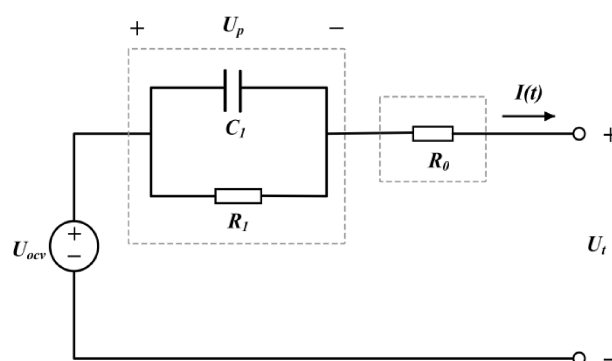


Figure 4. First-order RC equivalent circuit model.

The state variables of the first-order RC model are SOC and the polarization-branch voltage U_p . According to Kirchhoff's laws for the first-order RC equivalent circuit and its discrete form [27], the terminal-voltage output equation is

$$U_t(k) = U_{oc}^{ref}(z_k) - U_{p,k} - R_{0,k}I_k \quad (3)$$

For a sampling interval of Δt , discretization of the polarization branch gives

$$U_{p,k+1} = a_k U_{p,k} + b_k I_k \quad (4)$$

where

$$a_k = \exp\left(-\frac{\Delta t}{R_{1,k}C_{1,k}}\right) \quad (5)$$

$$b_k = R_{1,k}\left(1 - \exp\left(-\frac{\Delta t}{R_{1,k}C_{1,k}}\right)\right) \quad (6)$$

a_k is the dynamic decay coefficient of the polarization branch, and b_k is the current-input gain coefficient of the polarization branch.

The polarization-branch voltage in the first-order RC model cannot be measured directly. Direct least-squares identification from the original state equations therefore cannot readily produce a standard regression using only measurable inputs and outputs. Following the basic derivation for discretization and recursive parameter identification of a first-order RC model [27], the discrete model is further rewritten as an ARX one-step regression. The fixed 25 °C OCV-SOC reference and the current sign convention used in this study are also incorporated:

$$U_{t,k} = c_k + a_k U_{t,k-1} + b_{0,k} I_k + b_{1,k} I_{k-1} \quad (7)$$

Let $\theta_k = [c_k, a_k, b_{0,k}, b_{1,k}]^T$ denote the discrete regression-parameter vector to be identified. Based on its recursive estimates and the physical relationships of the first-order RC model, the equivalent parameters $R_{0,k}$, $R_{1,k}$, and $C_{1,k}$ can be obtained for subsequent model calculations. The constant term in the ARX regression only describes an equivalent bias under the fixed-reference model. It is not an identified low-temperature OCV. The OCV term used in the subsequent EKF recursion is always obtained from the fixed 25 °C OCV-SOC curve. These parameters describe the equivalent dynamic response under the fixed-reference model and should not be interpreted as the true electrochemical impedance parameters of the battery.

3.2.2. SOC Segmentation Mechanism

Under low-temperature dynamic conditions, the battery exhibits different polarization characteristics and parameter sensitivities in different SOC intervals [28]. When a single set of global parameters is used, intervals containing more samples dominate the update and mask local variations. Excessively fine segmentation, however, causes insufficient excitation and unstable covariance estimates within each interval. To balance these effects, the dynamic data are segmented by SOC, and an independent parameter vector and covariance matrix are assigned to each interval. At each sampling instant, only the parameters of the current SOC interval are updated. Parameters in the other intervals retain their previous values. This strategy improves the representation of local dynamic characteristics at different states of charge.

Different segmentation settings are used because the effective data range and parameter-identification stability vary with temperature. At 0 °C, data within an SOC range of 0.08–0.95 are selected and divided equally into two intervals. At –10 °C and –20 °C,

data within an SOC range of 0.18–0.95 are selected and divided into three intervals according to sample quantiles. This setting preserves local parameter differences while preventing insufficient samples and unstable recursive estimates caused by overly fine segmentation.

3.2.3. Design of the Variable Forgetting Factor

Compared with room-temperature operation, the same dynamic current excitation at low temperatures is more likely to cause strong polarization, delayed terminal-voltage response, and equivalent-parameter mismatch [29]. A fixed forgetting factor cannot easily balance rapid tracking of parameter changes against suppression of noise amplification [30]. A variable forgetting factor is therefore introduced after SOC segmentation. The one-step terminal-voltage prediction error at sampling instant k is defined as

$$e_k = U_k - \hat{U}_{k|k-1} \quad (8)$$

where U_k is the measured terminal voltage, and $\hat{U}_{k|k-1}$ is the one-step predicted terminal voltage. A normalized error term is constructed from the prediction error:

$$r_k = \min\left(\frac{|e_k|}{e_{ref}}, 1\right) \quad (9)$$

where e_{ref} is the reference error threshold. To represent the effect of dynamic current conditions on parameter changes, the current-magnitude term and current-change term are defined as

$$q_{I,k} = \text{clip}\left(\frac{|I_k| - I_{rest}}{I_{pulse} - I_{rest}}, 0, 1\right) \quad (10)$$

$$q_{\Delta I,k} = \text{clip}\left(\frac{|I_k - I_{k-1}|}{\Delta I_{th}}, 0, 1\right) \quad (11)$$

When a sample lies within a preset dynamic window after a current step, the relaxation-state term $q_{relax,k}$ is set to 1; otherwise, it is set to 0. The combined excitation intensity is expressed as

$$\xi_k = \max(q_{I,k}, q_{\Delta I,k}, q_{relax,k}) \quad (12)$$

The prediction error and current excitation are then jointly incorporated into the forgetting-factor adjustment:

$$\lambda_k = \text{clip}[\lambda_{max} - \max(r_k, \xi_k)(\lambda_{max} - \lambda_{min}) - \beta_z(0.5 - z_k), \lambda_{min}, \lambda_{max}] \quad (13)$$

where $\bar{z}_k$ is the normalized SOC and β_z is the SOC correction coefficient. When the prediction error is large or the current excitation is strong, the forgetting factor decreases to improve parameter tracking. When the model error is small, the forgetting factor approaches its upper bound to reduce the influence of noise on parameter updates. The forgetting factor can therefore adapt to the local identification state [30], which improves model adaptability to nonstationary low-temperature dynamics.

Figure 5 shows the synchronized relationship between the prediction error and the decrement of the forgetting factor. The blue curve is the smoothed and normalized result of $|e_k|$, and the red curve is the smoothed and normalized result of $\lambda_{max} - \lambda_k$. Near most error peaks, the forgetting-factor decrement increases simultaneously. This indicates that the soft-gating mechanism strengthens parameter updates when model mismatch or strong current excitation occurs. The two curves are not strictly in phase in some intervals because λ_k is jointly controlled by the error magnitude, the current value, ΔI , and the post-step relaxation indicator.

