

Article

Joint Estimation of Lithium Battery SOC-SOH Based on ASRCKF Algorithm

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Abstract

To achieve accurate estimates of a lithium-ion battery's charge level (SOC) and health condition (SOH), this paper tackles key issues in battery management by introducing a framework built around an adaptive square root cubature Kalman filter (ASRCKF) that tracks parameters in real time for better performance in changing environments. It uses ASRCKF to gauge SOC, while an extended Kalman filter (EKF) identifies battery traits online and monitors capacity loss, with a two-way feedback system that feeds SOH updates directly into the SOC calculations. Testing in high-speed driving, the New European Driving Cycle, and urban stop–start conditions showed the method keeps average SOC errors to 0.16% at most and peak errors to 0.33%, beating out standard EKF and SRCKF approaches in accuracy; SOH errors averaged 0.42%. Overall, this setup proves reliable for combined SOC-SOH tracking in diverse real-world situations, helping to ensure safer battery operations.

Keywords: lithium-ion battery; joint estimation of SOC-SOH; equivalent circuit model; square root cubature Kalman filter



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1. Introduction

With the rapid advancement of the electric vehicle industry, the precise monitoring of lithium-ion battery performance parameters has emerged as a core technical challenge in battery energy management systems. The accurate estimation of state of charge (SOC) and state of health (SOH) is crucial for optimizing energy management strategies, extending battery lifespan, and ensuring safe system operation [1]. However, due to the complexity and unobservability of electrochemical processes, SOC and SOH must be inferred through indirect measurements combined with advanced estimation algorithms, underscoring the significant theoretical and practical value of research into high-precision and adaptive estimation methods. However, despite extensive research on SOC and SOH estimation, existing approaches still struggle to achieve accurate, robust, and interpretable joint estimation under dynamic and time-varying conditions—a critical challenge this study aims to address.

Accurate SOC estimation for lithium batteries serves as a foundational function in battery management systems. While the traditional ampere-hour integration method is simple to implement, it suffers from error accumulation and initial value dependency [2]. Filter-based algorithms grounded in state observation theory have gained prominence for

their robustness and adaptability. A battery management system testing approach using dual extended Kalman filters demonstrates superior SOC estimation accuracy and convergence efficiency over conventional methods, with estimation deviations controlled within 1% and terminal voltage predictions accurate to ± 10 mV under standard conditions [3]. For novel battery systems, an improved extended Kalman filter (EKF) achieves high-precision SOC estimation in sodium-ion batteries with an average error of just 1.79% [4]. The unscented Kalman filter (UKF) addresses nonlinearity via unscented transformation, offering enhanced stability in complex scenarios [5]. The cubature Kalman filter (CKF) employs spherical-radial cubature rules for multidimensional integration, providing better numerical stability and computational efficiency than UKF. The square root cubature Kalman filter (SRCKF) further improves numerical stability by ensuring positive definiteness of the covariance matrix through Cholesky decomposition [6]. Multi-time-scale separation strategies integrated with Kalman filter frameworks effectively enhance SOC estimation accuracy and computational stability across wide temperature ranges [7]. Nevertheless, these filter-based algorithms rely on simplified system assumptions and fixed noise statistics, which limit their adaptability to nonlinear degradation effects and fluctuating environmental conditions.

Precise SOH monitoring is essential for preventing battery system failures and maintaining long-term operational stability. Current SOH assessment methods primarily fall into direct measurement, data-driven, and model-based categories. Direct measurement techniques quantify actual capacity via coulomb integration [8] or analyze frequency-domain features by applying alternating signals to compute health indices [9,10]. Although these methods offer high accuracy, they are often constrained by stringent experimental conditions, limiting their engineering applicability. Data-driven approaches leverage external degradation indicators as health features to construct nonlinear mapping structures for state inference [11]. In recent years, deep learning-based approaches have shown strong potential for capturing nonlinear dependencies in battery dynamics. For instance, Gong et al. [12] integrated a CNN-Transformer with a square root unscented Kalman filter (SRUKF) to improve SOC estimation accuracy at low temperatures; however, their model overlooked the coupled evolution of SOC and SOH, real-time parameter adaptation, and validation under complex dynamic conditions. Similarly, Zeng et al. [13] combined an unscented Kalman filter with an LSTM network, but their method relied on fixed parameters and lacked adaptability to nonlinear degradation or time-varying uncertainties. Yang et al. [14] (2022) further optimized a bidirectional LSTM network using Bayesian algorithms, yet their model remained purely data-driven without integrating electrochemical characteristics or adaptive feedback, limiting its interpretability and robustness under unseen operating conditions.

These studies demonstrate the capability of neural networks in feature extraction, but the absence of physical coupling modeling and adaptive correction mechanisms constrains their applicability in practical BMS environments. Researchers have innovatively combined LSTM networks with dual-exponential models to form hybrid estimation frameworks, optimizing parameters through error feedback iteration to achieve SOH monitoring with an average error of only 0.33% in lithium-ion batteries [15]. Related work using production-line big data-driven methods attains high-precision estimation at just 0.32% of standard capacity, confirming that cell quality is a key parameter influencing battery capacity [16]. Additionally, principal component analysis reduces feature redundancy, while optimized neural networks enable high-precision battery state estimation, markedly improving computational efficiency and model generalization [17,18].

SOC and SOH exhibit strong coupling relationships [19,20]. Capacity degradation during battery aging directly impacts SOC calculation accuracy; failure to promptly correct

capacity parameters can lead to significant accumulated errors in SOC estimates. Thus, developing joint SOC-SOH estimation frameworks holds substantial importance. Existing joint estimation methods mainly adopt multi-model fusion strategies or dual-filter collaborative architectures. A method combining BP networks with adaptive H_∞ filtering controls SOH and SOC estimation errors within 0.35% and 0.5%, respectively [21]. Nevertheless, current methods still fall short in handling strong nonlinearity and time-varying noise, with room for improvement in dynamic adaptability and numerical stability.

Despite these advances, existing SOC-SOH joint estimation frameworks still face several unresolved challenges: (1) traditional extended Kalman filters incur linearization errors in highly nonlinear systems; (2) covariance matrices may lose positive definiteness during filtering, compromising numerical stability; (3) fixed noise statistical models struggle to adapt to time-varying noise in real-world conditions; (4) existing joint estimation architectures lack effective feedback mechanisms for handling SOC-SOH coupling. To overcome these limitations, this study proposes an adaptive square root cubature Kalman filter (ASRCKF) for high-precision SOC estimation, integrated with an extended Kalman filter (EKF) for online parameter identification and real-time SOH tracking. Furthermore, a bidirectional feedback structure is designed to incorporate capacity degradation information back into the SOC estimation loop, enhancing dynamic adaptability and estimation accuracy under multiple operating conditions.

2. Lithium Battery Experimental Platform Construction and Modeling

2.1. Experimental Platform Construction

In this study, a battery testing experimental platform was established as illustrated in Figure 1, comprising primarily charge–discharge apparatus, a data acquisition system, a temperature control unit, and a host computer monitoring interface. All tests were performed within a programmable constant-temperature chamber, maintaining environmental temperature control with an accuracy of $\pm 0.5^\circ\text{C}$. The charge–discharge equipment utilized the Neware BTS-4000 series battery testing system (Shenzhen Neware New Energy Technology Co., Ltd., Shenzhen, China), featuring current measurement precision of $\pm 0.05\%$ and voltage measurement precision of $\pm 0.02\%$.

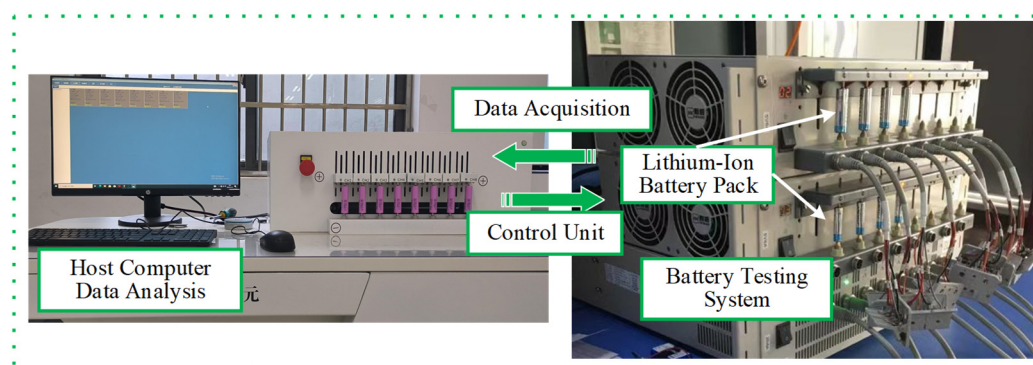


Figure 1. Battery testing experimental platform.

The Samsung ICR18650-26H (Shenzhen Neware New Energy Technology Co., Ltd., Shenzhen, China) lithium-ion battery was selected as the subject of investigation, a model extensively employed in electric vehicle applications, with key specifications including a nominal capacity of 2.60 Ah, nominal voltage of 3.63 V, charge cut-off voltage of 4.20 V, and discharge cut-off voltage of 2.75 V.

2.2. Establishment of Battery Model

The second-order RC equivalent circuit model for lithium-ion batteries strikes an optimal balance between structural simplicity and characterization accuracy, effectively capturing the battery polarization dynamics. To reconcile computational efficiency with precision demands [22], this study selects the second-order model depicted in Figure 2 as the foundational framework, thereby furnishing a robust mathematical representation for parameter identification and state estimation.

