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Online Parameter Optimization of an Adaptive Extended Kalman Filter Using the Starfish Optimization Algorithm for Lithium-Ion Battery State-of-Charge Estimation

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ABSTRACT: Accurate state-of-charge (SOC) estimation is an essential function of battery management systems (BMSs). Model-driven methods are widely used for SOC estimation because of their high estimation accuracy and moderate computational cost. However, the performance of the adaptive extended Kalman filter (AEKF) is highly dependent on the settings of the noise covariance parameters, which generally require case-specific tuning for different batteries and operating conditions. Accordingly, an starfish optimization algorithm (SFOA)-AEKF framework is developed to adaptively optimize the AEKF noise covariance parameters under dynamic operating conditions using the starfish optimization algorithm (SFOA). First, the battery model parameters are identified online using forgetting factor recursive least squares (FFRLS) and incorporated into the AEKF for SOC estimation. Subsequently, SFOA uses historical data from each optimization interval to update the filter noise covariance parameters, allowing the AEKF to adapt to current operating conditions. The weighting coefficient is also evaluated to determine the balance between SOC and terminal-voltage errors during optimization. The proposed method is evaluated under the US06 Driving Schedule (US06), Federal Urban Driving Schedule (FUDS), and Beijing Dynamic Stress Test (BJDST) driving cycles at 25°C and 45°C with both matched and mismatched initial SOC conditions and is compared with Extended Kalman Filter (EKF), AEKF, particle swarm optimization (PSO)-AEKF, genetic algorithm (GA)-AEKF, and grey wolf optimization (GWO)-AEKF. The results show that SFOA-AEKF improves SOC estimation accuracy, convergence, and robustness under different driving cycles, temperatures, and initial SOC conditions. The method is suitable for SOC estimation in dynamic applications, particularly in electric vehicle Battery Management Systems (BMSs).

KEYWORDS: Adaptive state-of-charge estimation; adaptive extended Kalman filter; starfish optimization algorithm; noise covariance optimization

1 Introduction

The global transition toward net-zero emissions has accelerated the adoption of electric vehicles (EVs), making them an important technology for transportation decarbonization. According to the International Energy Agency's Global EV Outlook 2025, global electric car sales exceeded 17 million units in 2024, increasing by more than 25% and accounting for over 20% of new car sales worldwide [1]. This rapid market expansion has increased the demand for reliable battery technologies. Lithium-ion batteries are widely used as the primary energy source for EVs because of high energy density, low self-discharge, and long cycle life. However, the nonlinear and coupled electrochemical behavior of lithium-ion batteries poses challenges to battery management. The battery management system (BMS) therefore plays a key role in ensuring safe,

reliable, and efficient battery operation. Its main functions include data acquisition and monitoring, state-of-charge (SOC) estimation, state-of-health (SOH) estimation, cell balancing, thermal management, and fault detection and diagnosis [2].

Battery modeling is a fundamental component of BMSs. The main battery models include electrochemical models, equivalent circuit models, and data-driven models. The electrochemical model (EM) is the most physics-based battery model. It is based on lithium-ion diffusion and electrochemical reactions in the electrodes, separator, and electrolyte. The EM consists of numerous coupled differential equations, making real-time implementation difficult. Representative electrochemical models include the pseudo-two-dimensional (P2D) model [3] and the single-particle model (SPM) [4]. The equivalent circuit model (ECM) uses electrical components to represent battery behavior. RC networks represent battery polarization behavior, and some ECMs incorporate hysteresis effects [5]. The ECM provides a balance between modeling accuracy and computational cost, making it suitable for real-time applications. Representative ECMs include the Rint model, the Thevenin model, the Partnership for a New Generation of Vehicles (PNGV) model, and first- and second-order RC models [6]. Data-driven models (DDMs) are generally regarded as black-box models. They learn battery behavior from battery operating data and provide high modeling accuracy [7]. However, DDMs require reliable and representative training data, and their generalization ability is limited under unseen operating conditions [8].

Battery parameter identification methods can be classified into experimental characterization, offline optimization, and online recursive identification. Experimental characterization methods use pulse tests, hybrid pulse power characterization (HPPC) [9], or electrochemical impedance spectroscopy (EIS) [10] to determine the ohmic resistance, polarization parameters, and time constants. The identified parameters are often stored in lookup tables as functions of SOC and temperature. Offline optimization methods estimate model parameters by minimizing the error between measured and simulated terminal voltages. These methods include least squares [11], nonlinear least squares [12], and metaheuristic algorithms such as genetic algorithm (GA) [13], particle swarm algorithm (PSO) [14], grey wolf optimization (GWO) [15], firefly algorithm (FA) [16], and whale optimization algorithm (WOA) [17]. Online recursive identification methods update the model parameters sequentially using measured current and voltage. Representative methods include recursive least squares (RLS), forgetting factor recursive least squares (FFRLS) [18], decoupled weighted recursive least squares (DWRLS) [19].

SOC estimation is a fundamental BMS function that provides information on the remaining battery charge and available energy. Inaccurate SOC estimation may compromise electric vehicle reliability, increase range anxiety, and lead to inappropriate charging or discharging decisions. Under severe circumstances, such errors may result in overcharge or overdischarge, accelerating battery degradation and increasing the risk of thermal runaway or other safety hazards. The principal SOC estimation techniques include coulomb counting (CC), open-circuit voltage (OCV)-based methods, data-driven methods, and model-driven methods. The CC method estimates SOC by integrating the measured battery current over time. However, errors in the initial SOC, measured current, and battery capacity accumulate over time. The OCV method estimates SOC from the OCV-SOC relationship. However, accurate OCV measurement requires the battery to rest until it reaches equilibrium. Under load, the terminal voltage differs from the OCV because of internal resistance and polarization, limiting its use for real-time estimation. Data-driven methods learn the nonlinear relationship between measurable battery variables and SOC directly from experimental data and are generally treated as black-box approaches. They can provide high estimation accuracy under operating conditions represented in the training dataset but require sufficient, representative, and reliable data, as well as considerable computational resources for model training and implementation. Representative approaches include convolutional neural networks (CNNs) [20] and physics-informed neural networks (PINNs) [21]. In

contrast, model-driven methods combine a battery model with a state observer to estimate SOC. They offer a practical balance among estimation accuracy, computational complexity, and physical interpretability. More importantly, these methods enable the analysis of internal battery dynamics and physically meaningful model parameters. Nevertheless, their estimation performance strongly depends on the accuracy of the selected battery model and its identified parameters. Representative model-based SOC estimation methods include the extended Kalman filter (EKF) [22], adaptive extended Kalman filter (AEKF) [23], unscented Kalman filter (UKF) [24], particle filter (PF) [25], sliding-mode observers (SMO) [26], H-infinity observers [27], dual Kalman filters [28], and adaptive UKF methods [29].

Model-driven methods are widely used for battery SOC estimation. However, the estimation performance is highly sensitive to the settings of the process and measurement noise covariance matrices. To improve the adaptability of the AEKF under dynamic driving conditions, this study proposes an online parameter optimization framework based on the starfish optimization algorithm (SFOA). Although SFOA provides strong global search capability, its iterative optimization increases the computational burden. In contrast, the AEKF offers efficient online estimation but is sensitive to the initial covariance settings. Therefore, SFOA is periodically employed to optimize the AEKF noise covariance parameters using historical operating data. This strategy allows the filter to adapt to varying battery operating conditions while limiting unnecessary computational cost and abrupt parameter changes, thereby improving SOC estimation performance. The main contributions are summarized as follows.

- An integrated FFRLS-SFOA-AEKF framework for online battery parameter identification and adaptive SOC estimation under dynamic operating conditions.
- An SFOA-based periodic optimization strategy using historical data to optimize the AEKF noise covariance parameters and reduce case-specific tuning.
- A sensitivity analysis of the weighting coefficient α to investigate the trade-off between SOC and terminal-voltage errors in the optimization objective.
- Comprehensive validation under different driving cycles, temperatures, and initial SOC conditions to demonstrate robustness.

2 Methodology

Model uncertainty and time-varying disturbances under dynamic operating conditions result in significant SOC estimation errors. SFOA optimizes the AEKF noise covariance matrices to reduce the sensitivity of the AEKF to noise covariance parameters. The proposed framework enables rapid adaptation to varying battery operating conditions while maintaining estimation accuracy and real-time performance. Fig. 1 presents the proposed method.