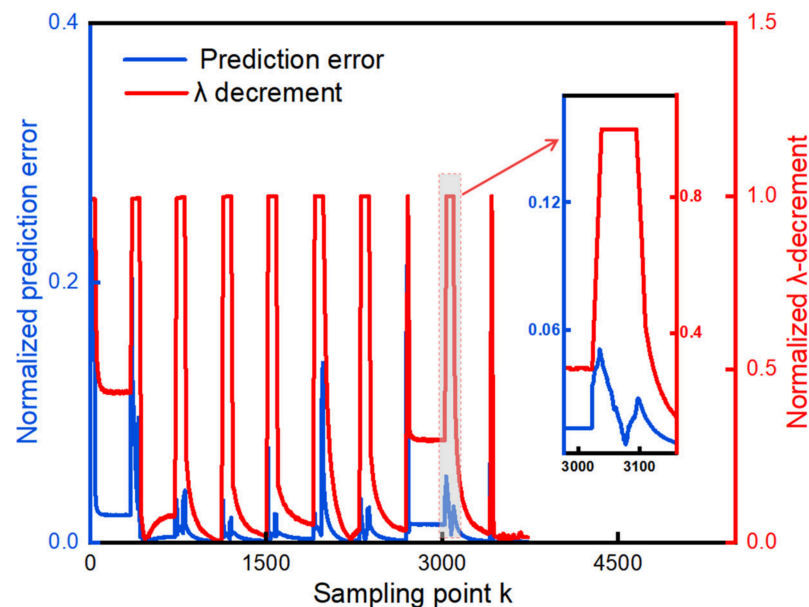


Figure 5. Synchronized relationship between the prediction error and the forgetting-factor decrement.

3.2.4. FFRLS Parameter Identification with SOC Segmentation and a Variable Forgetting Factor

After the SOC segmentation and variable forgetting factor are defined, both are incorporated into FFRLS parameter identification. The regression prediction, gain vector, parameter vector, and covariance matrix follow the standard recursive forms [27,30]. The proposed modification determines the interval $m(k)$ from the current SOC and updates only the parameter vector and covariance matrix of that interval. Parameters in the other intervals remain unchanged. The one-step terminal-voltage prediction at the current instant is

$$\hat{U}_t(k) = \varphi_k^T \theta_{m(k),k-1} \quad (14)$$

where φ_k is the regression vector constructed from historical terminal-voltage and current data, and $\theta_{m(k),k-1}$ is the parameter vector to be identified. Under the variable forgetting-factor mechanism, the prediction error e_k is used to calculate the current forgetting factor λ_k . After the current SOC interval and forgetting factor are determined, the FFRLS gain vector is written as

$$K_{m(k),k} = \frac{P_{m(k),k-1} \varphi_k}{\lambda_k + \varphi_k^T P_{m(k),k-1} \varphi_k} \quad (15)$$

The corresponding parameter-update equation is

$$\theta_{m(k),k} = \theta_{m(k),k-1} + K_{m(k),k} e_k \quad (16)$$

The covariance matrix is updated as

$$P_{m(k),k} = \frac{1}{\lambda_k} \left[P_{m(k),k-1} - K_{m(k),k} \varphi_k^T P_{m(k),k-1} \right] \quad (17)$$

The same soft-gated forgetting-factor structure is used at all three temperatures. The upper bound of the forgetting factor is 0.9999, and the reference error threshold is 0.020 V. The rest-current threshold, pulse-current threshold, and current-change threshold are 0.02 A, 0.15 A, and 0.12 A, respectively. The dynamic-window length is 120 s. At 0 °C, data within an SOC range of 0.08–0.95 are selected and divided equally into two intervals. The lower bound of the forgetting factor, the SOC correction coefficient, and the error-clipping

values are 0.9900, 0.0002, and 0.10 V, respectively. At $-10\text{ }^{\circ}\text{C}$ and $-20\text{ }^{\circ}\text{C}$, data within an SOC range of 0.18–0.95 are selected and divided into three quantile-based intervals. The corresponding values are 0.9850, 0.0003, and 0.50 V.

3.2.5. Analysis of Equivalent RC Parameter Identification Results

To analyze the variation in equivalent circuit parameters at low temperatures, the improved FFRLS is used to identify the first-order RC model parameters at different temperatures and SOC intervals. The results are shown in Figure 6. Figure 6a presents the identified equivalent ohmic resistance R_0 . As the temperature decreases, R_0 generally increases and differs across SOC intervals. This indicates that a larger current-related voltage drop is required for the fixed-reference model to match the low-temperature terminal-voltage response. The R_1 values in Figure 6b vary locally with temperature and SOC. The polarization-response amplitude is therefore affected by temperature, SOC interval, and dynamic excitation. In Figure 6c, C_1 varies considerably across temperatures and SOC intervals. Together with R_1 , it determines the dynamic characteristics of the polarization branch. Figure 6d shows the variation in $\tau = R_1 C_1$. The buildup and decay time scales of the polarization voltage are not constant but vary with temperature and SOC. These results describe equivalent parameter changes at the model level. They should not be interpreted as direct identification of the true electrochemical impedance or diffusion parameters of the battery.

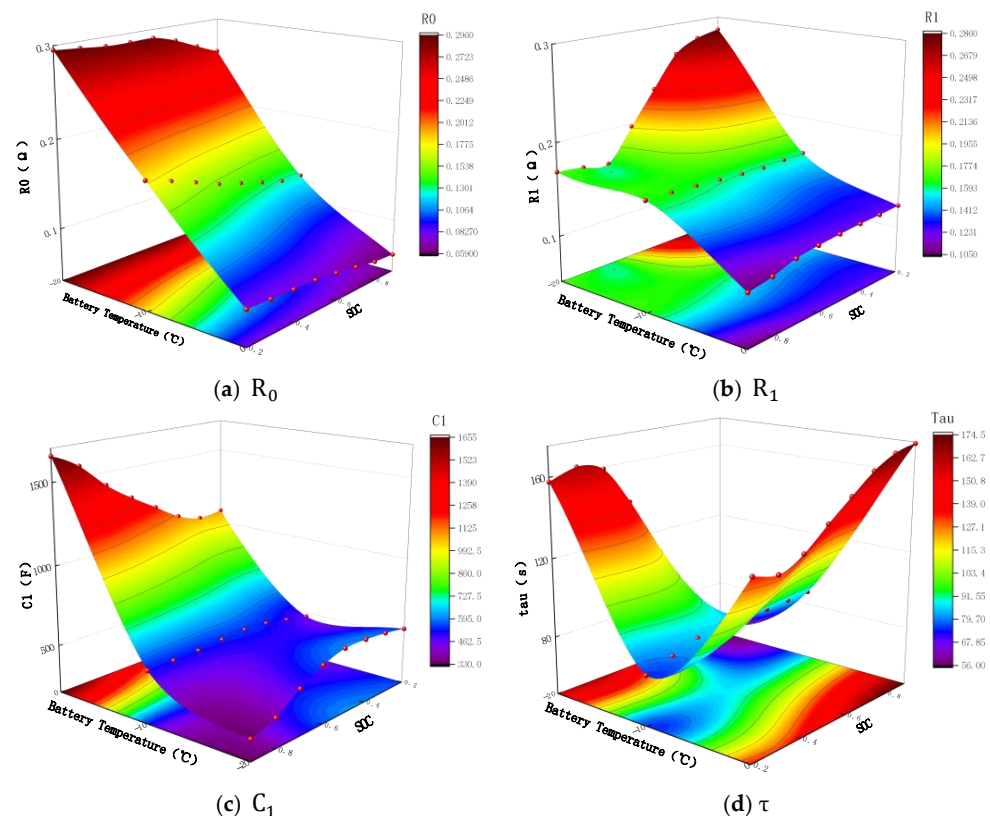


Figure 6. Identified equivalent RC parameters under the fixed-reference model.

The identification results show clear temperature dependence, SOC-interval differences, and dynamic coupling in the equivalent parameters under low-temperature conditions [31]. The improved FFRLS captures the trends of parameter variation with temperature and SOC interval and provides a relatively stable parameter basis for the subsequent 3D bridge compensation. The need for this compensation also indicates that first-stage identification alone cannot fully eliminate model mismatch at low temperatures.

