

Article

State of Charge Estimation Method for Lithium-Ion Batteries Based on Online Parameter Identification and QPSO-AUKF

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Abstract

Accurate estimation of the state of charge (SOC) is essential for the safe and efficient operation of lithium-ion batteries. Conventional Adaptive Unscented Kalman Filter (AUKF) methods often exhibit limited accuracy, primarily due to the empirical selection of process and measurement noise covariance matrices. To overcome this limitation, this study proposes a QPSO-AUKF algorithm based on a second-order RC equivalent circuit model, which integrates Quantum-behaved Particle Swarm Optimization (QPSO) with online parameter identification. In this approach, the QPSO algorithm optimizes the noise covariance matrices, which are subsequently used within the AUKF framework for SOC estimation. MATLAB R2020a simulations conducted on the Maryland and Wisconsin datasets demonstrate that the QPSO-AUKF reduces the root mean square error (RMSE) by more than 60% compared with the conventional AUKF, indicating a significant improvement in SOC estimation accuracy.

Keywords: lithium-ion batteries; state of charge; parameter identification; quantum-behaved particle swarm optimization; adaptive unscented Kalman filter

1. Introduction

In the context of advancing the “Dual Carbon” goals and promoting the development of the new energy vehicle industry, lithium-ion batteries are being increasingly recognized as the ideal power source for electric vehicles due to their high energy density, low environmental impact, and long cycle life [1]. The Battery Management System (BMS) plays a vital role in monitoring and safeguarding batteries, thereby improving their performance and extending their service life [2]. Among various state variables monitored by the BMS, the state of charge (SOC) serves as a fundamental indicator reflecting the available energy of the battery. Accurate SOC estimation is not only essential for driving range prediction, but also acts as a key feedback variable for power allocation, thermal and energy management coordination, and battery protection strategies. Inaccurate SOC information may lead to overly conservative power limitation, inefficient thermal control, or even safety risks under extreme operating conditions. Therefore, high-precision and robust SOC estimation is widely recognized as a core requirement for advanced BMS, particularly in electric vehicles and connected automated driving scenarios [3]. During operation, the battery temperature fluctuates with changes in ambient conditions, which complicates the accurate estimation of the State of Charge (SOC) [4]. Accurate State of Charge (SOC) estimation is crucial as it determines the remaining battery capacity, optimizes energy



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management, and enhances system safety and reliability [5]. Therefore, accurate SOC estimation is essential for managing and controlling lithium-ion batteries [6]. Developing an accurate equivalent circuit model is fundamental for reliably estimating battery SOC with efficiency. Model accuracy directly influences the precision and stability of subsequent SOC estimations. Current battery models used in research include neural network models [7], electrochemical models [8], and equivalent circuit models [9], among others. Data-driven SOC estimation methods based on deep learning have attracted increasing attention due to their strong capability in capturing the nonlinear dynamic characteristics of batteries. For instance, Li et al. [10] proposed a method combining a weight-clustering convolutional neural network and a long short-term memory network (WC-CNN-LSTM) to improve SOC estimation accuracy under varying temperature conditions. In addition, advanced Bayesian filtering strategies have been extensively investigated. For example, Tan et al. [11] developed an unscented Kalman filter based on variational Bayesian multi-kernel correlation, which significantly enhances robustness in complex noise environments. However, the accuracy of neural network models heavily depends on the quality and coverage of the training data. Insufficient data or incomplete operating conditions can substantially reduce their generalization capability. Furthermore, as “black-box” models, neural networks lack interpretability, which hinders fault diagnosis and mechanistic analysis. In contrast, electrochemical models typically involve numerous partial differential equations, whose numerical solutions are time-consuming and computationally intensive, making them challenging to apply in real-time scenarios. Conversely, the equivalent circuit model (ECM) is commonly used in model-based techniques due to its ease of implementation and computational efficiency, which facilitates the formulation of state-space equations [12]. This model offers straightforward parameter identification, high computational efficiency, and excellent real-time performance. Recently, Liang et al. modeled the hysteresis characteristics of LiFePO_4 batteries and integrated this with an ECM for SOC estimation, further validating the effectiveness of ECMs under complex operating conditions [13].