2.1 Battery Modeling

The dynamic load profiles were obtained from the University of Maryland. The tested battery was an INR18650-20 lithium-ion cell. A second-order RC equivalent circuit model was used to represent the battery dynamics, in which the two RC networks represented the charge-transfer and diffusion polarization. Fig. 2 and Eqs. (1)–(3) present the battery model and its governing equations, respectively. V_{oc} denotes the open-circuit voltage, V_t denotes the terminal voltage, and I denotes the terminal current. R_0 represents the ohmic resistance, whereas R_1C_1 and R_2C_2 represent the charge-transfer and diffusion polarization, respectively.

$$V_t = V_{oc} - V_1 - V_2 - iR_0 \quad (1)$$

$$V_1 = \frac{i}{C_1} - \frac{V_1}{R_1 \times C_1} \quad (2)$$

$$V_2 = \frac{i}{C_2} - \frac{V_2}{R_2 \times C_2} \quad (3)$$

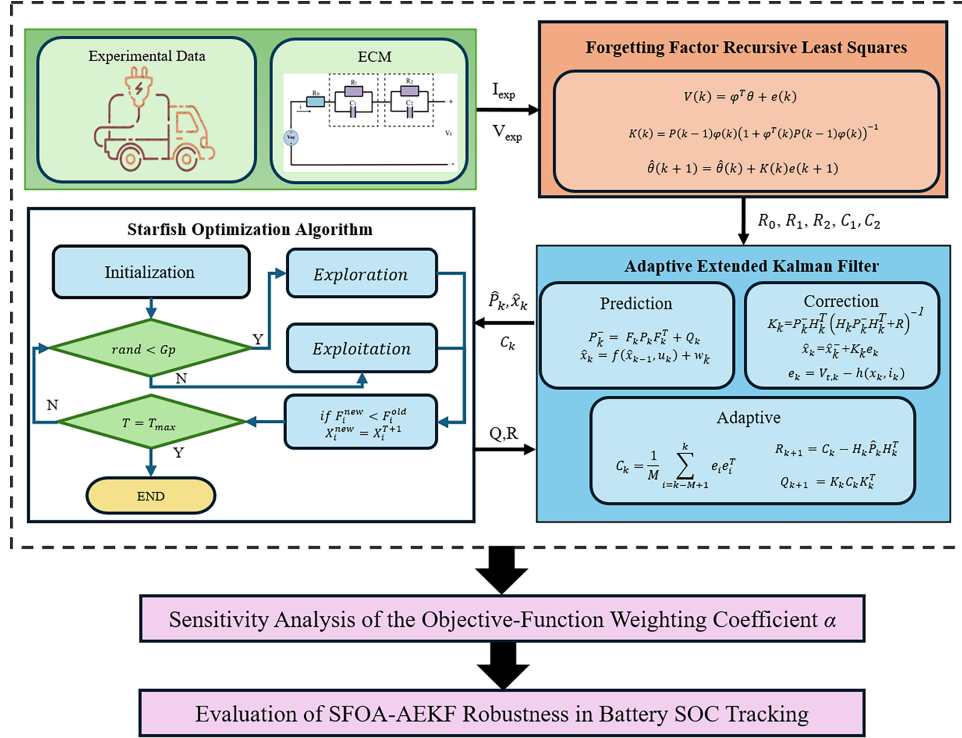


Figure 1: Flowchart of the proposed method.

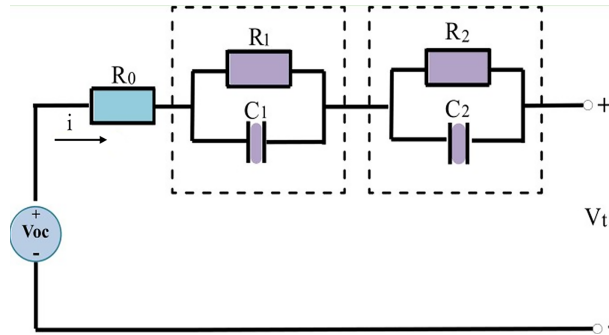


Figure 2: Second-order RC battery model.

2.2 Parameter Identification

The battery parameters were identified using the forgetting factor recursive least squares (FFRLS). Compared with the conventional method, FFRLS introduces a forgetting factor that assigns greater weight to recent data and less weight to historical data, thereby improving parameter tracking under dynamic operating conditions. The second-order RC equivalent circuit model was first transformed into the Laplace domain, as expressed in Eqs. (4)–(7).

$$V_{OC}(s) - V_t(s) = I(s) \left(R_0 + \frac{R_1}{R_1 C_1 s + 1} + \frac{R_2}{R_2 C_2 s + 1} \right) \quad (4)$$

$$G(s) = \frac{V(s)}{I(s)} = \left(\frac{R_0 + R_1 + R_2 + (R_0 \tau_1 + R_0 \tau_2 + R_2 \tau_1 + R_1 \tau_2)s + \tau_1 \tau_2 s^2}{1 + (\tau_1 + \tau_2)s + \tau_1 \tau_2 s^2} \right) \quad (5)$$

$$\begin{cases} a = R_0 \\ b = \tau_1 \tau_2 \\ c = \tau_1 + \tau_2 \\ d = R_0 + R_1 + R_2 \\ e = (R_0 \tau_1 + R_0 \tau_2 + R_2 \tau_1 + R_1 \tau_2) \end{cases} \quad (6)$$

$$G(s) = \frac{V(s)}{I(s)} = \frac{d + es + abs^2}{1 + cs + bs^2} \quad (7)$$

To preserve system consistency before and after discretization, the bilinear transformation was adopted. By substituting $s = \frac{2(1-Z^{-1})}{T(1+Z^{-1})}$ into the transfer function $G(s) = \frac{V(s)}{I(s)}$, the discrete transfer function was derived, as shown in Eq. (8).

$$G(Z^{-1}) = \frac{(dT^2 - 2Te + 4ab)Z^{-2} + (2dT^2 - 8ab)Z^{-1} + (dT^2 + 2Te + 4ab)}{(T^2 - 2Tc + 4b)Z^{-2} + (2T^2 - 8b)Z^{-1} + (T^2 + 2Te + 4b)} \quad (8)$$

To simplify parameter identification, the coefficients k_1 to k_5 were introduced. Substituting these coefficients into Eq. (8) yielded Eqs. (9) and (10).

$$\begin{cases} k_1 = \frac{(2T^2 - 8b)}{(T^2 + 2Tc + 4b)} \\ k_2 = \frac{(T^2 - 2Tc + 4b)}{(T^2 + 2Tc + 4b)} \\ k_3 = \frac{(dT^2 + 2Te + 4ab)}{(T^2 + 2Tc + 4b)} \\ k_4 = \frac{(2dT^2 - 8ab)}{(T^2 + 2Tc + 4b)} \\ k_5 = \frac{(dT^2 - 2Te + 4ab)}{(T^2 + 2Tc + 4b)} \end{cases} \quad (9)$$

$$G(Z^{-1}) = \frac{V(Z^{-1})}{I(Z^{-1})} = \frac{k_5 Z^{-2} + k_4 Z^{-1} + k_3}{1 - k_2 Z^{-2} - k_1 Z^{-1}} \quad (10)$$

For parameter identification, the regression vector $\varphi(k)$ and parameter vector θ were defined, where $e(k)$ denotes the prediction error. By combining Eqs. (11) and (12), the regression model in Eq. (13) was obtained, for FFRLS-based parameter identification.

$$V(k) = k_1 V(k-1) + k_2 V(k-2) + k_3 V(k) + k_4 I(k-1) + k_5 I(k-2) \quad (11)$$

$$\begin{cases} \varphi(k) = [V(k-1), V(k-2), V(k), I(k-1), I(k-2)]^T \\ \theta = [k_1, k_2, k_3, k_4, k_5]^T \end{cases} \quad (12)$$

$$V(k) = \varphi^T \theta + e(k) \quad (13)$$

Eq. (14) calculates the gain $K(k)$, which determines the weighting between historical information and newly acquired measurements. Eq. (15) updates the error covariance matrix $P(k)$. In Eq. (16), $V(k+1)$ denotes the measured output at sampling instant $k+1$, whereas $\varphi^T(k+1)\hat{\theta}(k)$ represents the predicted output of the current model. The prediction error $e(k+1)$ is obtained from the difference between the measured and predicted outputs. $\hat{\theta}(k)$ which denotes the *a priori* parameter estimate at sampling instant k , is updated using the weighted prediction error to obtain the parameter estimate $\hat{\theta}(k+1)$, as expressed in Eq. (17).

$$K(k) = P(k-1)\varphi(k)(\varphi^T(k)P(k-1)\varphi(k))^{-1} \quad (14)$$

$$P(k) = \lambda^{-1}[P(k-1) - K(k)\varphi^T(k)P(k-1)] \quad (15)$$

$$e(k+1) = V(k+1) - \varphi^T(k+1)\hat{\theta}(k) \quad (16)$$

$$\hat{\theta}(k+1) = \hat{\theta}(k) + K(k)e(k+1) \quad (17)$$

According to Eq. (18), the identification model was reformulated in terms of the coefficients a, b, c, d , and e , which are related to the battery parameters through Eq. (9). FFRLS was used to estimate these coefficients online. By combining Eqs. (6) and (18), the five parameters of the second-order RC equivalent circuit model were obtained, as expressed in Eq. (19).

$$\begin{cases} a = \frac{k_3 + k_5 - k_4}{1 + k_1 - k_2} \\ b = \frac{T^2(1 + k_1 - k_2)}{4(1 - k_3 - k_5)} \\ c = \frac{T(1 + k_2)}{1 - k_1 - k_2} \\ d = \frac{k_3 + k_4 + k_5}{1 - k_3 - k_5} \\ e = \frac{T(k_3 - k_5)}{1 - k_1 - k_2} \end{cases} \quad (18)$$

$$\begin{cases} R_0 = a \\ R_1 = \frac{\tau_1(d - a) - ac - e}{\tau_1 - \tau_2} \\ R_2 = d - a - R_1 \\ C_1 = \frac{\tau_1}{R_1} \\ C_2 = \frac{\tau_2}{R_2} \\ \tau_1, \tau_2 = \frac{-c \pm \sqrt{c^2 - 4b}}{2} \end{cases} \quad (19)$$

2.3 SOC Estimation

The AEKF was used for SOC estimation. The state vector, continuous-time state equation, and measurement function are defined in Eqs. (20)–(22), respectively.

$$x = [\text{SOC } V_1 \ V_2]^T \quad (20)$$

$$\dot{x} = \begin{bmatrix} -\frac{i}{3600Ah} \\ \frac{i}{C_1} - \frac{V_1}{R_1 \times C_1} \\ \frac{i}{C_2} - \frac{V_2}{R_2 \times C_2} \end{bmatrix} \quad (21)$$

$$V_t = h(x, i) = V_{oc}(SOC) - iR_0 - V_1 - V_2 \quad (22)$$

Since the EKF was implemented in discrete time, the continuous-time state equation in Eq. (21) was discretized using the sampling interval T_s . The resulting discrete-time process function is given in Eq. (23). The corresponding Jacobian matrices F_k and H_k are given in Eqs. (24) and (25), respectively.