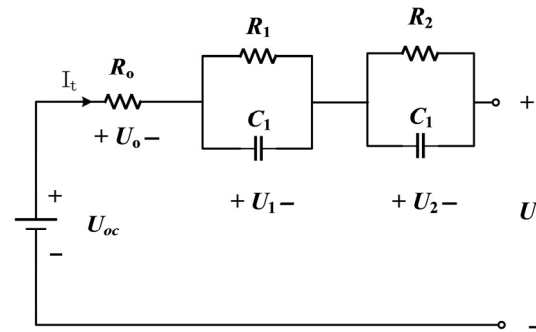


Figure 2. Second-order equivalent circuit model.

Based on the second-order equivalent circuit model, the following equation is derived from Kirchhoff's voltage law:

$$\begin{cases} U_1 = -\frac{1}{R_1 C_1} U_1 + \frac{1}{C_1} I_t \\ U_2 = -\frac{1}{R_2 C_2} U_2 + \frac{1}{C_2} I_t \\ U_{oc} = U + R_o I_t + U_1 + U_2 \end{cases} \quad (1)$$

where U_{oc} denotes the open-circuit voltage, which is a function of SOC; I_t represents the operating current at time t , taken as positive during discharge and negative during charge; U is the terminal voltage; R_o is the ohmic resistance, encompassing the aggregate resistance from electrodes, electrolyte, and current collectors; R_1 is the electrochemical polarization resistance; C_1 is the electrochemical polarization capacitance; R_2 and C_2 are the concentration polarization resistance and capacitance, respectively; and U_1 and U_2 are the voltages across the electrochemical polarization capacitance C_1 and the concentration polarization capacitance C_2 .

Discretizing Equation (1) and constructing the state-space model:

$$\mathbf{x}_k = \mathbf{A} \mathbf{x}_{k-1} + \mathbf{B} I_{k-1} \quad (2)$$

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau_1}} & 0 \\ 0 & 0 & e^{-\frac{\Delta t}{\tau_2}} \end{bmatrix} \quad (3)$$

$$\mathbf{B} = \left[-\frac{\eta \Delta t}{Q_n}, R_1 \left(1 - e^{-\frac{\Delta t}{\tau_1}} \right), R_2 \left(1 - e^{-\frac{\Delta t}{\tau_2}} \right) \right]^T \quad (4)$$

where $\mathbf{x}_k$ is the 3-dimensional state vector, $\mathbf{x}_k = [U_k^1 U_k^2 SOC_k]^T$; $\mathbf{A}$ is the state transition matrix at instant k ; $\mathbf{B}$ is the control input matrix at instant k ; Δt is the sampling interval; η is the coulombic efficiency of the lithium battery, assumed to be 1 in this study; Q_n is the nominal battery capacity; τ represents the time constants, where $\tau_1 = C_1 R_1$ and $\tau_2 = C_2 R_2$.

The measurement equation is:

$$U_k = U(SOC_k) - I_{m,k} R_o - U_{1,k} - U_{2,k} + v_k \quad (5)$$

where v_k denotes the measurement noise, adhering to a Gaussian distribution with zero mean and variance R_v ; $I_{m,k}$ represents the measured current.

To validate the accuracy of the circuit model, open-circuit voltage (OCV) tests were performed across diverse SOC intervals, thereby establishing the OCV-SOC relationship curve, with SOC determined via the ampere-hour integration method. A sixth-order polynomial fit was applied to the OCV and corresponding SOC values, as illustrated by the fitted curve in Figure 3, with the polynomial expression provided in Equation (6).

$$U_{oc} = 3.45 - 1.71s + 32.51s^2 - 195.28s^3 + 532.04s^4 - 803.90s^5 + 747.62s^6 - 403.80s^7 + 69.32s^8 \quad (6)$$

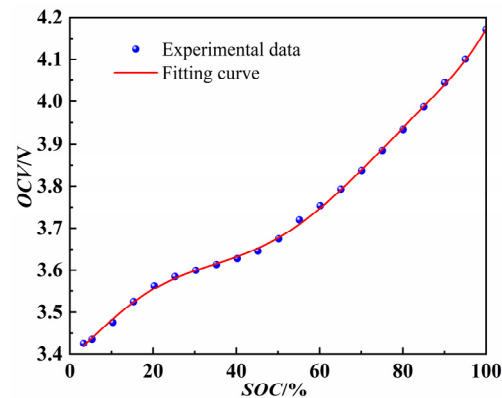


Figure 3. OCV-SOC fitting curve.

The terminal voltage error curve of the model is illustrated in Figure 4. As evident, the maximum error under discharge conditions remains below 0.027 V, underscoring the high precision achieved in the curve fitting.

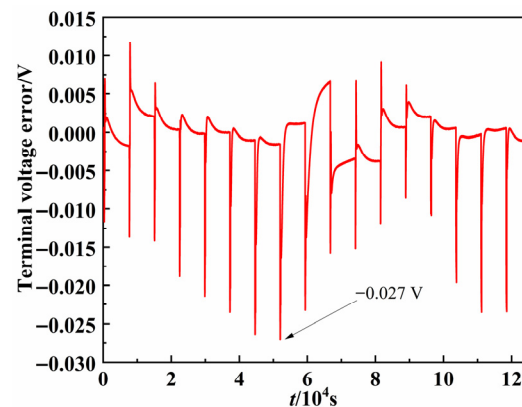


Figure 4. Model terminal voltage error curve under 25 °C and 1 C discharge condition.

3. Online Parameter Identification

3.1. Methodology Construction of Parameter Identification Method

In this study, initial parameter estimates obtained via the least squares method served as the starting conditions, yielding identification results of $R_0 = 27.8 \text{ m}\Omega$, $R_1 = 18.6 \text{ m}\Omega$, $R_2 = 28.2 \text{ m}\Omega$, $C_1 = 3.2 \text{ kF}$, $C_2 = 60.0 \text{ kF}$. The EKF algorithm was employed for real-time parameter identification and updating. This approach integrates the stability of batch-processing algorithms with the computational efficiency of recursive estimation, effectively mitigating inherent limitations of conventional identification techniques in nonlinear systems. By constructing a state-space model, the EKF enables continuous tracking of dynamic

variations in battery internal resistance and polarization parameters under evolving operating conditions, achieving high-precision identification without the need for supplementary adaptive mechanisms.

The fitted OCV-SOC relationship established was integrated with the equivalent circuit parameters identified herein, substituting into Equations (1) and (2) to formulate a comprehensive state-space representation. This establishes the mapping between terminal voltage measurements and internal states, collectively forming the theoretical foundation for state observer design and providing a mathematical basis for subsequent SOC estimation using the SRCKF algorithm.

A dual-time-scale filtering architecture was implemented to track key battery indicators, with x denoting the operational states and θ representing the model parameters. To accommodate differences in variation characteristics, differentiated sampling strategies were adopted: parameter and capacity estimation utilized 1 s observation intervals, whereas charge state monitoring employed 0.1 s high-frequency sampling. This facilitates wide-window tracking of slowly varying elements while preserving high dynamic responsiveness.

Based on Equations (2) and (5), the nonlinear expressions for the discrete state equation and observation equation of the lithium-ion battery were formulated as follows:

$$\begin{cases} x_{k,l} = f(x_{k,l-1}, \theta_k, u_{k,l-1}) + w_{k,l-1} \\ \theta_k = \theta_{k-1} + \rho_{k-1} \\ z_{k,l} = g(x_{k,l}, \theta_k, u_{k,l-1}) + v_{k,l} \end{cases} \quad (7)$$

where k denotes the sampling instant for model parameters; l represents the sampling index for state variables; $x_{k,l}$ is the system state vector at time $t_{k,l} = t_{k,0} + l \times T$ ($1 \leq l \leq L$), with L being the sampling period conversion constant; θ_k is the system parameter vector for the k -th cycle, $\theta_k = [R_0, R_1, R_2, C_1, C_2, Q_m]^T$; $u_{k,l-1}$ is the input load current at time $t_{k,l-1}$; $z_{k,l}$ is the observation result matrix; $f(\cdot)$ and $g(\cdot)$ are the system dynamic transition function and measurement function, respectively; $w_{k,l-1}$ is the process noise with covariance matrix Q_x ; ρ_k is the parameter noise with covariance matrix Q_θ ; and $v_{k,l}$ is the measurement random error with covariance matrix R_k .

3.2. Implementation of EKF Algorithm

The state-space equations based on the EKF algorithm are formulated as:

$$\begin{cases} x_{k,l} = f(x_{k,l-1}, \theta_k, u_{k,l-1}) + w_{k,l-1} \\ z_{k,l} = g(x_{k,l}, \theta_k, u_{k,l-1}) + v_{k,l} \end{cases} \quad (8)$$

where the Jacobian matrices for the EKF are defined as follows:

$$\begin{cases} A_{k,l-1} = \frac{\partial f(x, \theta_k, u_{k,l-1})}{\partial x} \Big|_{x=\hat{x}_{k,l-1}} \\ C_{k,l}^\theta = \frac{\partial g(x, \theta_k, u_{k,l-1})}{\partial \theta} \Big|_{x=\hat{x}_{k,l-1}} \end{cases} \quad (9)$$

The iterative process for online parameter identification using EKF is outlined below:

Step 1: Initialization

$$\begin{cases} \hat{\theta}_0 = E(\theta_0) \\ P_0 = E[(\theta_0 - \hat{\theta}_0)(\theta_0 - \hat{\theta}_0)^T] \end{cases} \quad (10)$$

Step 2: Time Update

Parameter filter time update: For the parameter time sequence $k \in \{1, \dots, \infty\}$, the long-period sampling filter performs the a priori parameter estimation:

$$\begin{cases} \hat{\theta}_k^- = \hat{\theta}_{k-1}^- \\ P_{\theta_k}^- = P_{\theta_{k-1}} + Q_{k-1}^\theta \end{cases} \quad (11)$$