Currently, the estimation of the state of charge (SOC) of lithium-ion batteries primarily relies on the open-circuit voltage (OCV) method and the ampere-hour (Ah) integration method [14]. The OCV method can accurately estimate SOC under non-operating conditions; however, it requires a prolonged resting period to obtain a stable OCV value, which is subsequently used to determine the corresponding SOC [15]. The ampere-hour integration method can effectively meet the real-time requirements of battery management systems; however, its estimation accuracy is susceptible to initial SOC errors and current measurement drift. As both of these open-loop estimation methods lack a measurement feedback mechanism, they are unable to perform online correction of the estimation results. Consequently, achieving precise SOC estimation in real-time applications remains challenging with these approaches. The traditional extended Kalman filter (EKF) can address nonlinear system problems by employing a first-order Taylor series expansion [16]. Although the EKF can achieve relatively high accuracy in lithium-ion battery SOC estimation, the first-order Taylor linearization of nonlinear models inevitably neglects second-order and higher-order terms, resulting in unavoidable linearization errors. The unscented Kalman filter (UKF) employs a recursive unscented transform (UT) technique to approximate the target state without requiring linearization of the system [17]. For strongly nonlinear systems, the UKF demonstrates higher estimation accuracy and better robustness than the EKF [18]. The adaptive performance of the AUKF algorithm is highly dependent on the empirical presetting and initialization of the noise covariance matrices. Its noise estimation process relies heavily on ideal assumptions. In particular, when model parameters are inaccurate, the adaptive adjustment of the process noise covariance matrix Q and the measurement noise covariance matrix R is often based on distorted error distributions, making convergence to

a globally optimal solution difficult. This inherent limitation fundamentally restricts the achievable accuracy and robustness of SOC estimation.

Based on the foregoing analysis, to address the time-varying nature of lithium-ion battery parameters and the reliance on empirically determined noise covariance matrices in the AUKF estimation process—both of which result in inaccurate SOC estimation—this paper proposes a novel joint estimation framework. The proposed framework integrates online parameter identification using the forgetting factor recursive least squares (FFRLS) algorithm to update model parameters in real time and introduces the quantum-behaved particle swarm optimization (QPSO) algorithm to dynamically optimize the noise covariance matrices of the AUKF. This integrated approach, referred to as the QPSO-AUKF method, is designed to significantly enhance the accuracy and robustness of SOC estimation.

2. Equivalent Circuit Modeling and Parameter Dynamics

2.1. Battery Equivalent Circuit Model Construction

The equivalent circuit model can accurately describe the dynamic characteristics of batteries [19]. In this study, the battery is modeled using a second-order RC equivalent circuit [20], as illustrated in Figure 1. In the model, U_{oc} represents the open-circuit voltage (OCV) of the battery under no-load conditions; R_0 corresponds to the ohmic internal resistance; R_1 denotes the polarization resistance associated with the electrode reaction process; C_1 represents the capacitive characteristics associated with the polarization effect; R_2 denotes the mass transfer resistance caused by concentration gradients, commonly referred to as the concentration polarization resistance; C_2 characterizes the dynamic buffering effect associated with concentration polarization; and U_t represents the terminal voltage measured across the battery under an external load.