$$f(x_k, i_k) = \begin{bmatrix} SOC_k - \frac{T_s}{3600Ah} \cdot i_k \\ e^{\frac{-T_s}{R_1 C_1}} \cdot V_{1,k} + R_1 \left(1 - e^{\frac{-T_s}{R_1 C_1}}\right) \cdot i_k \\ e^{\frac{-T_s}{R_2 C_2}} \cdot V_{2,k} + R_2 \left(1 - e^{\frac{-T_s}{R_2 C_2}}\right) \cdot i_k \end{bmatrix} \quad (23)$$

$$F_k = \frac{\partial f}{\partial x} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{\frac{-T_s}{R_1 C_1}} & 0 \\ 0 & 0 & e^{\frac{-T_s}{R_2 C_2}} \end{bmatrix} \quad (24)$$

$$H_k = \frac{\partial h}{\partial x} = \left[\frac{\partial V_{oc}}{\partial SOC} - 1 - 1 \right] \quad (25)$$

In the prediction stage, Eq. (26) predicts the state estimate $\hat{x}_k$ from the previous states $\hat{x}_{k-1}$ and the input u_k , where w_k denotes the Gaussian process noise. Eq. (27) updates the predicted error covariance matrix $\hat{P}_k$, where F_k is the state transition matrix and Q_k is the process noise covariance matrix.

$$\hat{x}_k = f(\hat{x}_{k-1}, u_k) + w_k \quad (26)$$

$$\hat{P}_k = F_k P_{k-1} F_k^T + Q_k \quad (27)$$

During the correction stage, the prior state estimate is updated using the measured terminal voltage. Eq. (28) defines the Kalman gain K_k , where H_k denotes the observation matrix. The error e_k is calculated as the difference between the measured value $V_{t,k}$ and the predicted value $h(x_k, i_k)$. Subsequently, the posterior state estimate and the corresponding error covariance P_{k+1} are updated based on the Kalman gain and the correction, E is the Identity matrix.

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \quad (28)$$

$$e_k = V_{t,k} - h(x_k, i_k) \quad (29)$$

$$\hat{x}_{k+1}^- = \hat{x}_k^- + K_k e_k \quad (30)$$

$$P_{k+1} = (E - K_k H_k) \hat{P}_k \quad (31)$$

The AEKF adaptively adjusts the noise covariance matrices using the innovation sequence e_i . A moving window of length M is employed to calculate the innovation covariance based on the measured and estimated

terminal voltages. The process and measurement noise covariance matrices are then updated using Eqs. (33) and (34).

$$C_k = \frac{1}{M} \sum_{i=k-M+1}^k e_i e_i^T \quad (32)$$

$$Q_{k+1} = K_k C_k K_k^T \quad (33)$$

$$R_{k+1} = C_k - H_k \hat{P}_k H_k^T \quad (34)$$

2.4 Optimization Algorithm

SFOA was employed to optimize the AEKF noise covariance matrices. SFOA consists of two search phases: exploration and exploitation. The exploration phase simulates the foraging behavior of starfish, whereas the exploitation phase combines the foraging and regeneration strategies [30].

2.4.1 Initialization

In the initialization stage, the initial population is generated according to Eq. (35), where X denotes the population matrix, N is the population size, and D is the problem dimension. The initialization process is defined in Eq. (36), where ub and lb denote the upper and lower bounds, respectively, and r_1 is a random number in the range $[0, 1]$.

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1D} \\ X_{21} & X_{22} & \cdots & X_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ X_{N1} & X_{N2} & \cdots & X_{ND} \end{bmatrix}_{N \times D} \quad (35)$$

$$\begin{cases} X_{ij} = lb_j + r_1 \cdot (ub_j - lb_j) \\ i = 1, 2, \dots, N, j = 1, 2, \dots, D \end{cases} \quad (36)$$

2.4.2 Exploration Phase

The exploration phase simulates the foraging behavior of starfish. SFOA uses the five arms of a starfish to represent different search directions. In this phase, the algorithm adopts five-dimensional search for $D > 5$ and unidimensional search for $D \leq 5$. The search position for the five-dimensional strategy is updated according to Eq. (37). $Y_{i,p}^T$ denotes the updated position of the i -th starfish, $X_{i,p}^T$ denotes its current position, and, $X_{best,p}^T$ denotes the current best position. p represents five randomly selected dimensions from the D -dimensional search space. Here, r_2 is a random number, a_1 and θ are calculated using Eqs. (38) and (39), respectively.

$$\begin{cases} Y_{i,p}^T = X_{i,p}^T + a_1 \left(X_{best,p}^T - X_{i,p}^T \right) \cos \theta, r_2 \leq 0.5 \\ Y_{i,p}^T = X_{i,p}^T - a_1 \left(X_{best,p}^T - X_{i,p}^T \right) \sin \theta, r_2 > 0.5 \end{cases} \quad (37)$$

$$a_1 = (2 \cdot r_3 - 1) \cdot \pi \quad (38)$$

$$\theta = \frac{\pi}{2} \cdot \frac{T}{T_{max}} \quad (39)$$

T is the current iteration, T_{max} is the maximum number of iterations. The $\cos$ and $\sin$ determine the probability of the starfish arms moving to the left or right, and r_3 is a random number. The parameter θ

varies with the iteration number, whereas a_l and θ regulate the influence of the distance between the current position and the best position.

When the optimization problem dimension is less than or equal to 5, SFOA adopts a one-dimensional search strategy to update the starfish position. Two starfish are randomly selected from the population, and only one arm is used to approach the prey. In Eq. (40), $(X_{k1,p}^T$ and $X_{k2,p}^T)$ denote the positions of the two selected starfish in the p -th dimension, whereas A_1 and A_2 are random numbers in the range $[-1, 1]$. The starfish energy E_t is calculated according to Eq. (41).

$$Y_{i,p}^T = E_t X_{i,p}^T + A_1 (X_{k1,p}^T - X_{i,p}^T) + A_2 (X_{k2,p}^T - X_{i,p}^T) \quad (40)$$

$$E_t = \frac{T_{max} - T}{T_{max}} \cdot \cos\theta \quad (41)$$

$$X_{i,p}^{T+1} = \begin{cases} Y_{i,p}^T & lb_p \leq Y_{i,p}^T \leq ub_p \\ X_{i,p}^T & otherwise \end{cases} \quad (42)$$

2.4.3 Exploitation Phase

The foraging and regeneration behaviors are combined in the exploitation phase. SFOA adopts a parallel bidirectional search strategy by utilizing the information from other starfish and the current global best position. First, the five distances between the global best position and the other starfish are calculated, as defined in Eq. (43), where $d_{m,p}$ denotes the distance between the global best position and the m -th selected starfish in the p -th dimension. Then, two distances are randomly selected as reference information to update the position of each starfish according to Eq. (44).

$$d_{m,p} = (X_{best,p}^T - X_{m,p}^T), m = 1, 2, \dots, 5 \quad (43)$$

$$Y_i^T = X_i^T + r_4 d_{1,p} + r_5 d_{2,p} \quad (44)$$

In nature, a starfish may sacrifice one of its arms to escape from predators, which inspires the regeneration strategy in SFOA. This strategy is applied only to the last starfish in the population. SFOA simulates the regeneration process by reducing the movement speed, allowing the selected starfish to update its position with a smaller step size. The regeneration strategy is expressed in Eq. (45).

If the updated position exceeds the predefined search bounds, Eq. (46) is applied for boundary handling. The updated position is set to the corresponding boundary if it exceeds the upper or lower bound; otherwise, the updated position is retained.

$$Y_i^T = \exp(-T \times N / T_{max}) X_i^T \quad (45)$$

$$X_i^{T+1} = \begin{cases} Y_i^T, & lb \leq Y_i^T \leq ub \\ lb, & Y_i^T < lb \\ ub, & Y_i^T > ub \end{cases} \quad (46)$$

2.5 Periodic Noise Covariance Optimization Strategy

In the conventional EKF, the process and measurement noise covariance matrices Q and R are fixed, which limits estimation accuracy under dynamic operating conditions. Although AEKF updates Q and R using measurement information, its adaptation capability remains limited because of measurement oscillation and inappropriate initial settings.

To overcome the limitation, SFOA was employed to optimize the noise covariance matrices and is integrated with the adaptive mechanism of the AEKF, thereby improving the adaptability and accuracy of SOC estimation under varying operating conditions. Fig. 3 presents the flowchart of the proposed method. The green, red, and blue arrows denote the execution flow, data recording process, and Q-R update process, respectively. The battery state vector, error covariance matrix, and innovation vector are provided to SFOA. Based on these variables and the previous 150 samples, SFOA optimizes the noise covariance matrices. The optimized Q and R are then updated every 150 samplings.

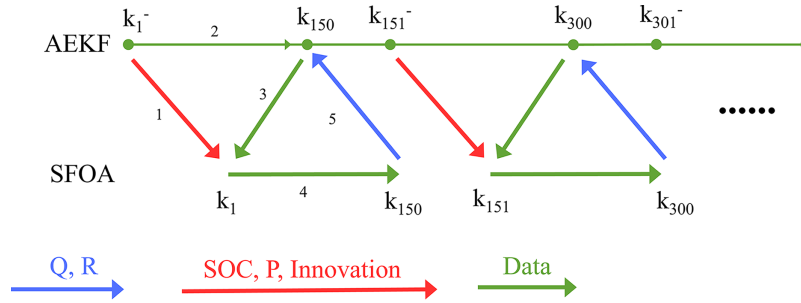


Figure 3: SFOA-optimized AEKF flowchart.