Step 3: Measurement Update

Corresponding to the state time index $l \in \{1, \dots, L\}$, the short-period sampling filter completes the a priori state prediction:

$$\begin{cases} \hat{x}_{k-1,l}^- = f(\hat{x}_{k-1,l-1}, \hat{\theta}_{k-1}^-, u_{k-1,l-1}) \\ P_{k-1,l}^- = A_{k-1,l-1} P_{k-1,l-1} A_{k-1,l-1}^T + Q_{k-1,l-1} \end{cases} \quad (12)$$

Kalman gain:

$$K_{k-1,l} = P_{k-1,l}^- (C_{k-1,l})^T [C_{k-1,l} P_{k-1,l}^- (C_{k-1,l})^T + R_{k-1,l}]^{-1} \quad (13)$$

Parameter update:

$$\begin{cases} \hat{\theta}_k = \hat{\theta}_k^- + K_{k-1,l} [z_{k,l} - g(\hat{x}_{k-1,l}^-, \hat{\theta}_k^-, u_{k,l-1})] \\ P_{\theta_k} = P_{\theta_k}^- - P_{\theta_k}^- K_{k-1,l} C_{k-1,l} \end{cases} \quad (14)$$

Step 4: State Update

$$\begin{cases} \hat{x}_{k-1,l} = \hat{x}_{k-1,l}^- + K_{k-1,l} [z_{k,l} - g(\hat{x}_{k-1,l}^-, \hat{\theta}_k^-, u_{k,l-1})] \\ P_{k-1,l} = P_{k-1,l}^- - P_{k-1,l}^- K_{k-1,l} C_{k-1,l} \end{cases} \quad (15)$$

4. SOC-SOH Joint Estimation Algorithm

4.1. ASRCKF Algorithm

The SRCKF algorithm offers substantial advantages in numerical stability over the conventional CKF by directly performing Cholesky decomposition on the covariance matrix. However, in practical battery state estimation scenarios, the alignment between measured values and the model, as well as the actual battery behavior, is influenced by environmental factors, resulting in time-varying and unknown noise statistical characteristics. Compared to the traditional UKF, SRCKF more accurately propagates higher-order statistical moments, particularly in strongly nonlinear systems, thereby significantly reducing linearization and sampling errors. Although the standard CKF excels in computational precision, it is prone to numerical instability when handling high-dimensional state vectors and covariance matrices with large condition numbers.

To address these challenges, this paper proposes an ASRCKF algorithm, which dynamically adjusts the process noise covariance matrix Q and the measurement noise covariance matrix R to enhance adaptability to parameter variations and measurement anomalies. The adaptive updates for Q and R in the filtering process are given by:

$$Q_k = K_{x,k} F_k (K_{x,k})^T \quad (16)$$

$$R_k = F_k + C_k \hat{P}_k (C_k)^T \quad (17)$$

where F_k represents an approximation of the innovation covariance; $K_{x,k}$ is the Kalman gain matrix; C_k is the Jacobian matrix of the measurement equation; and $\hat{P}_k$ is the predicted state covariance matrix, reflecting the degree of uncertainty in the state prediction.

For the lithium-ion battery system, a discrete state equation is constructed based on the second-order RC equivalent circuit model established earlier. The ASRCKF algorithm procedure is as follows:

Step 1: Initialization

Set the initial state estimate $\hat{x}_0$, initial noise covariance matrices Q_0 and R_0 , and the square root of the state covariance matrix $S_{x,0|0}$.

Step 2: Time Update

Compute the cubature points:

$$X_{i,k}^- = \hat{x}_{k-1} + S_{k-1} \cdot \zeta_i \quad (18)$$

$$\zeta_i = \begin{cases} \sqrt{n}[1]_i, i = 1, 2, \dots, n \\ \sqrt{n}[1]_i, i = n + 1, n + 2, \dots, 2n \end{cases} \quad (19)$$

where n is the dimension of the state vector, and $[1]_i$ denotes the i -th unit vector.

Propagate the cubature points:

$$X_{i,k}^* = f(X_{i,k}^-, u_k) \quad (20)$$

Compute the predicted state estimate:

$$\hat{x}_k^- = \frac{1}{2n} \sum_{i=1}^{2n} X_{i,k}^* \quad (21)$$

Update the square root of the predicted state error covariance:

$$S_{x,k}^- = \text{Tri}a\left(\left[\zeta_{x,k}^-, S_{Q,k-1}\right]\right) \quad (22)$$

$$\zeta_{x,k}^- = \frac{1}{\sqrt{2n}} \left[X_{1,k}^* - \hat{x}_k^-, X_{2,k}^* - \hat{x}_k^-, \dots, X_{2n,k}^* - \hat{x}_k^- \right] \quad (23)$$

where $S_{Q,k-1}$ is the square root matrix of the process noise covariance Q_{k-1} .

Compute the predicted state covariance:

$$P_k^- = S_{x,k}^- \left(S_{x,k}^- \right)^T \quad (24)$$

Step 3: Measurement Update

Compute the measurement cubature points:

$$Z_{i,k}^- = g(X_{i,k}^-, u_k) \quad (25)$$

Compute the predicted measurement:

$$\hat{z}_k^- = \frac{1}{2n} \sum_{i=1}^{2n} Z_{i,k}^- \quad (26)$$

Compute the innovation:

$$e_k = z_k - \hat{z}_k^- \quad (27)$$

where z_k is the measured battery terminal voltage.

Compute an approximation of the innovation covariance:

$$F_k = \lambda \sum_{i=k-L+1}^k e_i (e_i)^T \quad (28)$$

where F_k is the voltage residual covariance at instant k ; λ is the fading factor; and L is the covariance matching window size.

Step 4: Adaptive Mechanism

Update the noise covariance matrices:

$$Q_k = K_{x,k} F_k K_{x,k} + F_k \quad (29)$$

Based on the updated noise covariances, recompute the square root of the measurement covariance:

$$R_k = F_k + \frac{1}{2n} \sum_{i=1}^{2n} (Z_{i,k}^- - z_k) (Z_{i,k}^- - z_k)^T \quad (30)$$

where z_k is the measured terminal voltage at instant k .

Recompute the square root of the measurement covariance based on the updated noise covariances:

$$S_{z,k}^- = \text{Tria} \left(\left[\zeta_{z,k}^-, S_{R,k} \right] \right) \quad (31)$$

where $S_{R,k}$ is the square root matrix of the measurement noise covariance R_k .

$$\zeta_k^- = \frac{1}{\sqrt{2n}} \left[Z_{1,k}^- - \hat{z}_k^-, Z_{2,k}^- - \hat{z}_k^-, \dots, Z_{2n,k}^- - \hat{z}_k^- \right] \quad (32)$$

Compute the cross-covariance:

$$P_{xz,k} = \frac{1}{2n} \sum_{i=1}^{2n} (X_{i,k}^- - \hat{x}_k^-) (Z_{i,k}^- - \hat{z}_k^-)^T \quad (33)$$

Step 5: State Update

Compute the Kalman gain:

$$K_k = P_{xz,k} (S_{z,k}^-)^{-1} (S_{z,k}^-)^{-T} \quad (34)$$

Update the state estimate:

$$\hat{x}_k = \hat{x}_k^- + K_k \cdot e_k \quad (35)$$

Update the square root of the posterior state covariance:

$$S_{x,k} = \text{Tria} \left(\left[S_{x,k}^- - K_k S_{z,k}^- \cdot K_k^T S_{z,k}^- \right] \right) \quad (36)$$

Compute the posterior state covariance:

$$P_k = S_{x,k} (S_{x,k})^T \quad (37)$$

4.2. SOC-SOH Joint Estimation Framework

SOC and state of SOH in lithium-ion batteries evolve differentially throughout their usage lifecycle, exhibiting profound interdependency. Battery aging induces progressive capacity degradation, which in turn compromises the accuracy of SOC estimation. Given the inherent coupling between SOC and SOH, independent estimation of either parameter often fails to fully capture the battery's authentic operational dynamics. Consequently, enhancing the precision of their joint estimation holds paramount significance for optimizing battery management systems and forecasting battery longevity. To this end, this paper proposes a joint SOC-SOH estimation framework based on the ASRCKF and EKF, as illustrated in Figure 5.

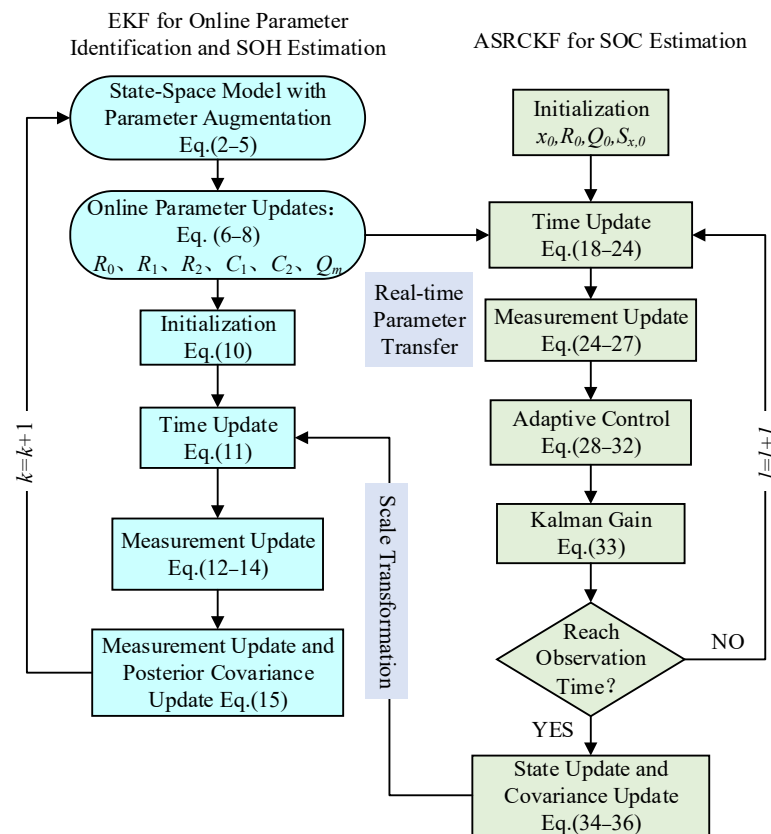


Figure 5. Joint estimation frame of SOC-SOH.