3.3. Three-Dimensional Bridge Compensation and Construction of Parameter Application Rules over a Limited Temperature Range

3.3.1. Definition of the Three-Dimensional Bridge Parameters

Under the fixed-reference OCV-SOC relationship and first-order RC equivalent circuit model, the residual terminal-voltage error can be divided into three categories according to its role in the output equation. These categories are a current-independent reference deviation that changes slowly over short periods, a resistive voltage-drop deviation related to current magnitude, and a time-scale deviation related to the buildup and decay rates of polarization. To reduce these residual model mismatches, a 3D bridge compensation is constructed using the equivalent voltage-bias compensation term U_s , the equivalent resistance scaling factor k_R , and the equivalent time-constant scaling factor s_τ . U_s enters the terminal-voltage equation as an additive correction and compensates for the equivalent voltage bias under the fixed-reference model. k_R acts on both the ohmic resistance R_0 and the polarization-branch resistance R_1 to adjust the resistance-related voltage drop and polarization-response amplitude. s_τ acts on the polarization-branch time constant τ to adjust the time scale of polarization buildup and decay. For the first-order RC model, the parameter relationships after bridge compensation are expressed as

$$R_0^* = k_R R_0, R_1^* = k_R R_1, \tau^* = s_\tau \tau \quad (18)$$

The bridge-compensated terminal-voltage model is expressed as

$$\hat{U}_{t,k} = U_{oc}^{\text{ref}}(\hat{z}_k) + U_s - U_{p,k}^* - R_{0,k}^* I_k \quad (19)$$

$$a_k^* = \exp\left(-\frac{\Delta t}{\tau_k^*}\right), b_k^* = R_{1,k}^* (1 - a_k^*) \quad (20)$$

$$U_{p,k+1}^* = a_k^* U_{p,k}^* + b_k^* I_k \quad (21)$$

Within the fixed-reference model, the same cell, and the limited low-temperature range considered in this study, U_s, k_R and s_τ can be treated as a set of low-dimensional joint correction variables. They are not a complete physical description of low-temperature error sources. Hysteresis, multiscale diffusion, internal temperature gradients, and aging may still produce residual errors that are not covered by these three parameters. Therefore, the parameters represent equivalent corrections at the model level and cannot be interpreted as unique changes in the true low-temperature OCV, internal resistance, or electrochemical time constant.

3.3.2. Bridge-Parameter Calibration and Local Interpolation Within a Limited Temperature Range

The bridge parameters are calibrated using UDDS dynamic-cycle data at 0 °C, −10 °C, and −20 °C. For a given set of bridge parameters, the EKF recursively estimates SOC and reconstructs the terminal voltage. The GA searches for the optimal bridge-parameter combination $[U_s, k_R, s_\tau]$ at each calibration temperature. The three bridge parameters only describe the equivalent residual mismatch of the fixed-reference model at a specific temperature. They are applied as temperature-indexed correction parameters. A weighted combination of SOC estimation error and terminal-voltage reconstruction error is used as the fitness function:

$$J = w_{\text{SOC}}(MAE_{\text{SOC}} + MSE_{\text{SOC}} + RMSE_{\text{SOC}}) + w_U RMSE_U \quad (22)$$

SOC is represented as a normalized state variable $z \in [0, 1]$. $MAE_{\text{SOC}}, MSE_{\text{SOC}}, RMSE_{\text{SOC}}$ measure the mean absolute SOC deviation, impose a stronger penalty on large

SOC deviations, and represent the overall error level, respectively. $RMSE_U$ measures the terminal-voltage reconstruction error. During calibration of the 3D bridge parameters, $w_{SOC} = 1.0$ and $w_U = 0.20$. The first 50 samples are excluded to reduce the influence of EKF initialization on the optimization result. At all three temperatures, the population size is 40 and the maximum number of generations is 60. The search ranges of k_R and s_τ are 0.005–0.30 and 0.20–5.00, respectively. The search range of U_s is set according to the initial voltage deviation at each temperature. It is limited to -0.20 – 0.10 V at 0°C , -0.30 – 0 V at -10°C , and -0.1442 – 0 V at -20°C . The default settings of the MATLAB R2024b genetic-algorithm function are used for crossover, mutation, and the other stopping criteria.

Minimizing this fitness function yields the optimal bridge parameters at the three calibration temperatures of 0°C , -10°C , and -20°C . During subsequent parameter application, the corresponding GA-optimal parameters are used directly at the calibration temperatures. For a target temperature between two adjacent calibration temperatures, the bridge parameters are obtained by piecewise interpolation. This avoids repeated GA searches. For any bridge parameter $p \in \{U_s, k_R, s_\tau\}$, the temperature-based application rule is

$$p(T) = \begin{cases} p_{-20} + \frac{T+20}{10}(p_{-10} - p_{-20}), & -20 \leq T \leq -10, \\ p_{-10} + \frac{T+10}{10}(p_0 - p_{-10}), & -10 < T \leq 0. \end{cases} \quad (23)$$

where T is the cell temperature. p_{-20} , p_{-10} , and p_0 are the optimal values of the bridge parameter obtained by the GA at -20°C , -10°C , and 0°C , respectively.

For computational complexity, let the length of the dynamic dataset be N . Because the parameter and state dimensions are fixed, the per-step computational costs of FFRLS and EKF are constant, and their complexity over the complete dataset is approximately $O(N)$. The GA repeatedly executes the EKF for different candidate parameters, giving an approximate complexity of $O(PGN)$, where P is the population size and G is the maximum number of generations. They are set to 40 and 60, respectively. In this study, the GA is used only for offline bridge-parameter calibration. After calibration, the HWFET and LA92 validation stages only apply the temperature-interpolated parameters and execute a two-state EKF. The GA search is not repeated. Therefore, the main computational cost during recursive state estimation comes from the fixed-dimensional EKF.

Table 1 lists the optimal bridge parameters obtained within the predefined search bounds at the three calibration temperatures. Taking these parameter points as nodes, a piecewise lookup relationship from -20°C to 0°C was constructed according to Equation (18), as shown in Figure 7.

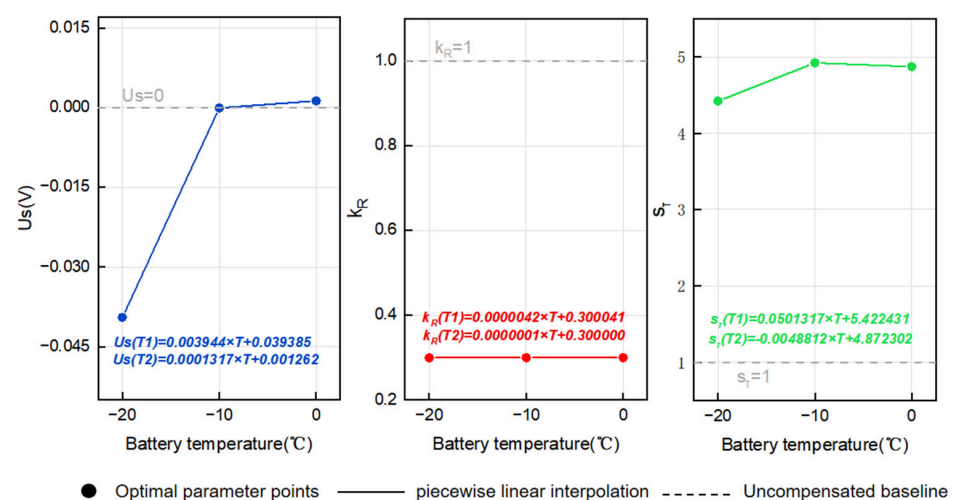


Figure 7. Three-point calibration results of the bridge parameters and the piecewise interpolation relationship over a limited temperature range.