The objective function (OB) was designed to evaluate the fitness of each candidate solution and guide SFOA in identifying the global optimal solution, as defined in Eq. (47). Here, SOC_{exp} and SOC_{est} denote the experimental and filter-estimated SOC values, respectively; V_{exp} and V_{est} represent the measured and filter-estimated terminal voltages, respectively; and V_{nom} denotes the nominal battery voltage. To improve the consistency between the estimation results and the measured battery signals, the objective function jointly minimizes the squared errors of SOC and terminal voltage rather than considering only the SOC error. This design improves the consistency between the model prediction and the measured voltage while enabling SFOA to identify the optimal noise covariance matrices Q and R.

$$OB = \alpha \cdot (SOC_{exp} - SOC_{est})^2 + (1 - \alpha) \cdot \left(\frac{V_{exp} - V_{est}}{V_{nom}} \right)^2 \quad (47)$$

Furthermore, a sensitivity analysis of the weighting coefficient α was conducted to evaluate its influence on the filter's tracking performance. The results are discussed below. The population size and maximum number of iterations were set to 30 and 50, respectively, and 10 independent runs were performed to evaluate the robustness of the algorithm.

3 Results and Discussion

The results are divided into three parts. The first part evaluates the sensitivity of the weighting coefficient α and analyzes the contributions of the SOC and terminal-voltage errors to the objective function. The second and third parts evaluate the effectiveness of the proposed SFOA-AEKF method for lithium-ion battery SOC estimation. To comprehensively analyze the performance of SFOA-AEKF under dynamic loading conditions, two temperatures, 25°C and 45°C, were considered under both matched and mismatched initial SOC conditions. The initial values of the filter parameters Q and R were set to 10^{-13} and 0.2, respectively [31]. The covariance parameters used for all filters are listed in Table 1. All simulations were conducted in MATLAB R2024a using an Intel Core Ultra 9 285H CPU. The battery specifications are listed in Table 1.

Table 1: Battery specifications and test conditions.

Item	Specification
Manufacture	Samsung
Capacity	2000 mAh
Operating temperature	Charge: 0°C~50°C; Discharge: -20°C~75°C
Cutoff conditions	Voltage: 2.5~4.2 V; Current: 20A
Sampling Frequency	1 Hz
SOC reference	Coulomb counting

The performance was evaluated using the sum of squared errors (SSE) for SOC and terminal voltage, as defined in Eqs. (48) and (49), respectively, where $SOC_{ref,k}$ and $SOC_{est,k}$ denote the reference and estimated SOC at the k -th sampling instant, respectively. $V_{ref,k}$ and $V_{est,k}$ represent the measured and estimated terminal voltages, respectively, and N is the total number of samples. Lower SSE values indicate better estimation performance.

$$SSE_{SOC} = \sum_{k=1}^N (SOC_{ref,k} - SOC_{est,k})^2 \quad (48)$$

$$SSE_V = \sum_{k=1}^N (V_{ref,k} - V_{est,k})^2 \quad (49)$$

3.1 Sensitivity Analysis of the Objective-Function Weighting Coefficient α

The weighting coefficient (α) directly affects the objective function and was therefore evaluated over the range of 0.1–0.9. SOC estimation accuracy represents the agreement between the estimated and reference SOC values, whereas terminal-voltage accuracy reflects the consistency between the battery model and the measured voltage. Because battery aging affect both the available capacity and the electrical characteristics of the battery, the terminal-voltage error mainly reflects the accuracy of the battery model. Under the initial SOC match condition, Tables 2 and 3 present the SOC and terminal-voltage errors, respectively, for different values of α . Fig. 4a,b presents boxplots of the SOC and terminal-voltage errors under the mismatched initial SOC condition, respectively.

Table 2: SOC error results for different values of α at an initial SOC of 0.8.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Best	2.267	2.724	2.202	2.748	2.337	2.237	2.225	2.534	2.443
Mean	2.364	2.393	2.371	2.334	2.383	2.336	2.422	2.463	2.457
Std.	0.238	0.259	0.316	0.269	0.109	0.349	0.330	0.293	0.344

Note: Abb: Std., standard deviation.

Table 3: Voltage error results for different values of α at an initial SOC of 0.8.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Best	3.064×10^{-2}	3.076×10^{-2}	3.082×10^{-2}	3.188×10^{-2}	3.102×10^{-2}	3.168×10^{-2}	3.195×10^{-2}	3.218×10^{-2}	3.172×10^{-2}
Mean	3.606×10^{-2}	3.630×10^{-2}	3.545×10^{-2}	3.635×10^{-2}	3.309×10^{-2}	3.595×10^{-2}	3.523×10^{-2}	3.672×10^{-2}	3.649×10^{-2}
Std.	6.806×10^{-3}	8.322×10^{-3}	6.040×10^{-3}	4.729×10^{-3}	2.566×10^{-3}	4.312×10^{-3}	3.083×10^{-3}	4.292×10^{-3}	4.215×10^{-3}

Note: Abb: Std., standard deviation.

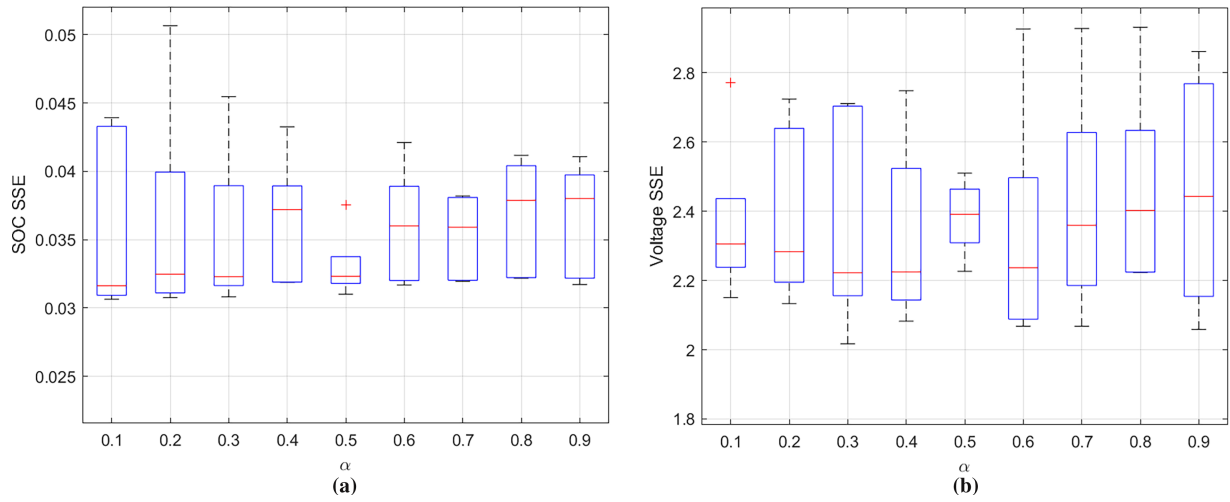


Figure 4: Boxplots of the (a) SOC and (b) Terminal-voltage error for different values of α at an initial SOC of 0.8. The boxes indicate the interquartile ranges, the red horizontal lines represent the median values, the whiskers extend to the most extreme non-outlier values, and the “+” symbols indicate outliers.

Under an initial SOC mismatch of 0.1, Tables 4 and 5 present the SOC and terminal-voltage errors, respectively, while Fig. 5a,b shows the corresponding boxplots for different values of α .

The sensitivity of the weighting coefficient α was evaluated over the range of 0.1–0.9 under matched and mismatched initial SOC conditions. At an initial SOC of 0.8, $\alpha = 0.5$ achieved the lowest mean and standard deviation of the SOC SSE, with values of 3.309×10^{-2} and 2.566×10^{-3} , respectively. It also produced the lowest standard deviation of the terminal-voltage SSE at 0.109. These results indicate that $\alpha = 0.5$ provided the most consistent optimization performance under the matched initial SOC condition.

Under the mismatched initial SOC condition of 0.1, the mean SOC SSE values were relatively similar for α values ranging from 0.3 to 0.9. Nevertheless, $\alpha = 0.5$ yielded the lowest mean SOC SSE of 54.472, with a standard deviation of 5.734×10^{-3} . Although the minimum standard deviations of the SOC and terminal-voltage SSE were obtained at $\alpha = 0.9$ and 0.7, respectively, $\alpha = 0.5$ maintained competitive error distributions and satisfactory tracking accuracy.

Table 4: SOC error results for different values of α at an initial SOC of 0.1.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Best	54.460	54.461	54.466	54.467	54.466	54.466	54.466	54.467	54.466
Mean	54.511	54.482	54.472	54.474	54.472	54.472	54.474	54.473	54.472
Std.	9.627×10^{-2}	2.879×10^{-2}	5.497×10^{-3}	6.304×10^{-3}	5.734×10^{-3}	6.103×10^{-3}	9.042×10^{-3}	6.660×10^{-3}	5.197×10^{-3}

Note: Abb: Std., standard deviation.

Table 5: Voltage error results for different values of α at an initial SOC of 0.1.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Best	24.365	24.215	24.258	24.035	24.061	24.057	24.051	24.042	24.036
Mean	23.976	24.204	24.057	24.208	24.177	24.168	24.078	24.088	24.203
Std.	0.399	0.325	0.143	0.272	0.316	0.309	0.133	0.158	0.344

Note: Abb: Std., standard deviation.