At its core, the framework leverages ASRCKF for high-precision SOC estimation, while EKF facilitates dynamic tracking of battery model parameters to delineate SOH degradation patterns. By incorporating real-time SOC monitoring with adaptive mechanisms, ASRCKF sustains elevated estimation accuracy under intricate operating conditions; concurrently, EKF bolsters SOH estimation reliability through continuous parameter updates.

5. Experiment and Analysis

To thoroughly validate the effectiveness and robustness of the proposed algorithm, this study selected three representative standard test cycles for experimental evaluation: the Highway Fuel Economy Test (HWFET), the New European Driving Cycle (NEDC), and the Urban Dynamometer Driving Schedule (UDDS). The HWFET simulates sustained high-speed cruising scenarios to assess the algorithm's stability during prolonged heavy load operation; the NEDC combines various urban and suburban driving conditions, focusing on the algorithm's ability to respond to frequent acceleration and braking transitions; the UDDS focuses on low-speed starts and stops, simulating urban congestion, to evaluate the algorithm's estimation accuracy and convergence characteristics under dynamic noise conditions. Figure 6 illustrates the current variation profiles for these three cycles, showing the overall current fluctuations for each test cycle.

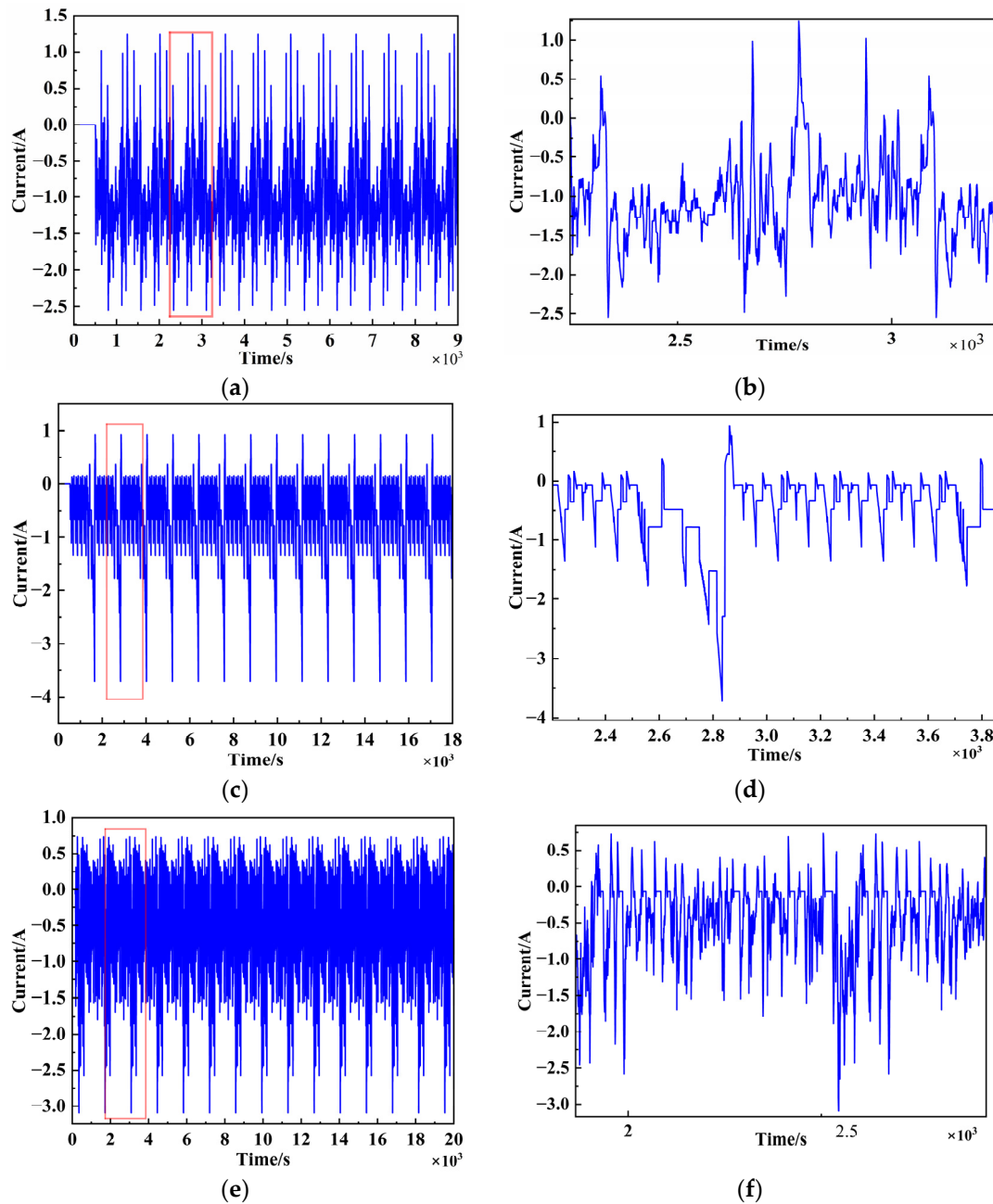


Figure 6. Current curves under different test conditions. (a) Overall current curve under HWFET condition; (b) local zoomed-in view of HWFET current fluctuations; (c) overall current curve under NEDC condition; (d) local zoomed-in view of NEDC current fluctuations; (e) Local zoomed-in view of UDDS current fluctuations; (f) overall current curve under UDDS condition. The red rectangles indicate the enlarged areas shown in the local zoomed-in views.

Specifically, Figure 6a presents the overall current curve under the HWFET conditions, showing steady fluctuations during long periods of high-speed cruising; Figure 6b is a zoomed-in view of the HWFET, highlighting rapid current fluctuations at high speeds; Figure 6c shows the overall current curve under the NEDC conditions, reflecting the fluctuations in current during urban and suburban driving; Figure 6d is a zoomed-in view of the NEDC, emphasizing the rapid changes in current during frequent acceleration and braking; Figure 6e shows the overall current curve under the UDDS conditions, focusing on the current characteristics during low-speed starts and stops; Figure 6f is a zoomed-in view of the UDDS, revealing the details of current fluctuations in urban congestion. These

current fluctuation profiles help to understand the stability and response characteristics of the algorithm under different driving conditions.

To provide a more comprehensive view of the voltage data, Figure 7 presents the voltage variation profiles under different test conditions, highlighting the voltage changes under various driving scenarios. Specifically, Figure 7a shows the overall voltage curve under the HWFET conditions, demonstrating the relative stability of voltage at high speeds; Figure 7b is a zoomed-in view of the voltage fluctuations under the HWFET, showing subtle changes in voltage during high-speed cruising; Figure 7c presents the overall voltage curve under the NEDC conditions, reflecting the voltage fluctuations during frequent acceleration and braking; Figure 7d is a zoomed-in view of the NEDC, highlighting voltage changes during acceleration and deceleration; Figure 7e shows the overall voltage curve under the UDDS conditions, focusing on the voltage characteristics during low-speed driving and stops; Figure 7f is a zoomed-in view of the UDDS, revealing subtle voltage fluctuations during low-speed starts and stops in urban traffic. These zoomed-in views provide a detailed perspective on the voltage changes, helping to better understand the voltage variations under different test conditions.

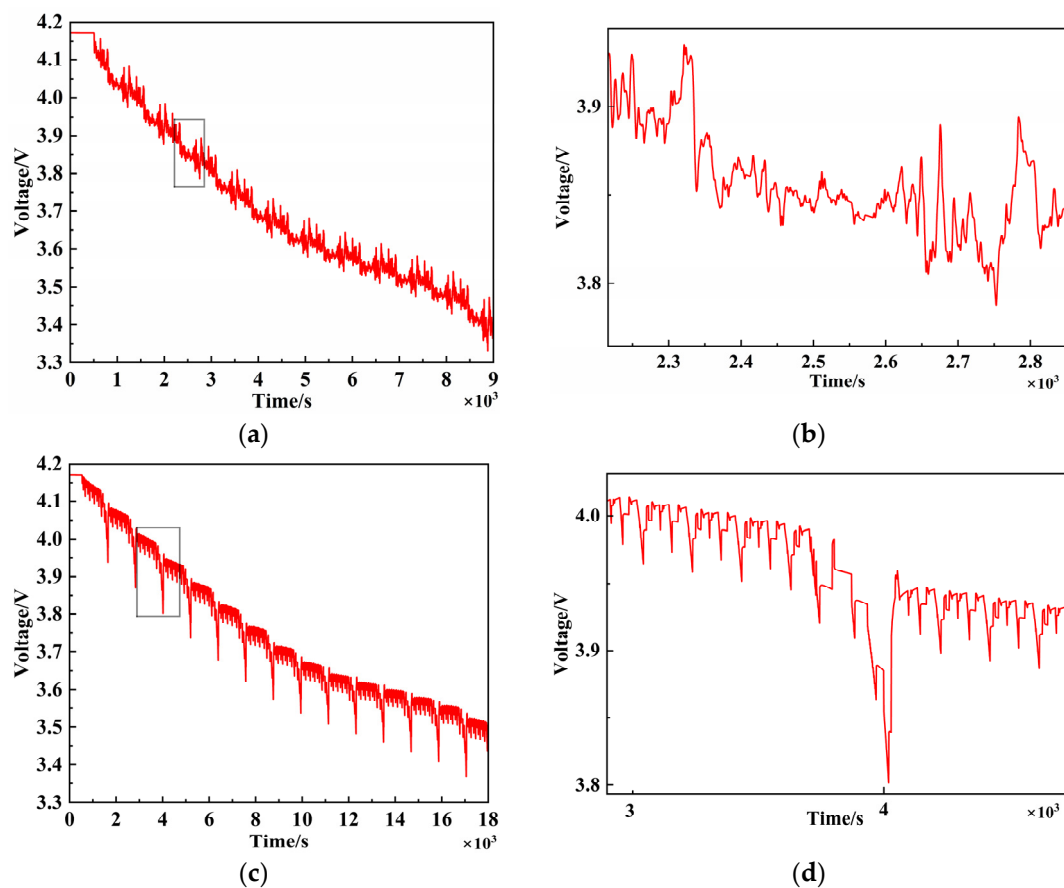


Figure 7. Cont.