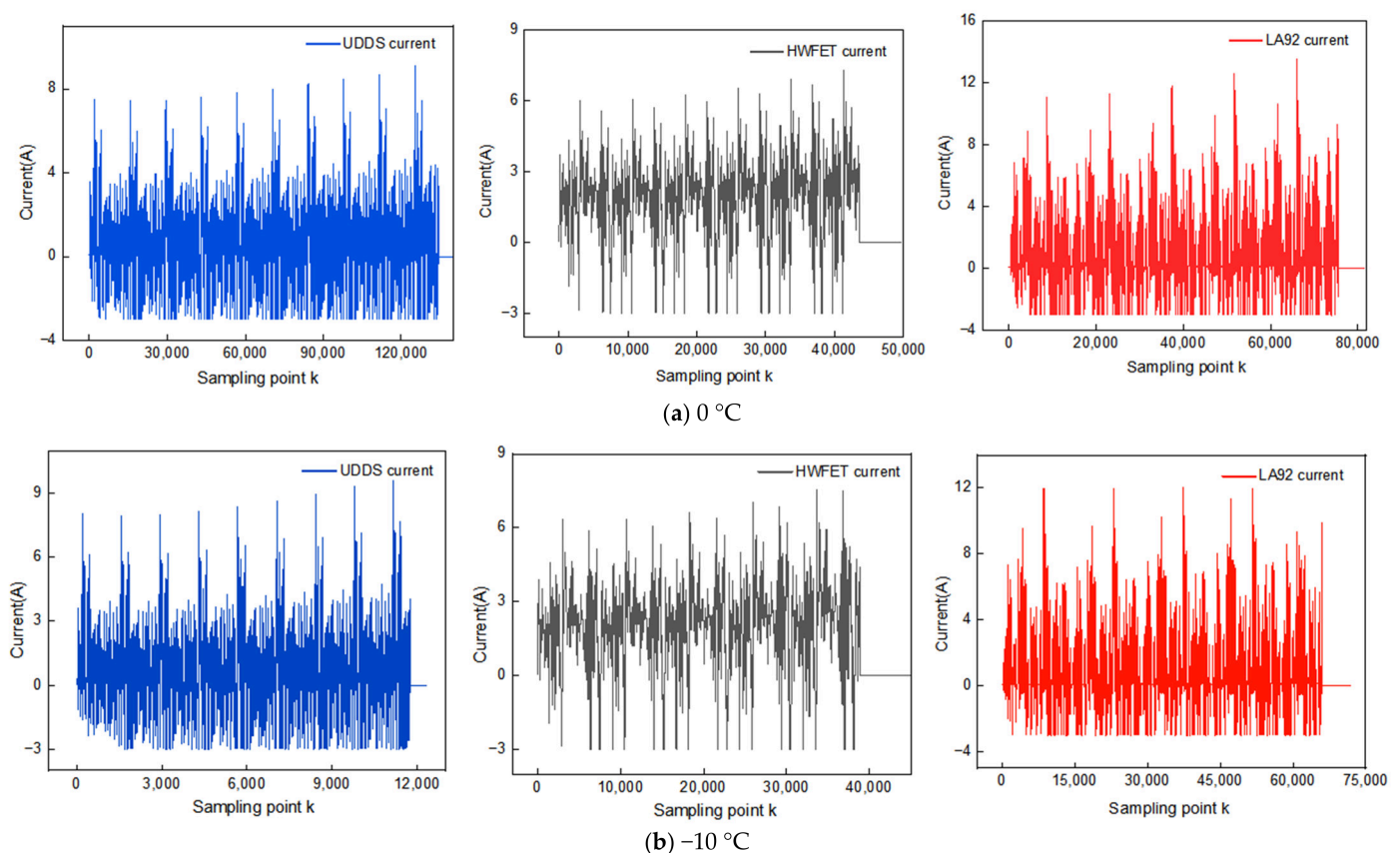
Table 1. Bridge parameters obtained by GA at different calibration temperatures.

Temperature (°C)	U_s (V)	k_R	s_τ
−20	−0.039495	0.299957	4.419797
−10	−0.000055	0.299999	4.921114
0	0.001262	0.300000	4.872302

Figure 7 shows that U_s clearly deviates from zero at -20°C but is close to zero at -10°C and 0°C . s_τ remains greater than the uncompensated baseline value of 1, which indicates that dynamic time-scale mismatch remains in the fixed-reference model. To reduce the residual mismatch in resistance-related voltage drop, the search range of the equivalent resistance scaling factor k_R is set to 0.005–0.3. A value of 0.3 means that, after bridge correction, R_0 and R_1 retain at most 30% of the values identified in the first stage. This range was selected from preliminary resistance-scaling trials to limit compensation intensity and avoid excessive parameter correction. k_R is close to the preset upper bound of 0.3 at all three calibration temperatures. Under the current model and search constraints, the optimization therefore favors a relatively strong equivalent scaling correction for the resistance-related response.

4. Experimental Results and Discussion

To illustrate the dynamic-load characteristics used for parameter calibration and cross-cycle validation, Figure 8 presents the input-current profiles of the UDDS, HWFET, and LA92 cycles at 0°C , -10°C , and -20°C . The UDDS data are used to calibrate the bridge parameters. The HWFET and LA92 data are used to evaluate whether the calibrated parameters remain applicable under different dynamic cycles.

**Figure 8.** Cont.

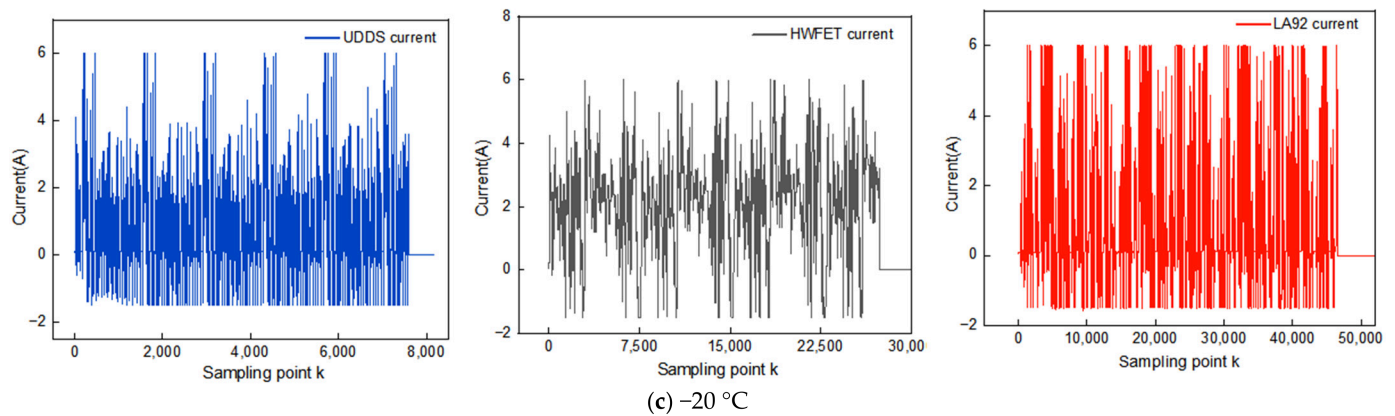


Figure 8. Model input-current profiles under different dynamic cycles.