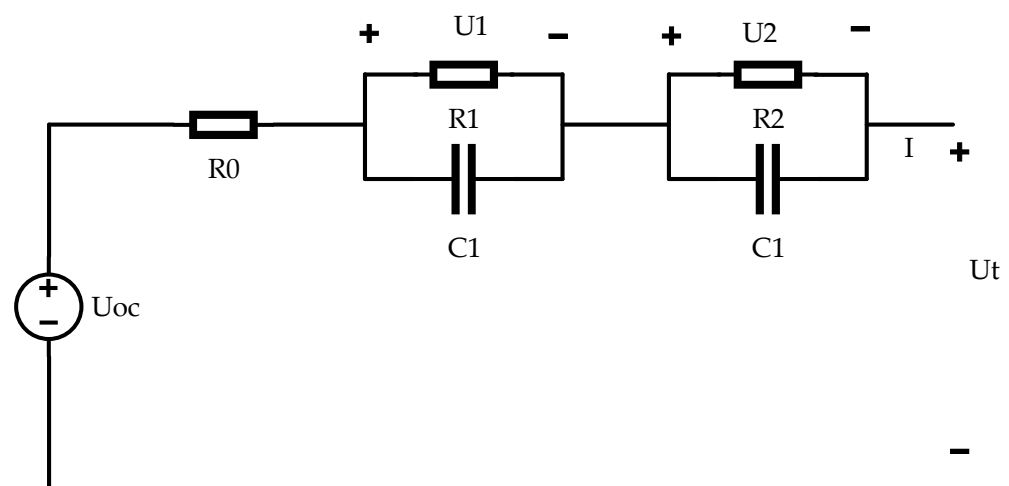


Figure 1. Dual-polarization circuit model.

Based on Kirchhoff's laws, the mathematical expressions of the equivalent circuit model are derived as follows:

$$\begin{cases} \frac{dU_1}{dt} = -\frac{1}{R_1 C_1} U_1 + \frac{1}{C_1} I \\ \frac{dU_2}{dt} = -\frac{1}{R_2 C_2} U_2 + \frac{1}{C_2} I \\ U_t = U_{ocv} - U_1 - U_2 - R_0 I \end{cases} \quad (1)$$

Through linear discretization, the state-space representation of the model at time step k is obtained, as shown in Equation (2).

$$\begin{bmatrix} \text{SOC}(k+1) \\ U_1(k+1) \\ U_2(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-T/\tau_1} & 0 \\ 0 & 0 & e^{-T/\tau_2} \end{bmatrix} \begin{bmatrix} \text{SOC}(k) \\ U_1(k) \\ U_2(k) \end{bmatrix} + \begin{bmatrix} -\frac{T}{Q_n} \\ R_1(1 - e^{-T/\tau_1}) \\ R_2(1 - e^{-T/\tau_2}) \end{bmatrix} I(k) \quad (2)$$

where T denotes the sampling period, $\tau_1 = R_1 C_1$; $\tau_2 = R_2 C_2$.

2.2. OCV-SOC Relationship Fitting

In lithium-ion battery modeling, the open-circuit voltage (OCV) typically exhibits a stable one-to-one relationship with the state of charge (SOC). Therefore, this relationship can be identified and fitted using experimental data. First, based on the discharge test data obtained under the Hybrid Pulse Power Characterization (HPPC) profile, the ampere-hour (Ah) integration method is employed to calculate the variation in battery capacity during the discharge process, thereby deriving the corresponding SOC curve. Then, following the sequence of SOC decreasing from 100% to the lower SOC range, the corresponding steady-state open-circuit voltage values are extracted point by point to form a set of OCV-SOC data samples. An eighth-order polynomial is adopted to fit the experimental OCV-SOC data. The resulting relationship is expressed in Equation (3), and the corresponding fitting curve is shown in Figure 2.

$$U_{ocv} = -0.372\text{SOC}^8 - 88.635\text{SOC}^7 + 352.2518\text{SOC}^6 - 557.6238\text{SOC}^5 + 448.3702\text{SOC}^4 - 190.9562\text{SOC}^3 + 40.8201\text{SOC}^2 - 3.2112\text{SOC} + 3.5320 \quad (3)$$