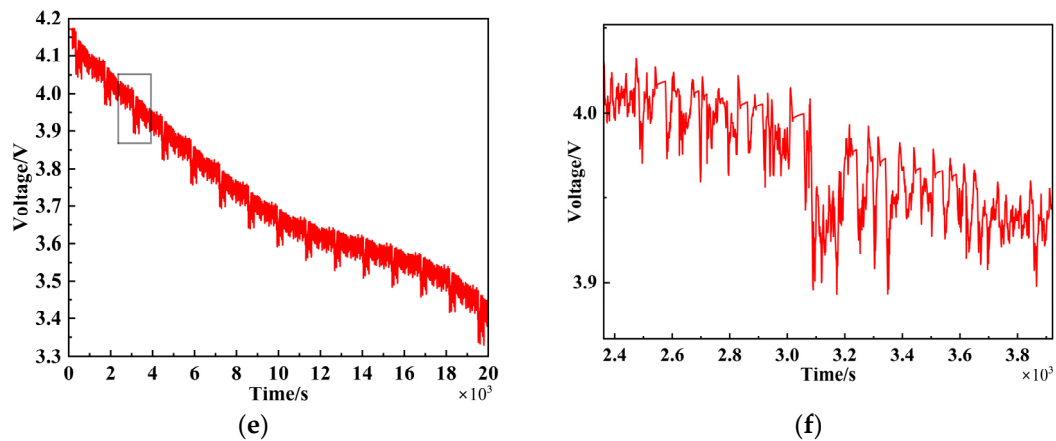


Figure 7. Voltage curves under different test conditions. (a) Overall voltage curve under HWFET condition; (b) local zoomed-in view of HWFET voltage response; (c) overall voltage curve under NEDC condition; (d) local zoomed-in view of NEDC voltage response; (e) local zoomed-in view of UDDS voltage response; (f) overall voltage curve under UDDS condition. The gray rectangles indicate the enlarged areas shown in the local zoomed-in views.

5.1. HWFET Condition Validation Results

The HWFET condition is a standardized dynamic load cycle that simulates sustained medium-to-high-speed cruising scenarios for electric vehicles on highways, with an initial SOC of 100% and discharge to approximately 20%. This condition emphasizes the algorithm's stability and anti-drift capabilities under prolonged high loads, making it suitable for evaluating the estimation framework's responsiveness to low-frequency noise and gradual dynamics. In this experiment, the aforementioned ASRCKF-EKF joint framework was employed for real-time SOC-SOH estimation on the Samsung ICR18650-26H battery, and compared against benchmark methods (ASRCKF, SRCKF, and EKF).

Figure 8 illustrates the temporal curves of SOC estimation results from each algorithm under the HWFET condition. The trajectory of the proposed ASRCKF-EKF algorithm closely aligns with the reference true value (REF), maintaining deviations within 1% throughout the process, particularly demonstrating high-resolution tracking of capacity gradients in the locally magnified region. In contrast, EKF and SRCKF exhibit larger offsets, with terminal errors of approximately 2–4%, while the standalone ASRCKF, although superior, still shows minor deviations in the mid-segment.

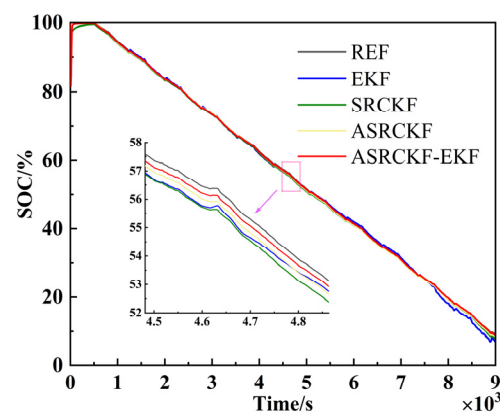


Figure 8. SOC Estimation results under the HWFET driving cycle.

Figure 9 presents the comparison curves of SOC true values against estimation errors from each algorithm under the HWFET condition. As evident from Figure 9a, the proposed ASRCKF-EKF algorithm yields SOC estimation trajectories that tightly conform to the true

SOC variations, with the minimal overall deviation, especially in the capacity degradation-sensitive region during the later cruising phase, where the estimation error remains within $\pm 0.2\%$. This highlights the effectiveness of the adaptive noise correction mechanism in compensating for time-varying model parameters. Comparatively, the standalone ASRCKF performs well initially but accumulates increasing errors up to approximately 2% in the later stages; SRCKF is constrained by numerical stability, resulting in minor oscillations (peak $\approx 4\%$) during high-load steady segments; and the conventional EKF induces significant deviations (peak $\approx 8\%$) due to linearization approximations, underscoring its limitations under nonlinear loads. To further quantify performance, Figure 9b depicts a bar chart of SOC estimation errors for each algorithm, from which it is apparent that the proposed algorithm achieves the lowest metrics, far outperforming the EKF.

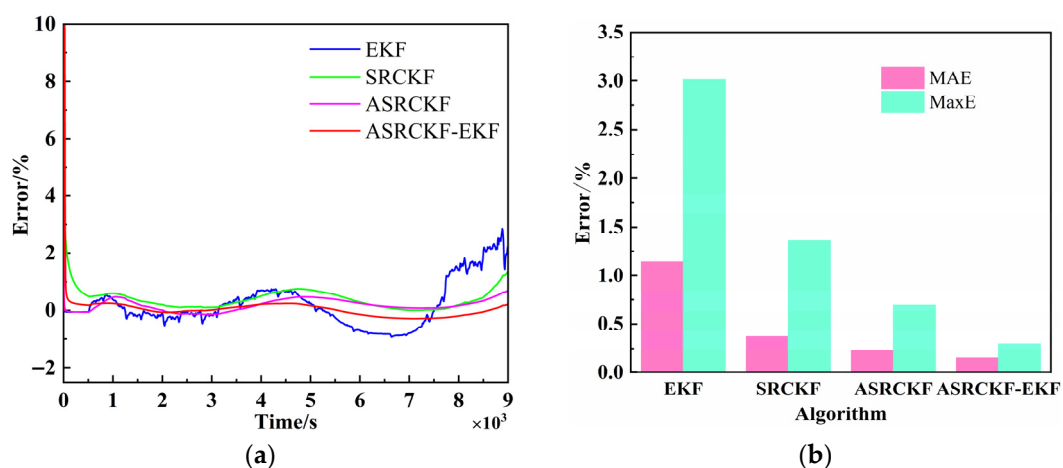


Figure 9. SOC Error Analysis: (a) SOC Estimation Error; (b) SOC Error Comparison.

Concurrently, a quantitative analysis of SOC estimation errors across the algorithms is provided in Table 1, showing that the proposed algorithm attains the lowest error levels under the HWFET condition. Relative to the standalone ASRCKF, the mean absolute error (MAE) is reduced by approximately 43%, and the maximum absolute error (Max AE) by about 57%; compared to SRCKF, the corresponding reductions are approximately 66% and 76%; and against the conventional EKF, the improvements are more pronounced, with MAE and Max AE decreased by about 88% and 90%, respectively.

Table 1. Performance comparison of the proposed algorithm under the HWFET condition.

Algorithm	MAE (%)	MaxE (%)
ASRCKF-EKF	0.12	0.28
ASRCKF	0.21	0.65
SRCKF	0.35	1.15
EKF	0.98	2.76

Furthermore, the SOH estimation errors, as shown in Figure 10, maintain trajectory deviations within $\pm 1.5\%$, further substantiating the contribution of EKF-based online parameter identification in dynamically tracking aging processes.

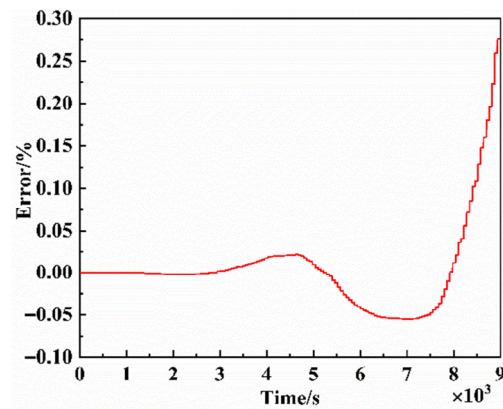


Figure 10. SOH estimation error.

5.2. NEDC Condition Validation Results

The NEDC condition combines typical urban and suburban driving characteristics with a total duration of approximately 1800 s. Its distinctive stop-and-go patterns followed by sustained cruising phases provide an ideal platform for validating algorithm performance under complex mixed scenarios.