4.1. In-Sample Evaluation Under the UDDS Calibration Condition

This section evaluates the calibrated model using the same UDDS data employed for bridge-parameter calibration. Because the 3D bridge parameters are jointly determined by GA-EKF from these UDDS data, the results mainly reflect fitting and correction performance under the calibration condition. They do not constitute independent validation.

The SOC estimation and terminal-voltage reconstruction results are shown in Figure 9. The baseline method does not apply the 3D bridge compensation. As the temperature decreases, both the SOC estimation error and terminal-voltage reconstruction error of the baseline method increase substantially. The statistical results show that the SOC RMSE and MAE of the baseline method are 0.0895 and 0.0834, respectively. After compensation, they decrease to 0.0031 and 0.0021. The terminal-voltage RMSE and MAE decrease from 0.1623 V and 0.1113 V to 0.0325 V and 0.0220 V, respectively. Compared with the baseline, the complete proposed procedure therefore achieves lower SOC estimation and terminal-voltage reconstruction errors under the calibration condition.

To facilitate a comprehensive comparison of the relative improvements achieved by different bridge-parameter combinations in SOC estimation and terminal-voltage reconstruction, the error-reduction rate of each metric relative to the baseline method without bridge compensation was used for comparison. The results are shown in Figure 10. For any error metric E , the relative improvement rate of a bridge-parameter combination is defined as

$$I = \frac{E_{\text{base}} - E_{\text{method}}}{E_{\text{base}}} \times 100\% \quad (24)$$

where E_{base} is the error of the baseline without bridge compensation and E_{method} is the error of the corresponding bridge-parameter combination. A larger improvement indicates a greater error reduction relative to the baseline. A larger radar-chart area therefore indicates a better overall correction of the residual mismatch in the fixed-reference model.

Figure 10 shows that introducing only U_s improves the SOC results, but a clear mismatch remains in terminal-voltage reconstruction. After s_τ is added, the dynamic response is better matched. When U_s , k_R , and s_τ are all included, both SOC estimation and terminal-voltage reconstruction achieve the best results. Within the model and data range of this study, the three bridge parameters can therefore be used as a set of joint equivalent corrections for the fixed-reference model to reduce residual mismatch under low-temperature dynamic conditions.

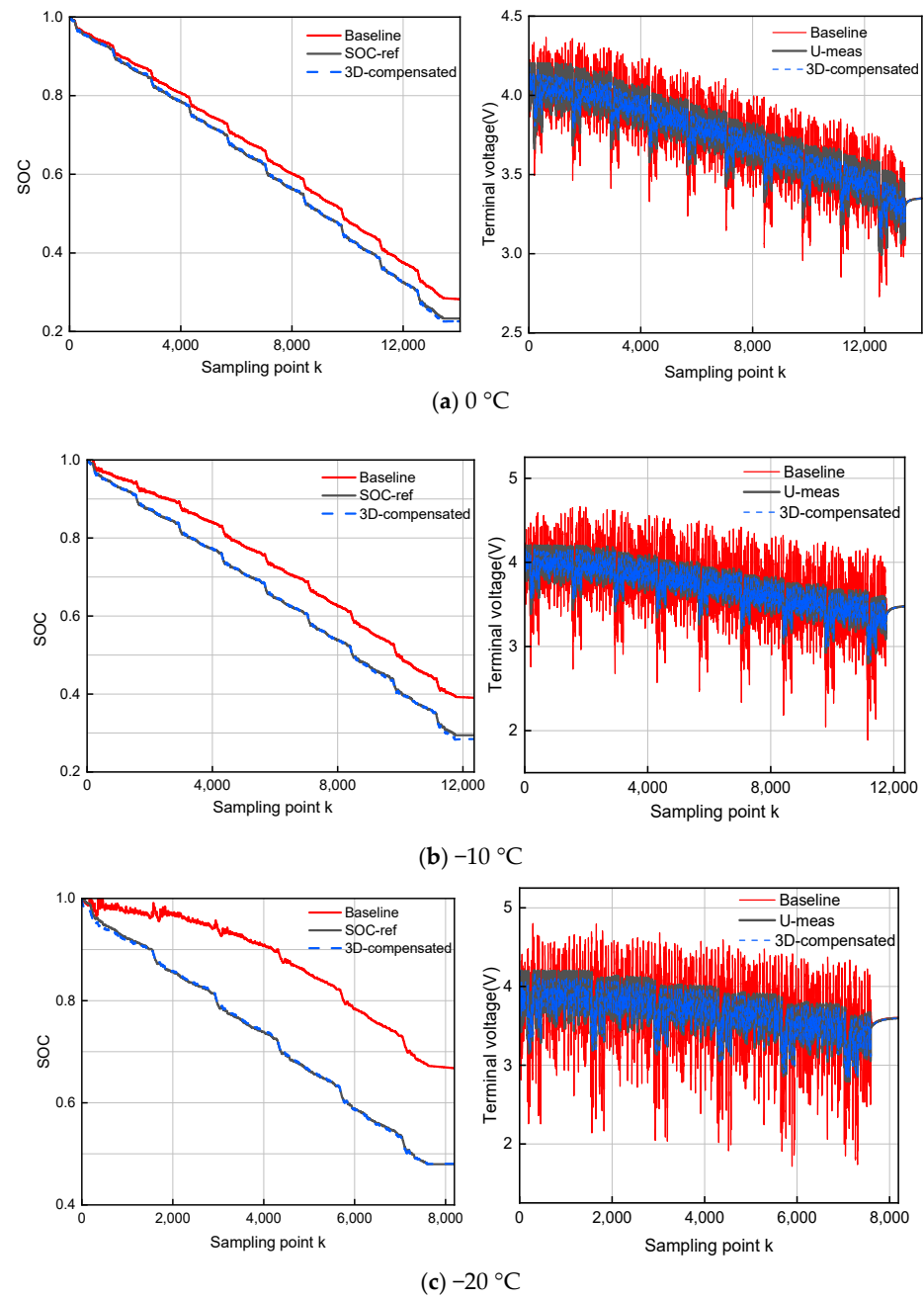


Figure 9. In-sample results under the calibration cycles.

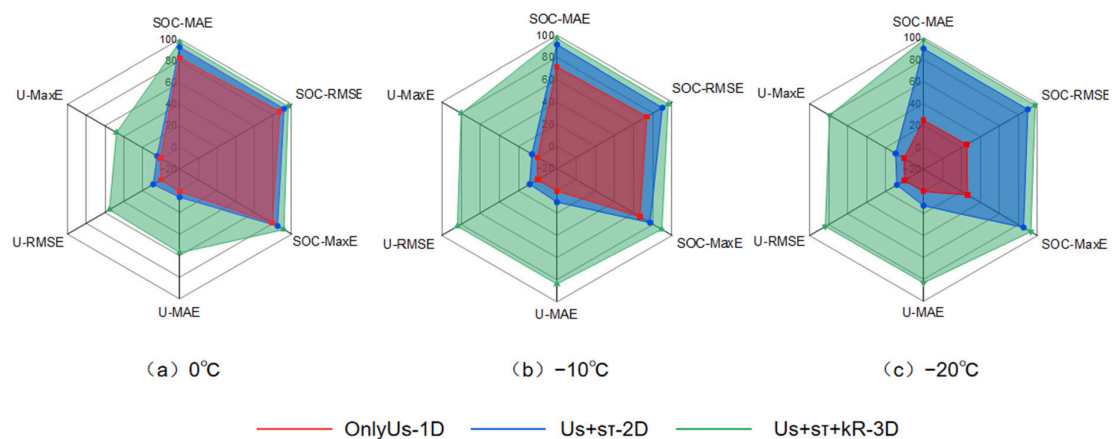


Figure 10. Comparison of error reductions for different bridge-parameter combinations.