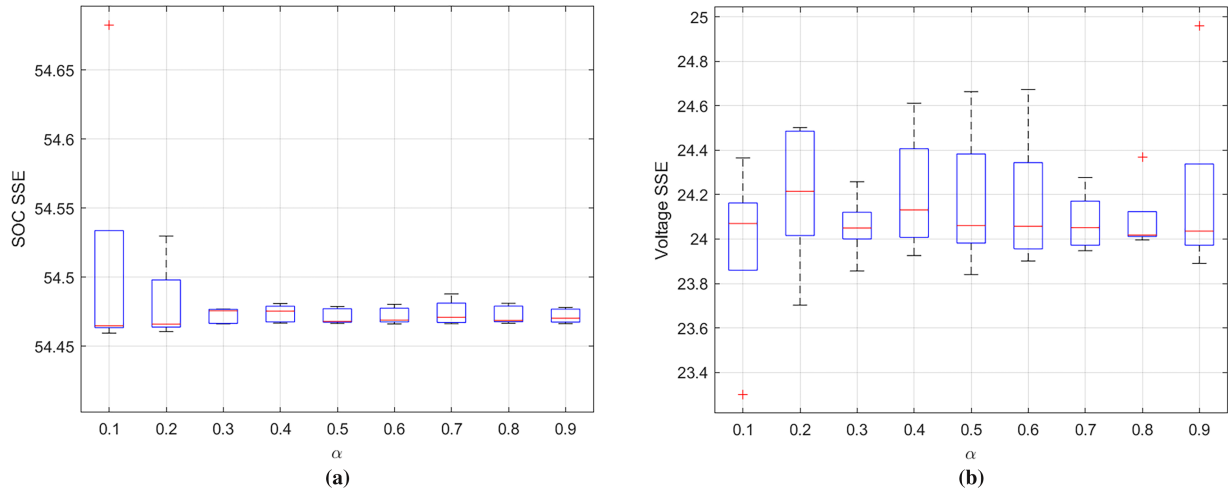


Figure 5: Boxplots of the (a) SOC and (b) Terminal-voltage error for different values of α at an initial SOC of 0.1. The boxes indicate the interquartile ranges, the red horizontal lines represent the median values, the whiskers extend to the most extreme non-outlier values, and the “+” symbols indicate outliers.

3.2 Evaluation of SFOA-AEKF Robustness in Battery SOC Tracking

Three representative driving cycles, namely US06, FUDS, and BJDST, were adopted to simulate dynamic operating conditions. In addition, different operating conditions (25°C and 45°C) and initial SOC conditions (0.8 and 0.1) were introduced to assess the robustness of the proposed method. The estimation performance was evaluated in terms of SOC and terminal-voltage accuracy and compared with that of other algorithms, including PSO, GA, and GWO.

3.2.1 US06

Under the US06 dynamic loading condition, the initial SOC was set to 0.8 for the matched case and 0.1 for the mismatched case. The SOC estimation performance was evaluated at 25°C and 45°C to investigate the robustness of the proposed method under different initial SOC and temperature conditions. Figs. 6 and 7 compare the SOC and terminal-voltage estimation results obtained using EKF, AEKF, SFOA-AEKF, PSO-AEKF, GA-AEKF, and GWO-AEKF at 25°C and 45°C, respectively. The quantitative results are summarized in Tables 6 and 7. For the optimization-based methods, the best, mean, and standard deviation values obtained from 10 independent runs are reported to evaluate both estimation accuracy and optimization stability.

At 45°C, a similar trend was observed. Under the matched initial SOC condition, all methods closely tracked the reference SOC, and the benefit of covariance optimization was limited, as shown in Fig. 7a. In contrast, under the mismatched condition, SFOA-AEKF exhibited faster convergence and lower mean estimation errors than other filters. The terminal-voltage trajectories also remained close to the experimental measurements, as shown in Fig. 7b,d.

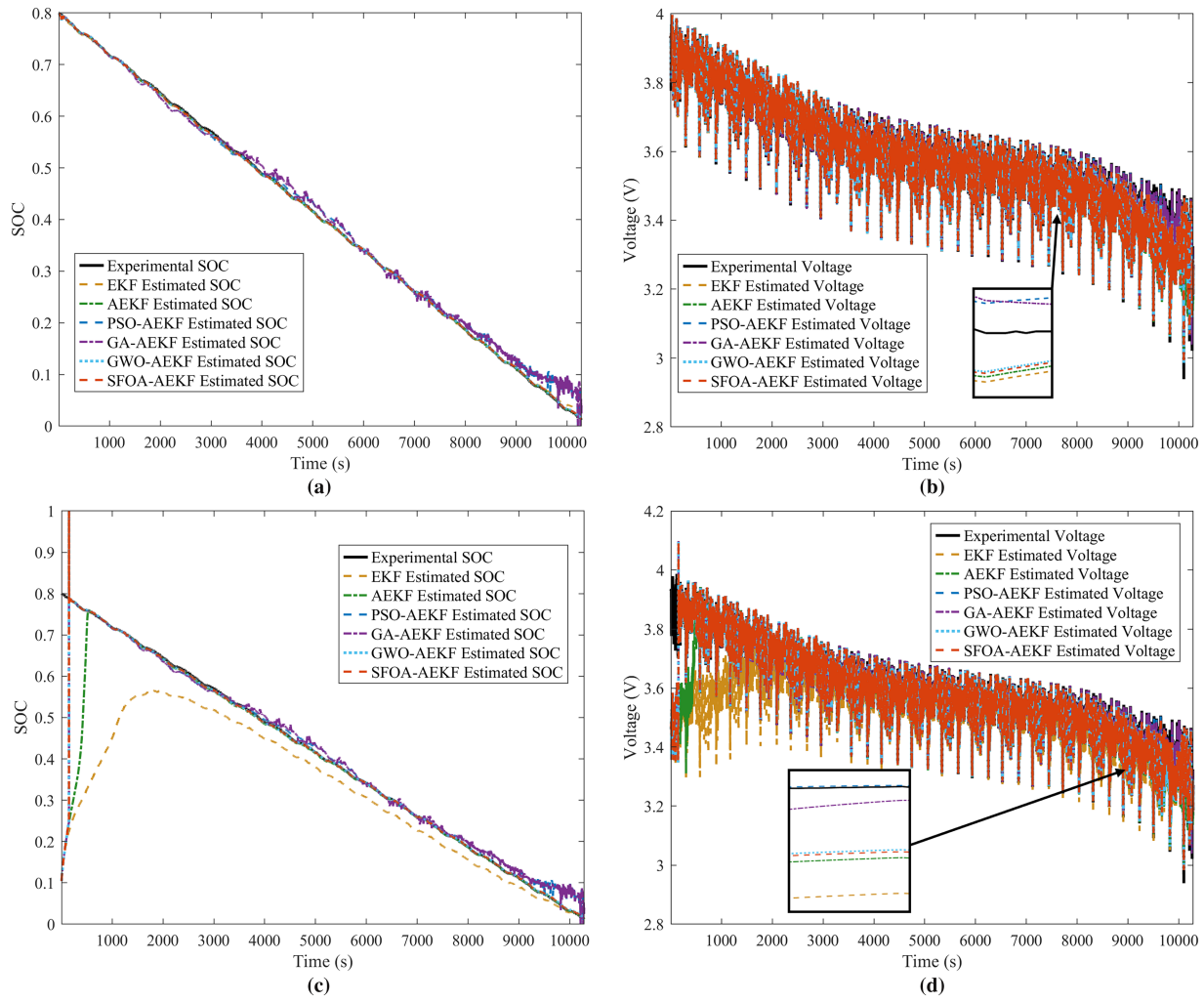


Figure 6: Performance comparison under the US06 driving cycle at 25°C for the matched initial SOC: (a) SOC estimation and (b) Terminal voltage; and for the mismatched initial SOC: (c) SOC estimation and (d) Terminal voltage.

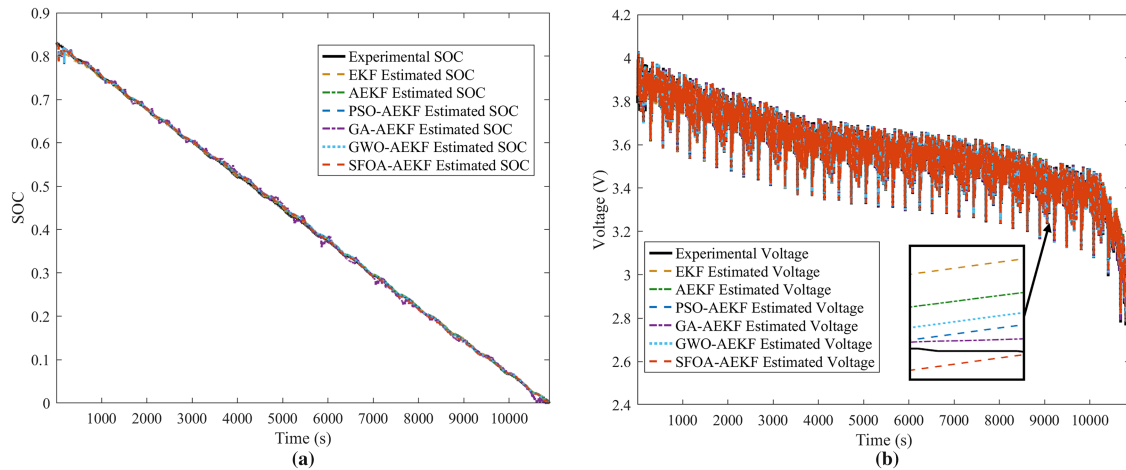


Figure 7: (Continued)

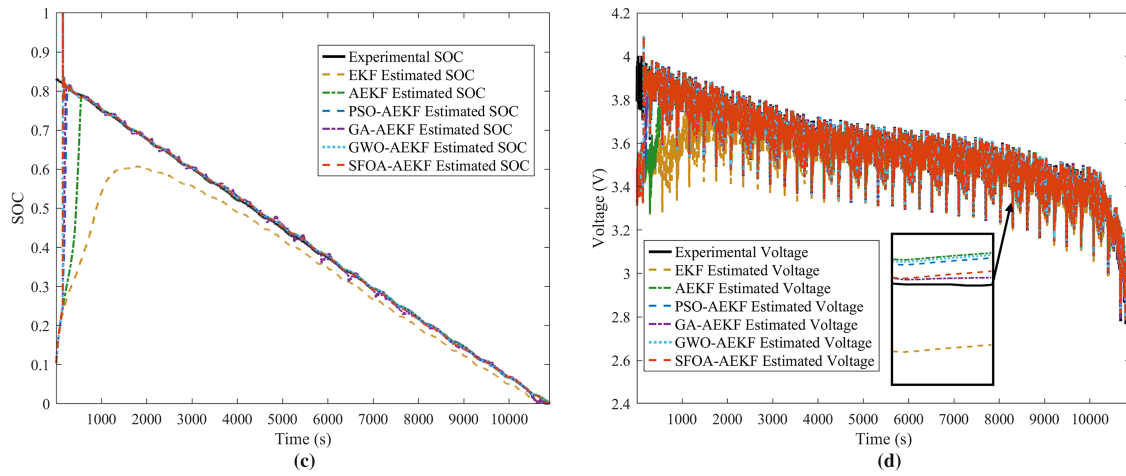


Figure 7: Performance comparison under the US06 driving cycle at 45°C for the matched initial SOC: (a) SOC estimation and (b) Terminal voltage; and for the mismatched initial SOC: (c) SOC estimation and (d) Terminal voltage.