Figure 11 presents a comparative analysis of SOC estimation trajectories for all evaluated algorithms under the NEDC condition. The results demonstrate that the ASRCKF-EKF algorithm maintains optimal alignment with the reference trajectory, while the conventional EKF exhibits significant deviations during dynamic load transitions, particularly during frequent acceleration–deceleration transition phases.

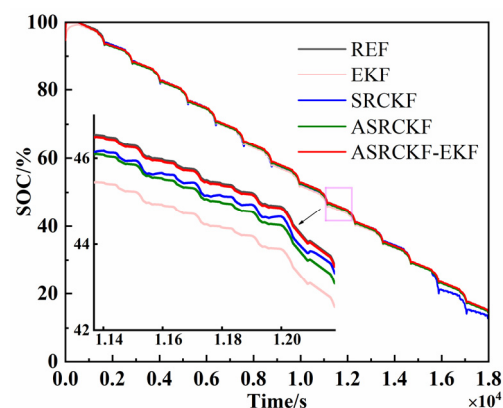


Figure 11. SOC Estimation results under the NEDC driving cycle.

To quantitatively assess the estimation accuracy of each algorithm, Figure 12 provides an in-depth analysis of error characteristics from both temporal and statistical perspectives. The temporal error curves in Figure 12a intuitively reflect the dynamic tracking performance of each algorithm. The ASRCKF-EKF demonstrates exceptional stability throughout the entire test cycle, with error fluctuations consistently constrained within $\pm 0.35\%$. In contrast, the EKF exhibits a pronounced error spike at approximately 1.6×10^4 s during the suburban high-speed segment, with maximum deviation reaching 3%, which correlates strongly with the aggressive acceleration conditions during this period. The SRCKF and ASRCKF show intermediate performance, with the ASRCKF demonstrating superior noise suppression capabilities through its adaptive mechanism.

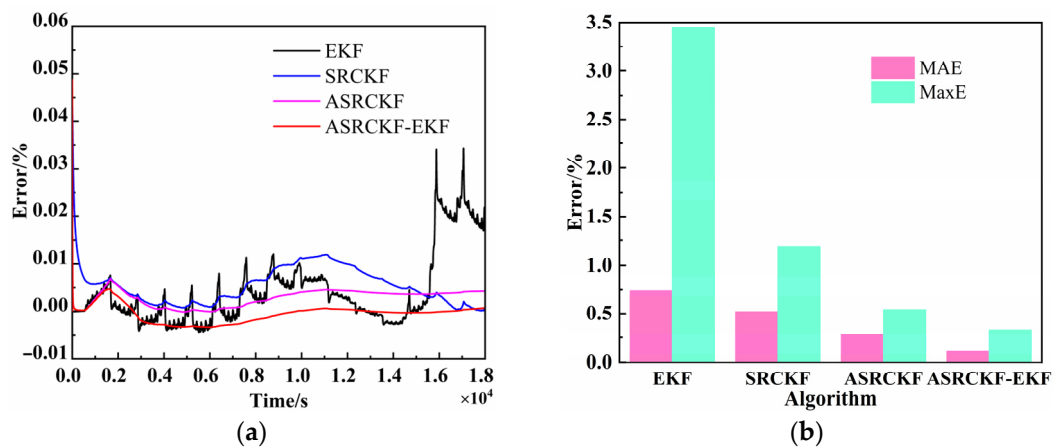


Figure 12. SOC Error Analysis: (a) SOC Estimation Error; (b) SOC Error Comparison.

Table 2 provides systematic quantification of the error metrics. The data reveal that the ASRCKF-EKF achieves significant reductions of 84% and 90% in MAE and MaxE, respectively, compared to the conventional EKF. Notably, the standalone ASRCKF reduces error metrics to MAE = 0.28% and MaxE = 0.54%, fully validating the critical role of adaptive noise covariance estimation. Figure 12b visualizes the quantitative results from Table 2 through bar charts, clearly illustrating the hierarchical distribution of algorithm performance. From EKF to SRCKF, ASRCKF, and finally ASRCKF-EKF, the error metrics exhibit progressive improvement, systematically validating the contribution of each technical enhancement.

Table 2. Performance comparison of the proposed algorithm under the NEDC condition.

Algorithm	MAE (%)	MaxE (%)
ASRCKF-EKF	0.12	0.33
ASRCKF	0.28	0.54
SRCKF	0.52	1.19
EKF	0.74	3.45

Figure 13 further illustrates the dynamic evolution characteristics of SOH estimation error. The error evolution exhibits distinct phase-dependent characteristics: the initial urban cycling segment ($0\text{--}0.8 \times 10^4$ s) maintains low error levels below 0.1%; the mid-phase transition segment ($0.8\text{--}1.2 \times 10^4$ s) shows error increases to approximately 0.3% due to operating condition transitions; and the final suburban cruising segment ($1.2\text{--}1.8 \times 10^4$ s) demonstrates gradual error growth to 0.5% due to cumulative effects. This evolution pattern strongly correlates with the SOC decline rate variations shown in Figure 10, revealing the intrinsic relationship between SOH estimation accuracy and battery operating states. Despite phase-dependent fluctuations, the EKF-assisted adaptive parameter identification mechanism successfully constrains SOH errors within engineering-acceptable limits, demonstrating the effectiveness of the proposed framework under complex operating conditions.

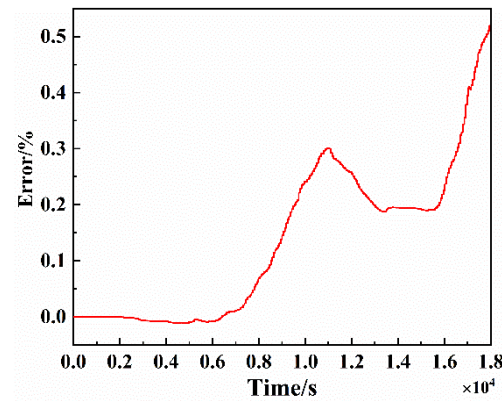


Figure 13. SOH estimation error.

5.3. UDDS Condition Validation Results

The UDDS condition represents typical urban driving scenarios with a total duration of approximately 20,000 s. Its characteristics of frequent stop-and-go patterns, aggressive accelerations/decelerations, and low-speed operations pose the most stringent challenges to the dynamic response capability and robustness of battery state estimation algorithms.

Figure 14 presents the SOC estimation trajectories of all algorithms under the UDDS driving cycle. Compared to the HWFET and NEDC conditions, UDDS condition exhibits more complex SOC variation patterns, with multiple plateau periods and rapid decline segments during the discharge from 100% to approximately 8%. The magnified inset captures a typical urban driving segment with continuous aggressive accelerations and decelerations, where the ASRCKF-EKF maintains tight alignment with the reference trajectory, while other algorithms exhibit varying degrees of tracking delays and deviations, with EKF showing the most significant divergence.

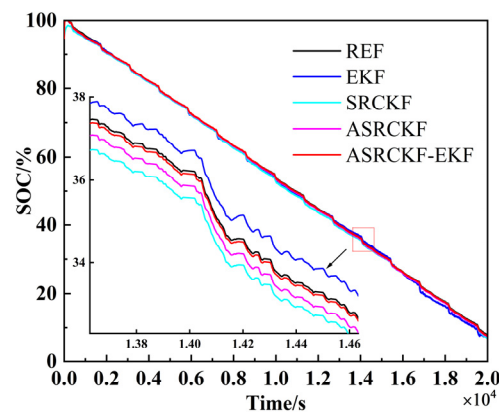


Figure 14. SOC Estimation results under the UDDS driving cycle.

Unlike the previous two driving conditions, the errors under UDDS exhibit more frequent fluctuation patterns, as illustrated in Figure 15. Figure 15a demonstrates that the ASRCKF-EKF algorithm exhibits superior stability, with errors essentially constrained within $\pm 0.005\%$. Notably, during the $1.0\text{--}1.2 \times 10^4$ s interval, all algorithms experience intensified error fluctuations, yet the ASRCKF-EKF maintains the smallest fluctuation amplitude. The EKF exhibits error peaks of approximately 0.015% in this interval, while the SRCKF, despite avoiding extreme peaks, demonstrates persistent oscillatory characteristics.

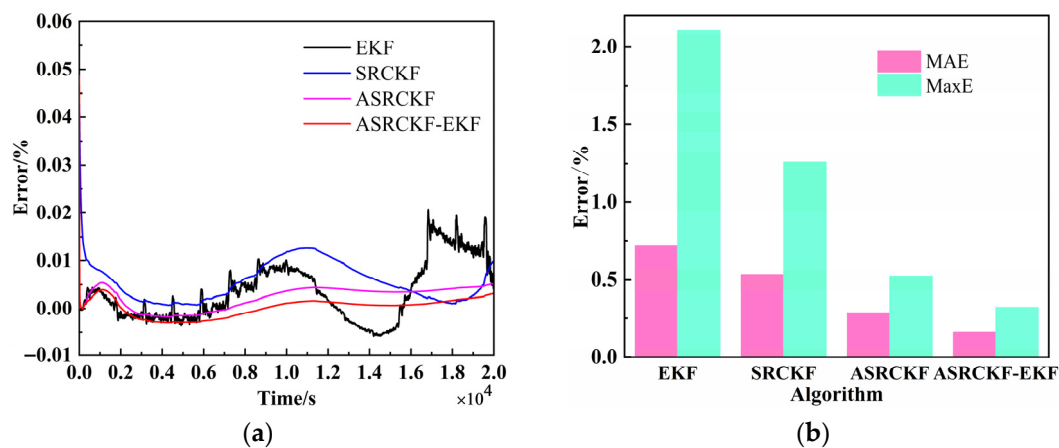


Figure 15. SOC Error Analysis: (a) SOC Estimation Error; (b) SOC Error Comparison.