4.2. Independent Cross-Cycle Validation Using HWFET and LA92

HWFET and LA92 are selected as independent validation cycles to examine the applicability of the calibrated parameters under different dynamic loads. The GA optimization is not repeated during validation. The corresponding bridge parameters are applied according to temperature, and the EKF recursion is then performed. The HWFET and LA92 results are therefore independent cross-cycle validation results and should be distinguished from the in-sample UDDS calibration results in Section 4.1. Tables 2 and 3 present the validation results. The maximum absolute error (MaxE) is used to evaluate the largest local deviation.

Table 2. SOC error statistics for the HWFET and LA92 profiles.

Profile	Temperature (°C)	Method	MAE	RMSE	MaxE
HWFET	0	Baseline	0.006523	0.007234	0.011132
		3D Compensation	0.000484	0.000744	0.002100
	−10	Baseline	0.018775	0.022022	0.04497
		3D Compensation	0.001022	0.001569	0.004127
	−20	Baseline	0.28546	0.3311	0.49401
		3D Compensation	0.003469	0.003554	0.006116
LA92	0	Baseline	0.0072078	0.0082719	0.017196
		3D Compensation	0.002039	0.003117	0.008907
	−10	Baseline	0.058458	0.069866	0.14857
		3D Compensation	0.002016	0.002747	0.008352
	−20	Baseline	0.29148	0.33567	0.52558
		3D Compensation	0.005406	0.005724	0.007694

Table 2 shows that the SOC estimation RMSE under HWFET increases from 0.000744 at 0 °C to 0.003554 at −20 °C. Under LA92, the SOC estimation RMSE at −20 °C is 0.005724. Overall, the SOC errors at −20 °C are higher than those at 0 °C and −10 °C. This indicates that lower temperatures intensify the mismatch between the fixed-reference model and the actual dynamic response. The overall errors under LA92 are higher than those under HWFET, which shows that its stronger dynamic variations place greater demands on parameter application and recursive state estimation.

Table 3. Terminal-voltage reconstruction error statistics for the HWFET and LA92 profiles.

Profile	Temperature (°C)	Method	MAE (V)	RMSE (V)	MaxE (V)
HWFET	0	Baseline	0.016261	0.025999	0.25122
		3D Compensation	0.004825	0.007818	0.080102
	−10	Baseline	0.043661	0.068917	0.61352
		3D Compensation	0.004292	0.008576	0.126822
	−20	Baseline	0.077838	0.1254	1.0271
		3D Compensation	0.007650	0.015629	0.196465
LA92	0	Baseline	0.031957	0.051787	0.41776
		3D Compensation	0.009135	0.014005	0.098381
	−10	Baseline	0.084013	0.13536	1.0774
		3D Compensation	0.008299	0.015434	0.164404
	−20	Baseline	0.13136	0.219	1.6768
		3D Compensation	0.013757	0.026713	0.345925

Table 3 further shows that the terminal-voltage RMSE values under HWFET are 0.007818 V, 0.008576 V, and 0.015629 V at 0 °C, −10 °C, and −20 °C, respectively. Under LA92, the corresponding values are 0.014005 V, 0.015434 V, and 0.026713 V. At −20 °C, the

maximum voltage error under LA92 reaches 0.345925 V. The proposed method reduces the overall reconstruction error, but short-duration mismatch remains during some strongly dynamic intervals. Both the temperature level and the dynamic characteristics of the cycle affect the final estimation accuracy.

The lowest test temperature in this study is $-20\text{ }^{\circ}\text{C}$. At this temperature, low-temperature mismatch in the fixed-reference model is more pronounced, making it suitable for evaluating the method under relatively severe conditions. Of the two validation cycles, HWFET has smoother load variations and clearer overall trends in SOC and terminal voltage. LA92 contains more frequent load switching and stronger transients, making it more suitable for evaluating robustness under complex dynamic conditions. Based on these considerations, the complete dynamic trajectories are presented for HWFET at $-20\text{ }^{\circ}\text{C}$. The cross-cycle SOC estimation and terminal-voltage reconstruction results are shown in Figure 11.

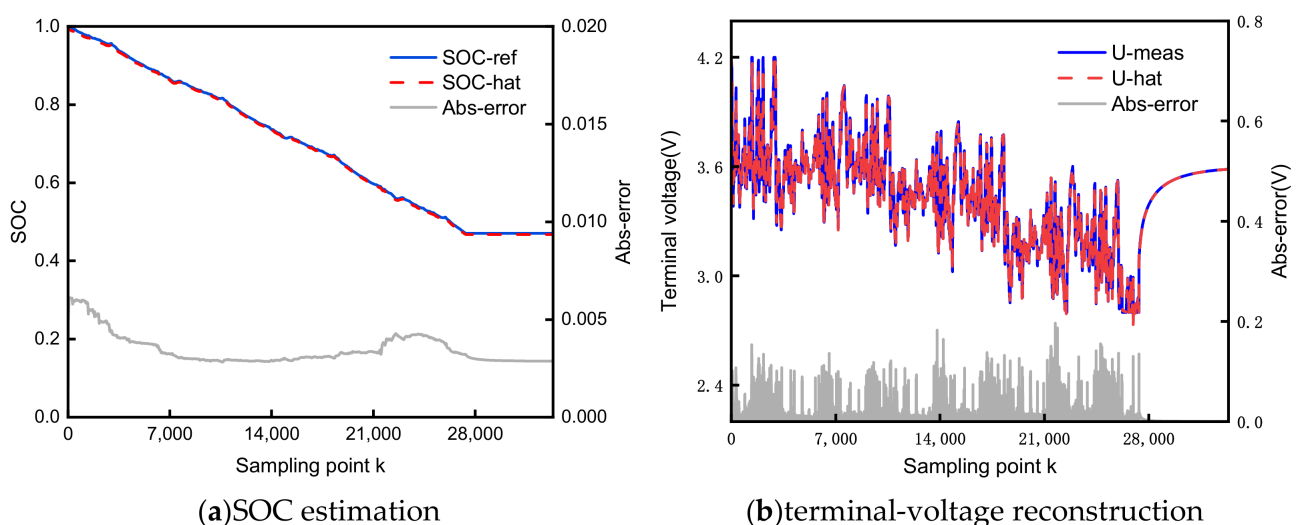


Figure 11. Validation results for the HWFET profile at $-20\text{ }^{\circ}\text{C}$.

Figure 11a presents the SOC estimation trajectory and absolute error under the HWFET cycle at $-20\text{ }^{\circ}\text{C}$. Together with the data in Table 2, the results show that the estimated SOC closely follows the reference SOC throughout the cycle. The SOC MAE, RMSE, and maximum error are 0.003469, 0.003554, and 0.006116, respectively. Thus, the parameters calibrated using UDDS maintain stable SOC tracking even though parameter optimization is not repeated for HWFET.

Figure 11b presents the terminal-voltage reconstruction under the same condition. Together with Table 3, the results show that the reconstructed voltage agrees with the measured voltage over most sampling intervals. The MAE and RMSE are 0.007650 V and 0.015629 V, respectively. Short error peaks remain during some local dynamic intervals, and the maximum error is 0.196465 V. Fixed bridge parameters therefore improve the overall voltage reconstruction but remain limited for certain rapid dynamic processes.