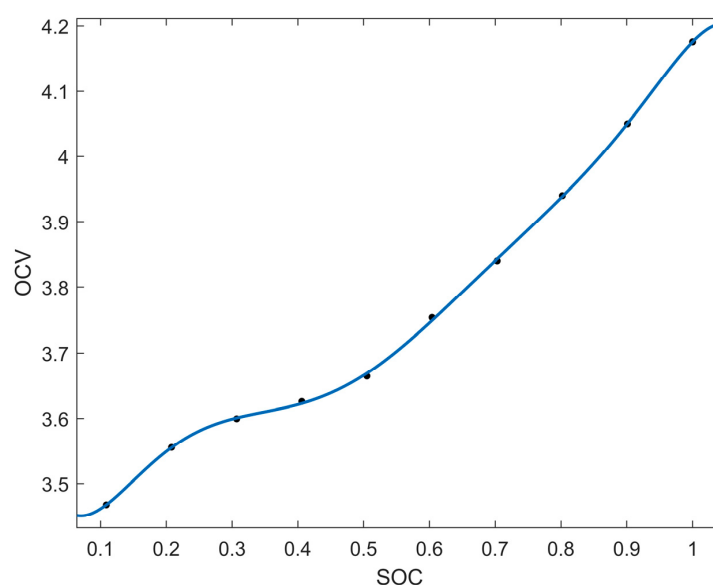


Figure 2. OCV-SOC fitting curve.

2.3. Parameter Identification

The parameters of the lithium-ion battery model are time-varying rather than fixed. Variations in key factors such as ambient temperature, cycling aging level, and state of charge (SOC) can induce complex nonlinear changes in these parameters. Therefore, during battery SOC estimation, it is necessary to perform parameter identification for the five model parameters: R_0, R_1, R_2, C_1, C_2 . Parameter identification methods can generally be categorized into online and offline approaches. Offline parameter identification assumes fixed system parameters; however, in practice, system parameters are time-varying. This

discrepancy causes offline identification results to gradually lose validity and fail to reflect the real-time battery state. In contrast, online parameter identification can promptly capture the dynamic changes in system parameters. It continuously optimizes parameter estimates concurrently with data acquisition, without the need to accumulate large volumes of historical data. Consequently, it can adapt efficiently to variations in operating conditions and provide continuously updated parameter information for real-time control systems. Accordingly, this study employs the forgetting factor recursive least squares (FFRLS) algorithm for online parameter identification. Compared with the traditional recursive least squares (RLS) algorithm, the primary enhancement of the FFRLS lies in the introduction of a forgetting factor mechanism. This mechanism enables the algorithm to place greater emphasis on recent measurement data during parameter updates while gradually diminishing the influence of historical data. Through appropriate configuration of the forgetting factor, the contribution of historical information in the estimation process can be regulated, enabling the model to rapidly adapt to changes in system parameters. The FFRLS algorithm demonstrates superior performance compared with the traditional RLS algorithm in terms of real-time capability, estimation accuracy, and robustness. The FFRLS-based model parameter identification procedure proceeds as follows:

Taking the Laplace transform of Equation (1) and rearranging it yields the expression for the polarization voltage in the complex frequency domain. Let $\tau_1 = R_1C_1$; $\tau_2 = R_2C_2$. Substituting this expression into the terminal voltage equation yields the system transfer function, as shown in Equation (4).

$$\frac{U_{ocv}(s) - U_t(s)}{I(s)} = R_0 + \frac{R_1}{R_1C_1s + 1} + \frac{R_2}{R_2C_2s + 1} \quad (4)$$

The bilinear transform is applied to discretize the system model. $s = \frac{2}{T} \cdot \frac{1-z^{-1}}{1+z^{-1}}$, the discretization is performed, yielding a discrete-time difference equation, as shown in Equation (5).

$$U_t(k) = c_0 + c_1U_t(k-1) + c_2U_t(k-2) + d_0I(k) + d_1I(k-1) + d_2I(k-2) \quad (5)$$

where c_0, c_1, c_2, d_0, d_1 , and d_2 are the coefficients of the difference equation. Their mapping to the model parameters is illustrated in Equation (6).