Table 3 provides precise quantitative performance metrics. The ASRCKF-EKF achieves excellent performance with MAE = 0.16% and MaxE = 0.32%, representing reductions of 78% and 85%, respectively, compared to EKF. Particularly noteworthy is that among the three driving conditions to be compared, UDDS condition exhibits the most pronounced performance disparity between algorithms: EKF's MaxE reaches 2.11% while ASRCKF-EKF maintains only 0.32%, a nearly seven-fold difference. This significant disparity highlights the critical role of the adaptive mechanism in handling frequent operating condition variations.

Table 3. Performance comparison of the proposed algorithm under the UDDS condition.

Algorithm	MAE (%)	MaxE (%)
ASRCKF-EKF	0.16	0.32
ASRCKF	0.28	0.52
SRCKF	0.53	1.26
EKF	0.72	2.11

The bar chart in Figure 15b intuitively presents the hierarchical distribution of algorithm performance. The SRCKF shows notable performance degradation under UDDS conditions, indicating that numerical stability improvements alone are insufficient to address the complex challenges of urban driving cycles. The ASRCKF further improves error metrics through the introduction of adaptive mechanisms, with the ASRCKF-EKF joint framework ultimately achieving optimal performance.

Figure 16 further illustrates the SOH estimation error evolution under UDDS conditions. Similarly to the NEDC condition, the error curve exhibits distinct phase-dependent characteristics but with larger fluctuation amplitudes. The initial phase ($0 \sim 0.6 \times 10^4$ s) maintains extremely low error levels; the mid-phase ($0.8 \sim 1.2 \times 10^4$ s) shows a local peak of approximately 0.28%, subsequently declining to around 0.2% and maintaining relative stability; the final phase (after 1.6×10^4 s) demonstrates rapid error growth to 0.7%. The frequent dynamic variations intensify parameter identification challenges, particularly in the later stages of cumulative charge–discharge cycles. Despite the final error reaching 0.7%, it still satisfies the engineering requirements for SOH estimation accuracy in BMS systems.

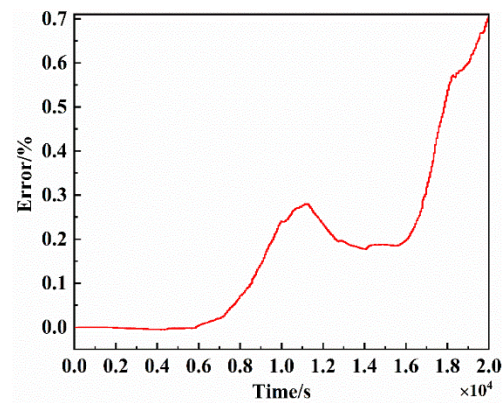


Figure 16. SOH estimation error.

5.4. Performance Verification of Algorithm with 3% Data Collection Error

Based on the performance verification results across three operating conditions with intentionally introduced 3% data collection error, the proposed ASRCKF-EKF framework demonstrates exceptional robustness and fault tolerance in practical scenarios where sensor measurement uncertainties are inevitable. As evidenced in subfigures Figure 17, the dual-loop estimation system maintains superior convergence characteristics and minimal error propagation even under significant noise perturbations: the SOC estimation accuracy degrades marginally from the ideal case, with maximum errors constrained below 0.5% across all driving profiles, while the error metrics (Figure 17b,d,f) reveal that the adaptive mechanism effectively suppresses noise amplification through dynamic covariance adjustment, keeping estimation variances stable throughout extended operation periods. Notably, the algorithm's resilience is particularly pronounced during the aggressive urban cycle (Figure 17e,f), where frequent acceleration–deceleration transients and current fluctuations typically challenge conventional filtering approaches, yet the ASRCKF-EKF maintains comparable performance to benign conditions through its square root formulation that preserves numerical stability and its bidirectional coupling that allows SOH feedback to compensate for parameter drift-induced SOC errors. This comprehensive validation under non-ideal measurement conditions substantiates the framework's practical viability for real-world battery management systems, where sensor precision limitations and environmental disturbances are unavoidable operational constraints.

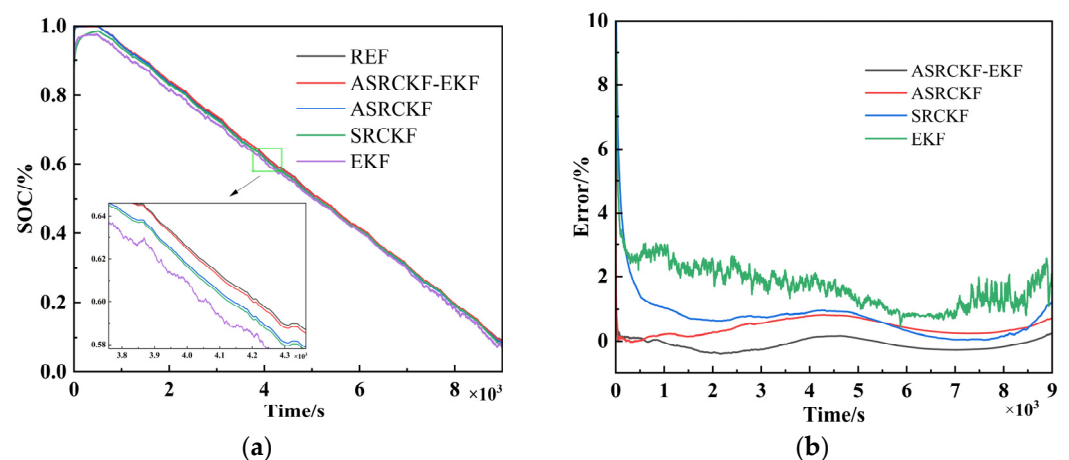


Figure 17. Cont.

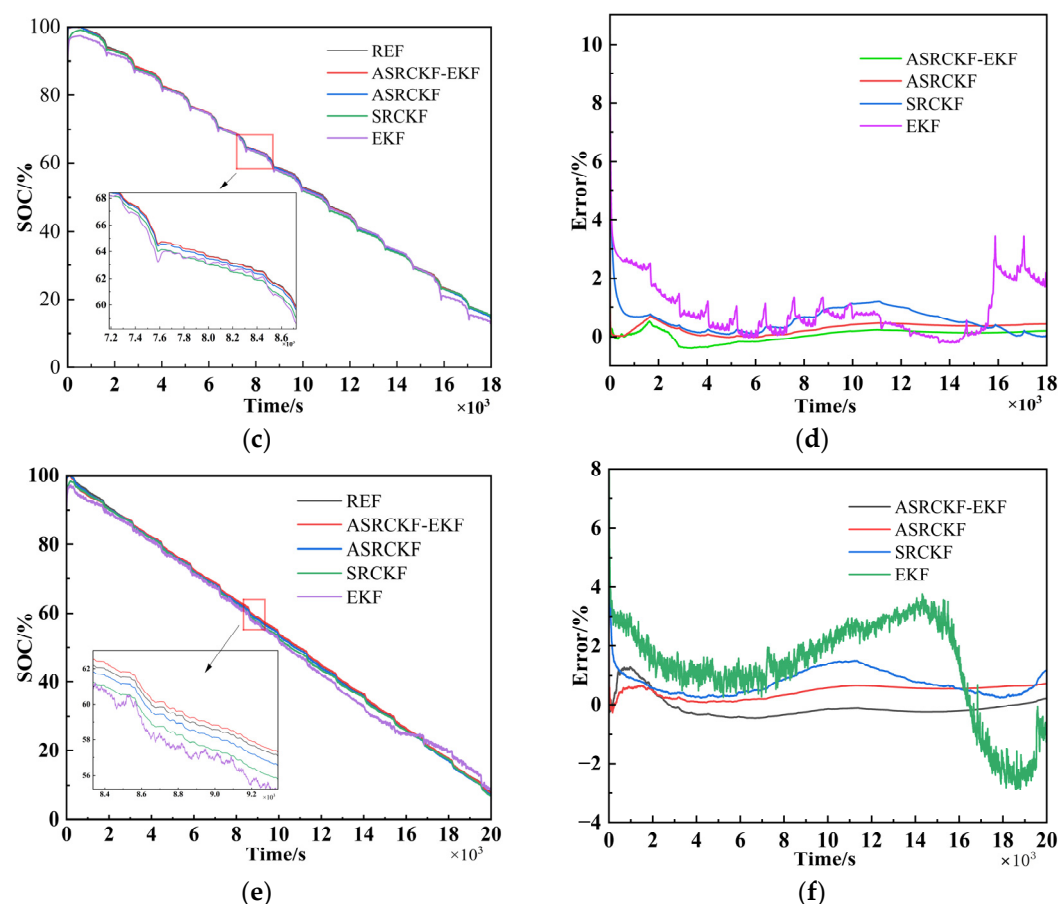


Figure 17. SOC and Error curves under different test conditions with 3% data collection error. (a) SOC estimation under HWFET condition; (b) error percentage under HWFET condition; (c) SOC estimation under NEDC condition; (d) error percentage under NEDC condition; (e) SOC estimation under UDDS condition; (f) error percentage under UDDS condition.

5.5. Comparative Analysis of Results

A comprehensive analysis of the test results across three standard driving cycles reveals both the vertical evolutionary patterns of algorithm performance and horizontal adaptability to different operating conditions. From the perspective of vertical technical evolution, the four algorithms form a clear performance gradient: the conventional EKF serves as the baseline with an average MAE of 0.81% and MaxE reaching 2.77% across the three driving cycles; the SRCKF, through improved numerical stability, reduces the average MAE to 0.47% (a 42% reduction) though MaxE remains at 1.21%; the ASRCKF, by introducing adaptive noise covariance mechanisms, further reduces the average MAE to 0.26% (45% reduction compared to SRCKF), demonstrating the critical role of adaptive mechanisms; ultimately, the ASRCKF-EKF achieves optimal performance with average MAE = 0.13% and MaxE = 0.31% through integrated online parameter identification, representing an additional 50% improvement over the standalone ASRCKF. This progressive enhancement not only validates the independent contributions of each technical component but, more importantly, demonstrates their synergistic amplification effects.