4.3. Comparison with Recent Low-Temperature SOC Estimation Methods

To further evaluate the performance of the proposed method in low-temperature SOC estimation, it is compared with several recent methods, as shown in Table 4. All selected studies consider low-temperature dynamic conditions and report the MAE or RMSE of SOC estimation. For consistency, the error metrics in the table are expressed as percentages.

Table 4 shows that current low-temperature SOC estimation studies mainly use data-driven methods, equivalent-model compensation, or combinations of neural networks and state filters. The proposed method achieves competitive estimation accuracy under HWFET at $-20\text{ }^{\circ}\text{C}$. Its 3D bridge parameters are calibrated using UDDS data, and the GA optimization is not repeated during HWFET validation. The results therefore reflect, to some extent, cross-cycle applicability for the same cell within a limited low-temperature range.

Table 4. Comparison of the proposed method with recent low-temperature SOC estimation methods.

Source	Test Cell	Temperature	Training and Test Cycles	Method	SOC MAE	SOC RMSE
Gong et al., 2024 [12]	133 Ah and 170 Ah traction battery packs	$-20\text{ }^{\circ}\text{C}$	CLTC discharge cycle; battery pack A for training and battery pack B for testing	CNN-Transformer/SRUKF	1.677	2.217
Xiong et al., 2025 [10]	Two types of lithium-ion batteries	Minimum temperature: $-20\text{ }^{\circ}\text{C}$	Calibration at two temperatures; validation using three dynamic cycles and five temperatures	Polarization-voltage compensation-GA-EKF	<3.0	<3.0
Li et al., 2026 [32]	Panasonic 18650PF	$-20\text{ }^{\circ}\text{C}$	Training with low-temperature data; testing under the US06 cycle	CNN-Bi-LSTM-AM	0.77	0.94
This study	INR18650HG2	$-20\text{ }^{\circ}\text{C}$	UDDS calibration; independent HWFET validation	Improved FFRLS-3D bridge-EKF	0.3469	0.3554

The studies in Table 4 use different cell types, test temperatures, reference-SOC construction methods, training-test splits, and dynamic cycles. The results are therefore provided only for general comparison and do not constitute a strictly fair comparison on the same dataset. This study does not claim that the proposed method outperforms all existing methods under every condition. Instead, the comparison indicates that it provides good overall performance under the present experimental setting.

4.4. Scope, Limitations, and Engineering Implementation

A $25\text{ }^{\circ}\text{C}$ OCV-SOC curve is used as the fixed reference, and the 3D bridge parameters correct the equivalent voltage bias, resistance-related response-amplitude deviation, and dynamic time-scale mismatch at low temperatures. As the temperature decreases, polarization and dynamic delay become stronger, and the deviation between the fixed-reference model and the actual response becomes more pronounced. Bridge compensation therefore provides a larger correction at lower temperatures. U_s , k_R and s_τ are equivalent correction variables at the model level and do not provide a complete description of low-temperature electrochemical mechanisms.

The experiments are limited to an INR18650HG2 cell, with parameter calibration performed at $0\text{ }^{\circ}\text{C}$, $-10\text{ }^{\circ}\text{C}$, and $-20\text{ }^{\circ}\text{C}$. The conclusions mainly apply to the same cell type, a fixed SOH, and dynamic cycles within $-20\text{ }^{\circ}\text{C}$ to $0\text{ }^{\circ}\text{C}$. They should not be directly extrapolated to other cell types, aging states, or uncalibrated temperatures. Estimation accuracy may also decrease when temperature changes rapidly, measurement signals contain persistent bias, operating excitation is insufficient, or the first-order RC model cannot describe complex polarization processes.

In terms of computation, FFRLS and EKF are fixed-dimensional recursive algorithms, and their computational cost increases approximately linearly with data length. The GA is used only for offline parameter calibration. After calibration, the validation stage only applies the bridge parameters and executes the EKF recursion, without repeating the GA search. The method has potential for deployment in a BMS. However, its actual runtime, storage requirements, and real-time performance on embedded platforms still require hardware validation.

5. Conclusions

Low-temperature polarization can substantially increase the errors of conventional SOC estimation methods for lithium-ion batteries. To address this problem, an offline low-temperature SOC estimation method based on improved FFRLS and 3D bridge compensation is proposed. The following conclusions are obtained from method development and experimental validation:

(1) At low temperatures, the SOC estimation accuracy obtained by combining a conventional first-order RC equivalent circuit model with EKF decreases substantially. Under the fixed-reference model and identification framework used in this study, the low-temperature error results from the combined effects of an equivalent voltage-reference residual under the fixed OCV relationship, equivalent-parameter identification deviation, and dynamic time-scale mismatch.

(2) SOC segmentation and the variable forgetting factor serve as front-end parameter-update strategies in the complete procedure. They improve local parameter tracking across different SOC intervals and dynamic stages and provide the model basis for subsequent bridge correction.

(3) The proposed 3D bridge compensation introduces the equivalent voltage-bias compensation term U_s , equivalent resistance scaling factor k_R , and equivalent time-constant scaling factor s_T . These parameters jointly correct the voltage bias, resistance-parameter deviation, and dynamic time-scale deviation of the fixed-reference model at low temperatures. The method improves both SOC estimation accuracy and terminal-voltage reconstruction.

(4) Under the validation cycles, the bridge parameters calibrated using UDDS maintain good SOC estimation and terminal-voltage reconstruction without rerunning the GA optimization. The proposed method therefore shows a degree of cross-cycle applicability for the same cell within the calibrated temperature range.

Author Contributions: Conceptualization, X.J.; methodology, X.J.; writing—original draft preparation, X.G.; data curation, X.G.; investigation, Y.L. (Yang Liu); validation, Y.L. (Yuwei Li); writing—review and editing, S.W.; supervision, S.W.; funding acquisition, S.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Jilin Provincial Science and Technology Development Plan Project (Grant No. 20260201029GX).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article are available by the authors on request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Tian, J.; Xiong, R.; Shen, W.; Lu, J. State-of-charge estimation of LiFePO₄ batteries in electric vehicles: A deep-learning enabled approach. *Appl. Energy* **2021**, *291*, 116812. [CrossRef]
2. Tian, J.; Chen, C.; Shen, W.; Sun, F.; Xiong, R. Deep learning framework for lithium-ion battery state of charge estimation: Recent advances and future perspectives. *Energy Storage Mater.* **2023**, *61*, 102883. [CrossRef]
3. Tao, J.; Wang, S.; Cao, W.; Fernandez, C.; Blaabjerg, F. A comprehensive review of multiple physical and data-driven model fusion methods for accurate lithium-ion battery inner state factor estimation. *Batteries* **2024**, *10*, 442. [CrossRef]
4. Hossain, M.; Haque, M.E.; Arif, M.T. Online model parameter and state of charge estimation of Li-ion battery using unscented Kalman filter considering effects of temperatures and C-rates. *IEEE Trans. Energy Convers.* **2022**, *37*, 2498–2511. [CrossRef]
5. Chen, J.; Lu, C.; Chen, C.; Cheng, H.; Xuan, D. An improved gated recurrent unit neural network for state-of-charge estimation of lithium-ion battery. *Appl. Sci.* **2022**, *12*, 2305. [CrossRef]