Table 6: Performance comparison of the six filtering methods under the US06 driving cycle at 25°C.

	EKF	AEKF	SFOA-AEKF	PSO-AEKF	GA-AEKF	GWO-AEKF
Matched SOC setting						
Best	9.381×10^{-2}	2.860×10^{-2}	3.173×10^{-2}	2.220	2.374	3.305×10^{-2}
Mean	9.381×10^{-2}	2.860×10^{-2}	3.640×10^{-2}	2.289	2.414	1.263×10^{-1}
Std.	-	-	5.271×10^{-3}	4.771×10^{-2}	2.061×10^{-2}	2.756×10^{-1}
Time (s)	1.014×10^{-1}	1.283×10^{-1}	139.912	142.035	138.778	138.678
Mismatched SOC setting						
Best	240.090	109.034	54.463	56.565	56.800	54.465
Mean	240.090	109.034	54.476	56.681	56.838	54.473
Std.	-	-	8.000×10^{-3}	6.418×10^{-2}	2.061×10^{-2}	1.498×10^{-2}
Time (s)	9.999×10^{-2}	1.281×10^{-1}	140.802	143.004	140.645	138.694

Note: “-” indicates that the standard deviation across independent runs is not applicable to EKF and AEKF because they are deterministic methods. Std., standard deviation.

Table 7: Performance comparison of the six filtering methods under the US06 driving cycle at 45°C.

	EKF	AEKF	SFOA-AEKF	PSO-AEKF	GA-AEKF	GWO-AEKF
Matched SOC setting						
Best	6.643×10^{-2}	1.620×10^{-1}	1.765×10^{-1}	2.317×10^{-1}	4.660×10^{-1}	1.622×10^{-1}
Mean	6.643×10^{-2}	1.620×10^{-1}	1.923×10^{-1}	3.051×10^{-1}	4.774×10^{-1}	1.922×10^{-1}
Std.	-	-	1.329×10^{-2}	3.563×10^{-2}	5.552×10^{-3}	1.490×10^{-2}
Time (s)	1.111×10^{-1}	1.327×10^{-1}	149.882	151.508	150.152	147.895

(Continued)

Table 7 (continued)

	EKF	AEKF	SFOA-AEKF	PSO-AEKF	GA-AEKF	GWO-AEKF
Mismatched SOC setting						
Best	233.680	125.886	59.807	70.791	66.563	59.784
Mean	233.680	125.886	59.842	89.522	82.631	63.444
Std.	-	-	3.770×10^{-2}	10.100	13.290	7.544
Time (s)	1.084×10^{-1}	1.273×10^{-1}	150.513	151.687	150.477	147.263

Note: “-” indicates that the standard deviation across independent runs is not applicable to EKF and AEKF because they are deterministic methods. Std., standard deviation.

3.2.2 FUDS

To further evaluate the applicability of the proposed method under a different dynamic load profile, the FUDS driving cycle was employed. Figs. 8 and 9 present the SOC and terminal-voltage estimation results at 25°C and 45°C, respectively, while the corresponding quantitative results are summarized in Tables 8 and 9.

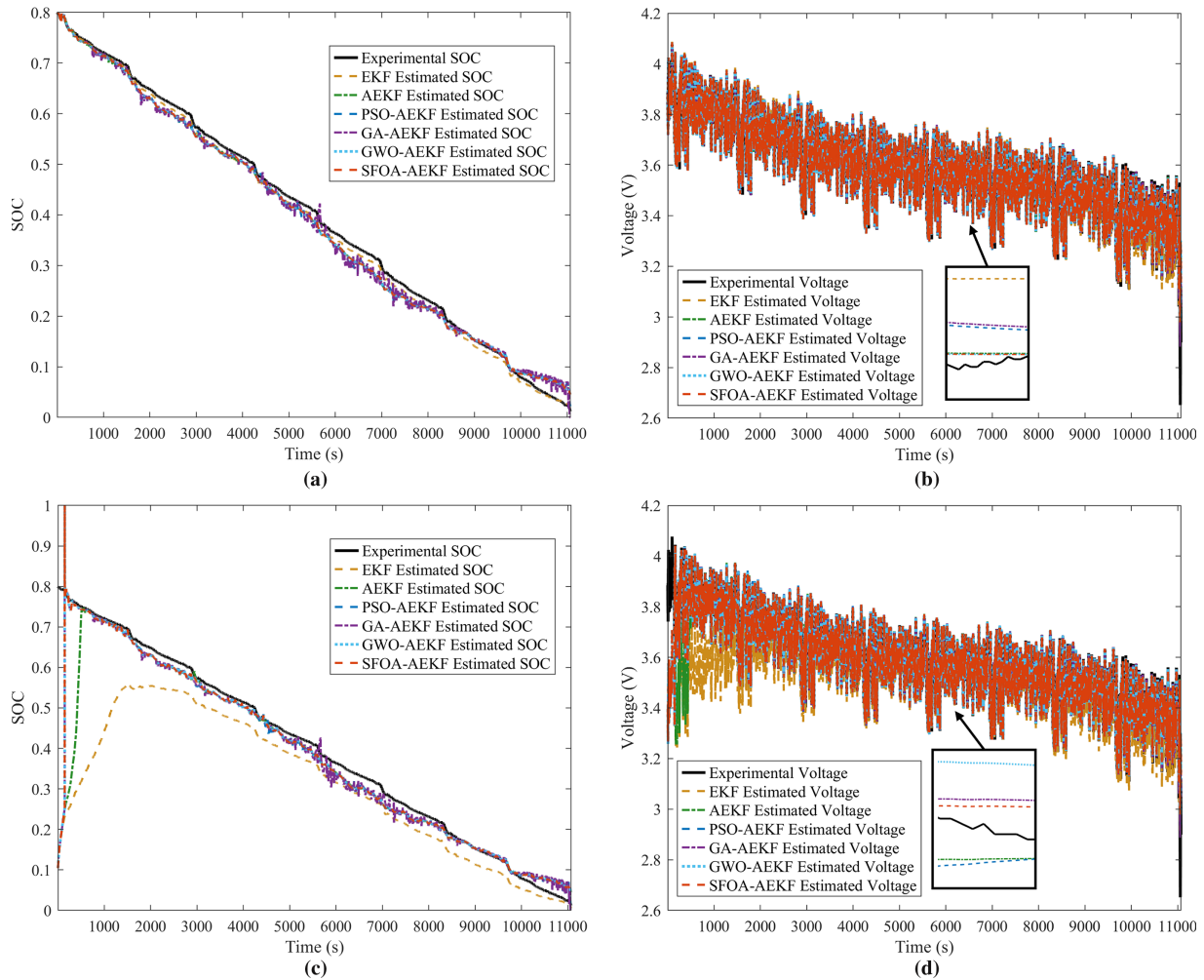


Figure 8: Performance comparison under the FUDS driving cycle at 25°C for the matched initial SOC: (a) SOC estimation and (b) Terminal voltage; and for the mismatched initial SOC: (c) SOC estimation and (d) Terminal voltage.