From the perspective of horizontal cross-condition comparison, significant differences in algorithm robustness are evident. The ASRCKF-EKF exhibits minimal performance variation across the three driving cycles (MAE range of only 0.12–0.16%), whereas the EKF's MaxE values under HWFET, NEDC, and UDDS are 2.76%, 3.45%, and 2.11%, respectively, showing fluctuation amplitudes exceeding 60%, reflecting high sensitivity to operating condition variations. Particularly under the most challenging UDDS urban driving cycle,

the ASRCKF-EKF maintains stable performance with $\text{MaxE} = 0.32\%$, while the EKF and SRCKF errors reach 2.11% and 1.28%, respectively, expanding the performance gap to 6.6-fold and 4-fold. SOH estimation exhibits similar trends, with the ASRCKF-EKF constraining errors within 0.7%, far exceeding engineering requirements. These results conclusively demonstrate that the proposed ASRCKF-EKF framework not only achieves multi-level technical innovation theoretically but also exhibits superior accuracy, stability, and adaptability in practical applications, providing a reliable technical solution for next-generation intelligent BMS.

6. Conclusions

In this paper, the ASRCKF algorithm is developed by incorporating adaptive noise covariance estimation into the SRCKF framework, and a joint ASRCKF-EKF architecture is proposed for simultaneous SOC-SOH estimation of lithium-ion batteries. The two-layer estimation structure employs ASRCKF for SOC tracking and EKF for online parameter identification to address model uncertainties and aging effects. The proposed framework is validated under HWFET, NEDC, and UDDS driving cycles. Results demonstrate that the ASRCKF-EKF algorithm achieves MAE below 0.16% and MaxE below 0.33% for SOC estimation across all conditions, outperforming conventional EKF by over 80%. The SOH estimation error remains within 0.7%, meeting practical BMS requirements. The high-precision SOC estimation (error $<0.33\%$) of the proposed framework can significantly improve range prediction and user experience in electric vehicles, while the continuous SOH monitoring capability (error $<0.7\%$) supports predictive maintenance strategies to extend battery lifespan and reduce operating costs. Regarding embedded implementation, the computational load of the ASRCKF algorithm is approximately 2.1 times that of standard EKF, with an execution time of about 6–10 milliseconds per cycle and a memory requirement of approximately 28–35 KB, making it suitable for modern automotive-grade microcontrollers (e.g., ARM Cortex-M4, 168 MHz), and its square root formulation ensures numerical stability and long-term operational reliability. In summary, the consistent performance under diverse operating conditions confirms the robustness and accuracy of the proposed joint estimation framework, providing a more intelligent and industrially viable battery state monitoring solution for next-generation electric vehicle applications.

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Abbreviations

Term	Definition
SOC	state of charge
SOH	state of health
EKF	extended Kalman filter
UKF	unscented Kalman filter
CKF	cubature Kalman filter
SRCKF	square root cubature Kalman filter
SRUKF	square root unscented Kalman filter
HWFET	Highway Fuel Economy Test
NEDC	New European Driving Cycle
UDDS	Urban Dynamometer Driving Schedule
REF	reference true value

References

- Demirci, O.; Taskin, S.; Schaltz, E.; Demirci, B.A. Review of battery state estimation methods for electric vehicles-Part I: SOC estimation. *J. Energy Storage* **2024**, *87*, 111435. [\[CrossRef\]](#)
- Yang, F.; Shi, D.; Mao, Q.; Lam, K.-h. Scientometric research and critical analysis of battery state-of-charge estimation. *J. Energy Storage* **2023**, *58*, 106283. [\[CrossRef\]](#)
- Hernandez-Melendez, L.E.; Escobar-Jiménez, R.F.; Canela-Sánchez, I.J.; García-Beltrán, C.D.; Borja-Jaimes, V. Experimental Estimation of Heat Transfer Coefficients in a Heat Exchange Process Using a Dual-Extended Kalman Filter. *Processes* **2025**, *13*, 21176. [\[CrossRef\]](#)
- Khodadadi, H.; Jazayeri-Rad, H. Applying a dual extended Kalman filter for the nonlinear state and parameter estimations of a continuous stirred tank reactor. *Comput. Chem. Eng.* **2011**, *35*, 2426–2436. [\[CrossRef\]](#)
- Paruthipulli Kalarikkal, R.M.; Subbaiah, J. Modified Dual EKF with Machine Learning Model for Fouling Prediction of Industrial Heat Exchanger. *Korean J. Chem. Eng.* **2024**, *41*, 1013–1027. [\[CrossRef\]](#)
- Zhang, Y.; Xia, Q.; Yang, C.; Song, R.; Wu, D.; Zhang, X.; Zhou, R.; Ma, S. Dual-Mode Square Root Cubature Kalman Filter for Miniaturized Underwater Profiler Dead Reckoning. *J. Mar. Sci. Eng.* **2024**, *12*, 1146. [\[CrossRef\]](#)
- Muenthong, S.; Chattakarn, S.; Lersbamrungsuk, V. Fouling Detection in Heat Exchangers using Extended Kalman Filter. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *778*, 012083. [\[CrossRef\]](#)
- Hildebrand, S.; Friesen, A.; Haetge, J.; Meier, V.; Schappacher, F.; Winter, M. Delayed Thermal Runaway Investigation on Commercial 2.6 Ah NCM-LCO Based 18650 Lithium Ion Cells with Accelerating Rate Calorimetry. *ECS Trans.* **2016**, *74*, 85–94. [\[CrossRef\]](#)
- Wu, Z.; Wang, G.; Xie, Z.; He, Y.; Lu, X. Lithium battery SOC estimation based on whale optimization algorithm and un-scented Kalman filter. *J. Renew. Sustain. Energy* **2020**, *12*, 065501. [\[CrossRef\]](#)
- Fahmy, H.M.; Hasanien, H.M.; Alsaleh, I.; Ji, H.; Alassaf, A. State of health estimation of lithium-ion battery using dual adaptive unscented Kalman filter and Coulomb counting approach. *J. Energy Storage* **2024**, *88*, 111557. [\[CrossRef\]](#)
- Vazquez-Arenas, J.; Fraser, R.; Fowler, M.; Afshar, S.; Stevens, M. Battery state of the charge estimation using Kalman filtering. *J. Power Sources* **2013**, *239*, 294–307. [\[CrossRef\]](#)
- 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. [\[CrossRef\]](#)
- Zeng, Y.; Li, Y.; Yang, T. State of Charge Estimation for Lithium-Ion Battery Based on Unscented Kalman Filter and Long Short-Term Memory Neural Network. *Batteries* **2023**, *9*, 358. [\[CrossRef\]](#)
- Yang, B.; Wang, Y.; Zhan, Y. Lithium Battery State-of-Charge Estimation Based on a Bayesian Optimization Bidirectional Long Short-Term Memory Neural Network. *Energies* **2022**, *15*, 4670. [\[CrossRef\]](#)
- Hannan, M.A.; Hoque, M.M.; Hussain, A.; Yusof, Y.; Ker, P.J. State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations. *IEEE Access* **2018**, *6*, 19362–19378. [\[CrossRef\]](#)
- Braun, J.; Júnior, A.O.; Berger, G.; Pinto, V.H.; Soares, I.N.; Pereira, A.I.; Lima, J.; Costa, P. A robot localization proposal for the Robot AI Factory 4.0: A novel robotics competition within the Industry 4.0 concept. *Front. Robot. AI* **2022**, *9*, 1023590. [\[CrossRef\]](#)
- Hannan, M.A.; How, D.N.T.; Lipu, M.S.H.; Ker, P.J.; Dong, Z.Y.; Mansur, M.; Blaabjerg, F. SOC estimation of Li-ion batteries with learning rate-optimized deep fully convolutional network. *IEEE Trans. Power Electron.* **2020**, *36*, 7349–7353. [\[CrossRef\]](#)
- Ma, Y.; Wang, S.; Liu, G.; Tian, G.; Zhang, J.; Liu, R. State-of-charge balancing strategy of battery energy storage units with a voltage balance function for a Bipolar DC microgrid. *Appl. Energy* **2024**, *356*, 122367. [\[CrossRef\]](#)

19. Deng, Z.; Lin, X.; Huang, Z.; Meng, J.; Zhong, Y.; Ma, G.; Zhou, Y.; Shen, Y.; Ding, H.; Huang, Y. Recent progress on advanced imaging techniques for lithium-ion batteries. *Adv. Energy Mater.* **2021**, *11*, 2000806. [[CrossRef](#)]
20. Yu, X.; Ma, Z.; Wen, J. Joint estimation of SOH and RUL for lithium batteries based on variable frequency and model integration. *Int. J. Electrochem. Sci.* **2024**, *19*, 100842. [[CrossRef](#)]
21. Liu, Y.; Cai, T.; Liu, J.; Gao, M.; He, Z. State of charge estimation for lithium batteries based on an unscented H-infinity filter. *J. Electr. Eng. Technol.* **2020**, *1*, 2529–2538. [[CrossRef](#)]
22. Zhang, D.; He, Z.; Guan, J.; Tang, S.; Shen, C. Heat transfer and flow visualization of pulsating heat pipe with silica nanofluid: An experimental study. *Int. J. Heat Mass Transf.* **2022**, *183*, 122100. [[CrossRef](#)]

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