6. Piao, N.; Gao, X.; Yang, H.; Guo, Z.; Hu, G.; Cheng, H.-M.; Li, F.; Cheng, H. Challenges and development of lithium-ion batteries for low temperature environments. *eTransportation* **2022**, *11*, 100145.
7. Cui, Z.; Kang, L.; Li, L.; Wang, L.; Wang, K. A hybrid neural network model with improved input for state of charge estimation of lithium-ion battery at low temperatures. *Renew. Energy* **2022**, *198*, 1328–1340. [[CrossRef](#)]
8. Fan, K.; Wan, Y.; Wang, Z.; Jiang, K. Time-efficient identification of lithium-ion battery temperature-dependent OCV-SOC curve using multi-output Gaussian process. *Energy* **2023**, *268*, 126724. [[CrossRef](#)]
9. Shen, J.; Xiong, J.; Shu, X.; Li, G.; Zhang, Y.; Chen, Z.; Liu, Y. State of charge estimation framework for lithium-ion batteries based on square root cubature Kalman filter under wide operation temperature range. *Int. J. Energy Res.* **2021**, *45*, 5586–5601.
10. Xiong, R.; Li, Z.; Li, H.; Wang, J.; Liu, G. A novel method for state of charge estimation of lithium-ion batteries at low-temperatures. *Appl. Energy* **2025**, *377*, 124514. [[CrossRef](#)]
11. Mao, L.; Hu, Q.; Zhao, J.; Yu, X. State-of-charge of lithium-ion battery based on equivalent circuit model–relevance vector machine fusion model considering varying ambient temperatures. *Measurement* **2023**, *221*, 113487. [[CrossRef](#)]
12. Gong, X.; Jiang, T.; Zou, B.; Wang, H.; Yang, K.; Liu, X.; Ma, B.; Lin, J. SOC estimation of a lithium-ion battery at low temperatures based on a CNN-transformer and SRUKF. *Batteries* **2024**, *10*, 426. [[CrossRef](#)]
13. Tian, J.; Xiong, R.; Lu, J.; Chen, C.; Shen, W. Battery state-of-charge estimation amid dynamic usage with physics-informed deep learning. *Energy Storage Mater.* **2022**, *50*, 718–729. [[CrossRef](#)]
14. Tran, M.-K.; Mathew, M.; Janhunen, S.; Panchal, S.; Raahemifar, K.; Fraser, R.; Fowler, M. A comprehensive equivalent circuit model for lithium-ion batteries, incorporating the effects of state of health, state of charge, and temperature on model parameters. *J. Energy Storage* **2021**, *43*, 103252. [[CrossRef](#)]
15. Tan, S.; Shadike, Z.; Cai, X.; Lin, R.; Kludze, A.; Borodin, O.; Lucht, B.L.; Wang, C.; Hu, E.; Xu, K.; et al. Review on low-temperature electrolytes for lithium-ion and lithium metal batteries. *Electrochem. Energy Rev.* **2023**, *6*, 35. [[CrossRef](#)]
16. Mei, P.; Zhang, Y.; Zhang, W. Low-temperature lithium-ion batteries: Challenges and progress of surface/interface modifications for advanced performance. *Nanoscale* **2023**, *15*, 987–997. [[CrossRef](#)] [[PubMed](#)]
17. Bedwal, K.; Moulik, B.; Vandana. Novel equivalent circuit battery model with adaptive parameters for hybrid state of charge estimation. *J. Energy Storage* **2025**, *137*, 118653. [[CrossRef](#)]
18. Zhang, H.; Hu, B.; Yu, Z.; Wang, H.; Qu, L.; Wang, J.; Li, W.; Bai, C.; Sun, Y. State-of-charge estimation of lithium-ion battery based on improved equivalent circuit model considering hysteresis combined with adaptive iterative unscented Kalman filtering. *J. Energy Storage* **2024**, *102*, 114105. [[CrossRef](#)]
19. Tian, J.; Xiong, R.; Shen, W.; Sun, F. Electrode ageing estimation and open circuit voltage reconstruction for lithium ion batteries. *Energy Storage Mater.* **2021**, *37*, 283–295. [[CrossRef](#)]
20. Zhang, S.; Zhang, C.; Jiang, S.; Zhang, X. A comparative study of different adaptive extended/unscented Kalman filters for lithium-ion battery state-of-charge estimation. *Energy* **2022**, *246*, 123423. [[CrossRef](#)]
21. Hu, Z.; Ren, G.; Zhang, J.; Si, Y.; Duan, Y. A parameter identification and state of charge estimation method of lithium-ion battery considering temperature bias. *J. Energy Storage* **2023**, *68*, 107650. [[CrossRef](#)]
22. Sun, D.; Yu, X.; Wang, C.; Zhang, C.; Huang, R.; Zhou, Q.; Amietszajew, T.; Bhagat, R. State of charge estimation for lithium-ion battery based on an intelligent adaptive extended Kalman filter with improved noise estimator. *Energy* **2021**, *214*, 119025. [[CrossRef](#)]
23. Wang, X.; Gao, Y.; Lu, D.; Li, Y.; Du, K.; Liu, W. Lithium battery SoC estimation based on improved iterated extended Kalman filter. *Appl. Sci.* **2024**, *14*, 5868. [[CrossRef](#)]
24. Mohammadi, F. Lithium-ion battery state-of-charge estimation based on an improved Coulomb-counting algorithm and uncertainty evaluation. *J. Energy Storage* **2022**, *48*, 104061. [[CrossRef](#)]
25. Ge, D.; Zhang, Z.; Kong, X.; Wan, Z. Online SoC estimation of lithium-ion batteries using a new sigma points Kalman filter. *Appl. Sci.* **2021**, *11*, 11797. [[CrossRef](#)]
26. Xing, L.; Wu, X.; Ling, L.; Lu, L.; Qi, L. Lithium battery SOC estimation based on multi-innovation unscented and fractional order square root cubature Kalman filter. *Appl. Sci.* **2022**, *12*, 9524. [[CrossRef](#)]
27. Xiao, W.J.; Wang, S.L.; Yu, C.M.; Yang, X.; Qiu, J.S.; Fernandez, C. Online parameter identification and state of charge estimation of lithium-ion batteries based on improved artificial fish swarms forgetting factor least squares and differential evolution extended Kalman filter. *J. Electrochem. Soc.* **2022**, *169*, 120534. [[CrossRef](#)]
28. Oyewole, I.; Chehade, A.; Kim, Y. A controllable deep transfer learning network with multiple domain adaptation for battery state-of-charge estimation. *Appl. Energy* **2022**, *312*, 118726. [[CrossRef](#)]
29. Wu, M.; Qin, L.; Wu, G.; Huang, Y.; Shi, C. State of charge estimation of power lithium-ion battery based on a variable forgetting factor adaptive Kalman filter. *J. Energy Storage* **2021**, *41*, 102841. [[CrossRef](#)]
30. Ouyang, T.; Xu, P.; Chen, J.; Lu, J.; Chen, N. Improved parameters identification and state of charge estimation for lithium-ion battery with real-time optimal forgetting factor. *Electrochim. Acta* **2020**, *353*, 136576. [[CrossRef](#)]

31. Nicodemo, N.; Di Rienzo, R.; Lagnoni, M.; Bertei, A.; Baronti, F. Estimation of lithium-ion battery electrochemical properties from equivalent circuit model parameters using machine learning. *J. Energy Storage* **2024**, *99*, 113257. [[CrossRef](#)]
32. Li, R.; Hao, Y.; Zhang, M.; Lv, Y. State-of-charge estimation of lithium-ion batteries based on the CNN-Bi-LSTM-AM model under low-temperature environments. *Sensors* **2026**, *26*, 264. [[CrossRef](#)] [[PubMed](#)]

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