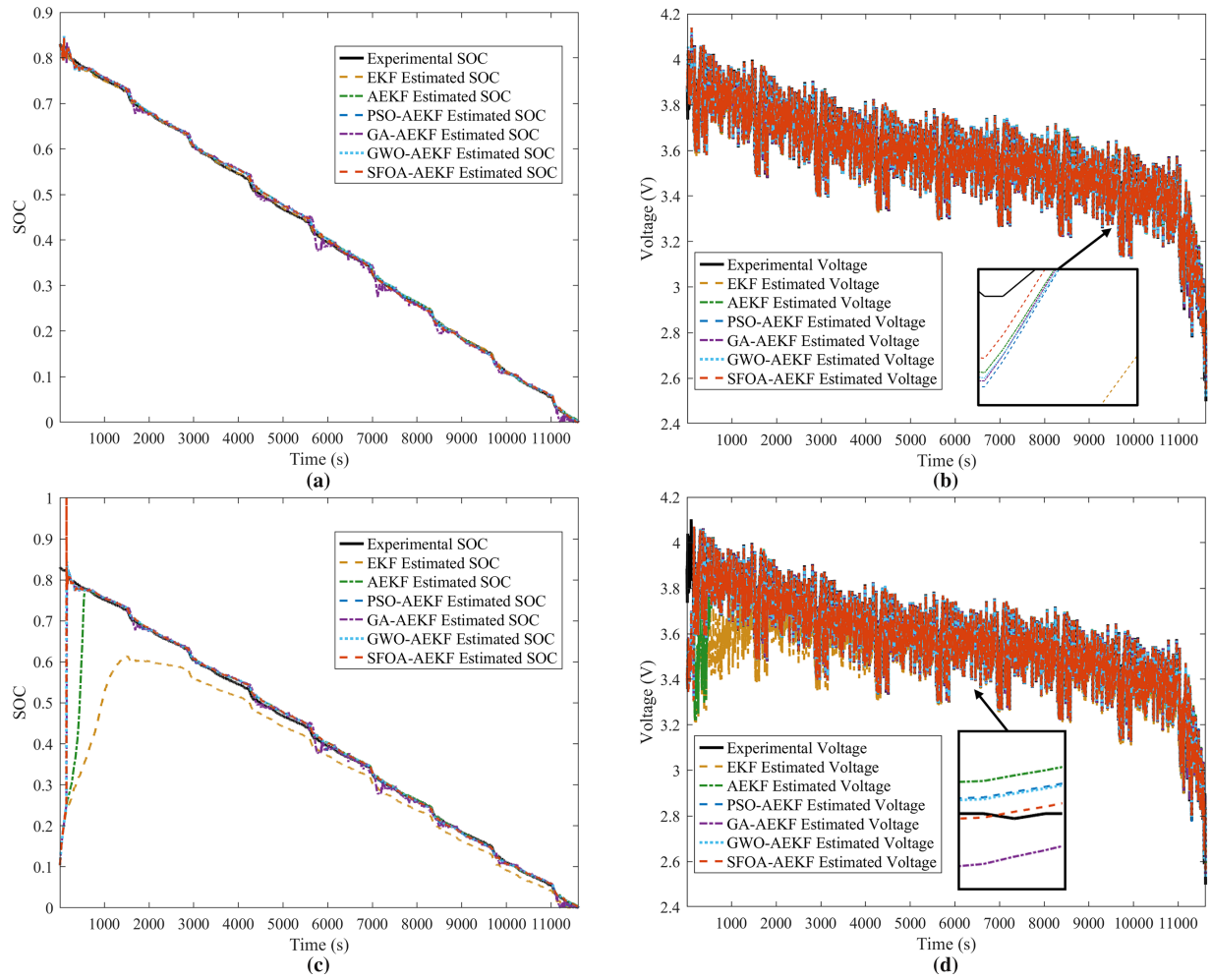


Figure 9: Performance comparison under the FUDS driving cycle at 45°C for the matched initial SOC: (a) SOC estimation and (b) Terminal voltage; and for the mismatched initial SOC: (c) SOC estimation and (d) Terminal voltage.

Table 8: Performance comparison of the six filtering methods under the FUDS driving cycle at 25°C.

	EKF	AEKF	SFOA-AEKF	PSO-AEKF	GA-AEKF	GWO-AEKF
Matched SOC setting						
Best	1.201	3.756	3.681	4.023	4.203	3.681
Mean	1.201	3.756	3.684	4.110	4.463	3.746
Std.	-	-	3.165×10^{-3}	5.594×10^{-2}	9.436×10^{-2}	1.159×10^{-1}
Time (s)	1.349×10^{-1}	1.349×10^{-1}	152.114	153.679	149.396	149.967
Mismatched SOC setting						
Best	252.568	111.328	57.926	57.927	58.376	57.917
Mean	252.568	111.328	57.926	58.025	58.421	57.922
Std.	-	-	2.990×10^{-4}	5.153×10^{-2}	2.643×10^{-2}	2.786×10^{-3}
Time (s)	1.139×10^{-1}	1.361×10^{-1}	152.156	153.807	149.838	150.461

Note: “-” indicates that the standard deviation across independent runs is not applicable to EKF and AEKF because they are deterministic methods. Std., standard deviation.

Table 9: Performance comparison of the six filtering methods under the FUDS driving cycle at 45°C.

	EKF	AEKF	SFOA-AEKF	PSO-AEKF	GA-AEKF	GWO-AEKF
Matched SOC setting						
Best	7.530×10^{-2}	3.230×10^{-1}	3.254×10^{-1}	3.784×10^{-1}	7.967×10^{-1}	3.183×10^{-1}
Mean	7.530×10^{-2}	3.230×10^{-1}	3.362×10^{-1}	4.600×10^{-1}	8.348×10^{-1}	3.411×10^{-1}
Std.	-	-	9.481×10^{-3}	9.595×10^{-2}	1.401×10^{-2}	1.559×10^{-2}
Time (s)	1.144×10^{-1}	1.368×10^{-1}	159.749	160.736	157.998	158.346
Mismatched SOC setting						
Best	238.334	126.553	60.020	60.074	61.902	59.982
Mean	238.334	126.553	60.032	67.706	65.060	68.211
Std.	-	-	1.269×10^{-2}	5.964	6.027	4.366
Time (s)	1.203×10^{-1}	1.405×10^{-1}	160.430	161.609	157.489	158.714

Note: “-” indicates that the standard deviation across independent runs is not applicable to EKF and AEKF because they are deterministic methods. Std., standard deviation.

At 25°C, all methods showed similar SOC tracking trends under the matched initial SOC condition, as shown in Fig. 8a. Under the mismatched condition, SFOA-AEKF rapidly converged toward the reference SOC and significantly reduced the estimation error compared with EKF and AEKF. Its mean SSE was also lower than those of PSO-AEKF and GA-AEKF and was comparable to that of GWO-AEKF. The terminal-voltage results in Fig. 8b,d showed good agreement with the experimental measurements.

At 45°C, all methods maintained good SOC tracking under the matched condition, as shown in Fig. 9a. Under the mismatched condition, SFOA-AEKF exhibited faster convergence and achieved the lowest mean SSE among the optimization-based methods. The terminal-voltage estimates also closely followed the experimental voltage, as shown in Fig. 9b,d. These results indicate that SFOA-AEKF maintains robust estimation performance under the FUDS cycle at different temperatures.

3.2.3 BJDST

The BJDST driving cycle was further used to evaluate the proposed method under another dynamic load profile. Figs. 10 and 11 show the SOC and terminal-voltage estimation results at 25°C and 45°C, respectively, with the corresponding quantitative results summarized in Tables 10 and 11.

At 25°C, all methods generally followed the reference SOC with correct initialization, although some optimization-based methods exhibited larger deviations during the middle stage of the cycle. With an incorrect initial SOC, SFOA-AEKF showed rapid convergence and maintained estimation performance comparable to the best-performing optimization-based methods.

At 45°C, the estimators maintained close SOC tracking under the matched condition. When the initial SOC was mismatched, SFOA-AEKF rapidly corrected the initial error and achieved the lowest mean SSE among the optimization-based methods. Overall, the results demonstrate stable estimation performance across different temperatures and initial SOC conditions. Table 12 summarizes the improvement of SFOA-AEKF under mismatched initial SOC conditions.

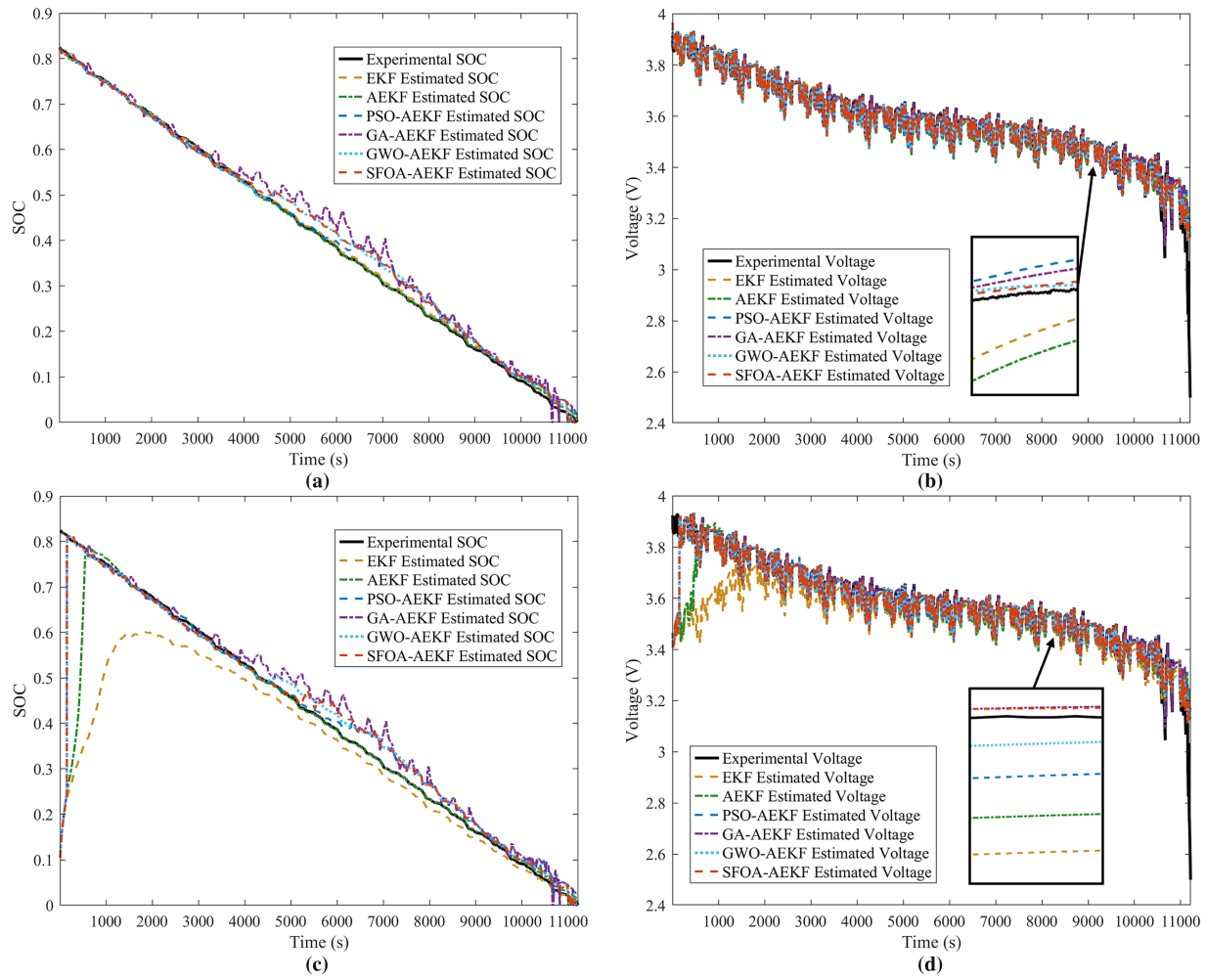


Figure 10: Performance comparison under the BJDSST driving cycle at 25°C for the matched initial SOC: (a) SOC estimation and (b) Terminal voltage; and for the mismatched initial SOC: (c) SOC estimation and (d) Terminal voltage.

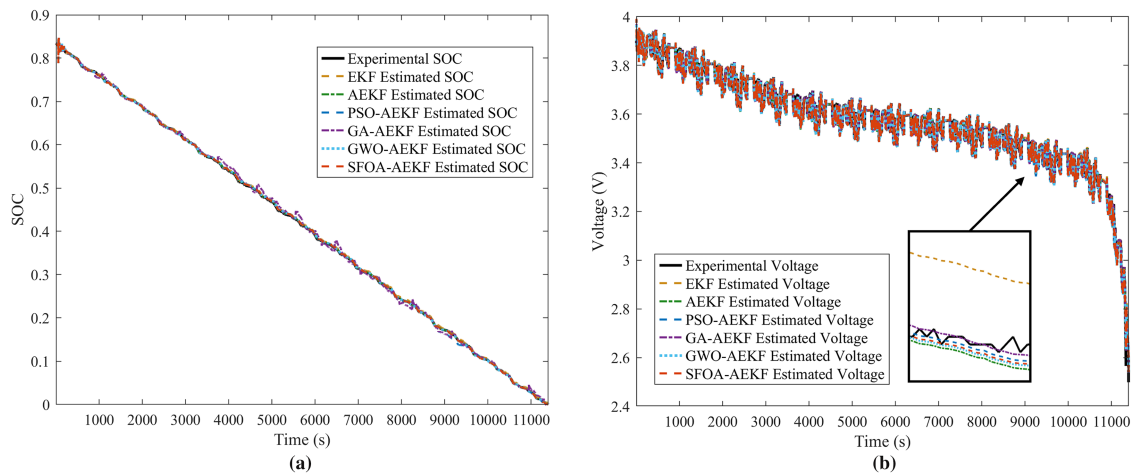


Figure 11: (Continued)

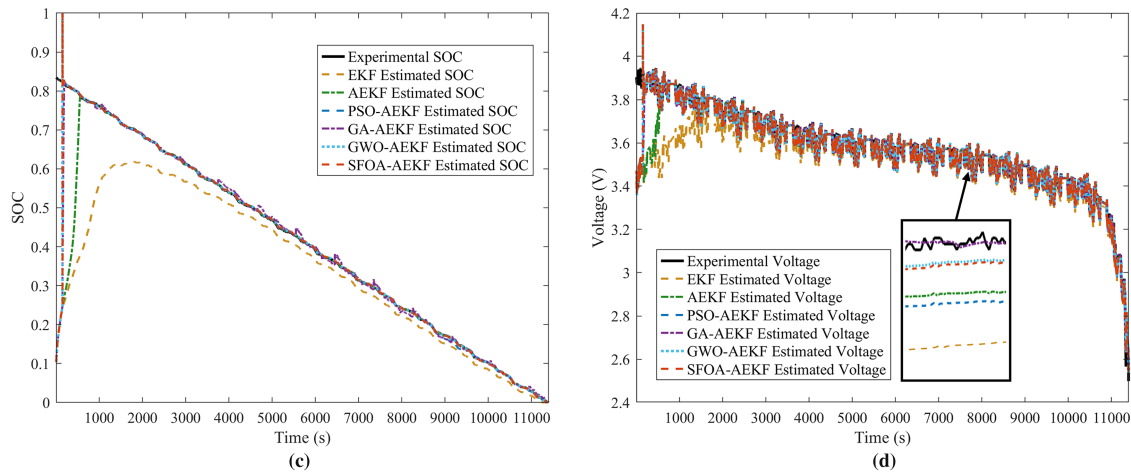


Figure 11: Performance comparison under the BJDST driving cycle at 45°C for the matched initial SOC: (a) SOC estimation and (b) Terminal voltage; and for the mismatched initial SOC: (c) SOC estimation and (d) Terminal voltage.

Table 10: Performance comparison of the six filtering methods under the BJDST driving cycle at 25°C.

	EKF	AEKF	SFOA-AEKF	PSO-AEKF	GA-AEKF	GWO-AEKF
Matched SOC setting						
Best	3.300×10^{-1}	2.480×10^{-1}	4.615	3.521	11.087	4.308
Mean	3.300×10^{-1}	2.480×10^{-1}	5.890	5.947	11.192	5.637
Std.	-	-	8.949×10^{-1}	1.367	1.053×10^{-1}	6.121×10^{-1}
Time (s)	1.383×10^{-1}	1.140×10^{-1}	155.035	161.947	150.706	152.451
Mismatched SOC setting						
Best	236.529	125.153	63.637	62.699	69.839	63.560
Mean	236.529	125.153	65.383	64.902	70.075	64.293
Std.	-	-	1.302	1.016	2.345×10^{-1}	4.799×10^{-1}
Time (s)	1.070×10^{-1}	1.335×10^{-1}	154.156	158.040	151.016	153.464

Note: “-” indicates that the standard deviation across independent runs is not applicable to EKF and AEKF because they are deterministic methods. Std., standard deviation.

Table 11: Performance comparison of the six filtering methods under the BJDST driving cycle at 45°C.

	EKF	AEKF	SFOA-AEKF	PSO-AEKF	GA-AEKF	GWO-AEKF
Matched SOC setting						
Best	9.555×10^{-2}	1.999×10^{-2}	2.319×10^{-2}	8.558×10^{-2}	4.190×10^{-1}	2.545×10^{-2}
Mean	9.555×10^{-2}	1.999×10^{-2}	2.567×10^{-2}	1.653×10^{-1}	4.302×10^{-1}	2.699×10^{-2}
Std.	-	-	1.576×10^{-3}	2.957×10^{-2}	7.185×10^{-3}	1.082×10^{-3}
Time (s)	1.155×10^{-1}	1.426×10^{-1}	156.393	158.038	154.125	154.696

(Continued)

Table 11 (continued)

	EKF	AEKF	SFOA-AEKF	PSO-AEKF	GA-AEKF	GWO-AEKF
Mismatched SOC setting						
Best	227.092	128.634	60.055	60.099	63.097	60.054
Mean	227.092	128.634	60.058	64.826	72.952	60.506
Std.	-	-	2.424×10^{-3}	5.929	7.452	1.412
Time (s)	1.097×10^{-1}	1.342×10^{-1}	156.596	158.535	154.747	154.644

Note: “-” indicates that the standard deviation across independent runs is not applicable to EKF and AEKF because they are deterministic methods. Std., standard deviation. Std., standard deviation.

Table 12: Improvement of SFOA-AEKF over EKF and AEKF under mismatched initial SOC conditions.

Driving Cycle	Error Reduction (%)	
	vs. EKF	vs. AEKF
US06 at 25°C	77.316	50.050
US06 at 45°C	74.407	52.491
FUDS at 25°C	77.065	47.968
FUDS at 45°C	74.817	52.573
BJDST at 25°C	73.095	49.153
BJDST at 45°C	73.555	53.313

4 Conclusion

This study developed an FFRLS-SFOA-AEKF framework for lithium-ion battery SOC estimation by integrating online parameter identification, adaptive state estimation, and SFOA-based noise covariance optimization. Historical data were used to determine suitable noise covariance parameters and reduce abrupt parameter variations. Sensitivity analysis showed that $\alpha = 0.5$ provided the best overall balance between SOC and terminal-voltage errors.

The effectiveness of SFOA-AEKF was closely related to the initial SOC condition. When the initial SOC was correctly specified, EKF and AEKF already provided satisfactory tracking performance, leaving limited room for further improvement. Under mismatched initial SOC conditions, SFOA-AEKF achieved faster convergence and lower SOC errors, reducing the SOC estimation SSE by 73.095%–77.316% compared with EKF and by 47.968%–53.313% compared with AEKF across the evaluated driving cycles. The improvement remained consistent at different temperatures, indicating robust performance under inaccurate initialization. Comparisons with PSO-AEKF, GA-AEKF, and GWO-AEKF further showed competitive estimation accuracy and stable optimization performance, while the estimated terminal voltage remained in good agreement with the experimental measurements.

The proposed method effectively mitigated state-estimation deviations caused by inaccurate filter initialization under dynamic loading conditions while maintaining reliable performance across different driving cycles and temperatures. These findings demonstrate the practical applicability of adaptive filtering for battery SOC estimation and provide a basis for future applications in state-of-health estimation, fault diagnosis, and other battery management functions.

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Availability of Data and Materials: The data that support the findings of this study are available from the Corresponding Author, En-Jui Liu, upon reasonable request.

Ethics Approval: Not applicable.

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

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