$$\begin{cases} c_1 = \frac{2(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T}) - 2[(1+\frac{\tau_1}{T}) + (1+\frac{\tau_2}{T})]}{(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T})} \\ c_2 = \frac{(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T}) - 2[(1+\frac{\tau_1}{T}) + (1+\frac{\tau_2}{T})]}{(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T})} \\ d_0 = \frac{R_0(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T}) + R_1(1+\frac{\tau_2}{T}) + R_2(1+\frac{\tau_1}{T})}{(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T})} \\ d_1 = \frac{-2[R_0(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T}) + R_1 + R_2]}{(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T})} \\ d_2 = \frac{R_0(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T}) + R_1(1-\frac{\tau_2}{T}) + R_2(1-\frac{\tau_1}{T})}{(1+\frac{\tau_1}{T})(1+\frac{\tau_2}{T})} \end{cases} \quad (6)$$

The regression vector and the parameter vector are defined as shown in Equation (7).

$$\begin{cases} \varphi(k) = [1, U_t(k-1), U_t(k-2), I(k), I(k-1), I(k-2)]^T \\ \hat{\theta}(k) = [c_0, c_1, c_2, d_0, d_1, d_2]^T \end{cases} \quad (7)$$

The established difference equation is reformulated into a linear observation form $U_t(k) = \varphi^T(k)\hat{\theta}(k) + v(k)$, where $v(k)$ represents the measurement noise.

Based on the recursive least squares (RLS) algorithm, a forgetting factor λ (ranging between 0 and 1) is introduced. The forgetting factor exponentially reduces the influence

of older data while assigning greater weight to newer data, enabling the algorithm to track the most recent characteristics of time-varying systems. Consequently, more accurate real-time estimation can be achieved in environments with time-varying parameters. In this study, the forgetting factor λ is set to 0.98. The FFRLS algorithm is formulated as shown in Equation (8).

$$\begin{cases} e(k) = U_t(k) - \varphi^T(k)\hat{\theta}(k-1) \\ \hat{\theta}(k) = \hat{\theta}(k-1) + K(k)e(k) \\ K(k) = \frac{P(k-1)\varphi(k)}{\varphi^T(k)P(k-1)\varphi(k)+\lambda} \\ P(k) = \frac{1}{\lambda}[I - K(k)\varphi^T(k)]P(k-1) \end{cases} \quad (8)$$

$e(k)$ is the residual between the measured terminal voltage and the model-predicted value at time step k ; $\hat{\theta}(k)$ is the estimated parameter vector to be identified; $K(k)$ is the gain matrix; $P(k)$ is the covariance matrix of the parameter estimation error; and $\varphi(k)$ is the regression vector.

After $\hat{\theta}(k)$ is identified using the FFRLS algorithm, the model parameters can be obtained by mapping them through the coefficient equations, as shown in Equation (9).

$$\begin{cases} \tau_1 = \frac{T(1-c_2)}{1+c_1+c_2} \\ \tau_2 = \frac{T(1-c_1+c_2)}{1-c_1+c_2} \\ R_0 = \frac{d_0+d_2}{2+c_1} \\ R_1 = \frac{(d_0-R_0)(1+\tau_2/T)}{1+\tau_1/T} \\ R_2 = \frac{(d_0-R_0)(1+\tau_1/T)}{1+\tau_2/T} \\ C_1 = \frac{\tau_1}{R_1} \\ C_2 = \frac{\tau_2}{R_2} \end{cases} \quad (9)$$

3. SOC Estimation

3.1. Quantum-Behaved Particle Swarm Optimization Algorithm

The Quantum-behaved Particle Swarm Optimization (QPSO) algorithm is an intelligent optimization method based on quantum-behavioral characteristics. Unlike the traditional particle swarm optimization (PSO), QPSO models the distribution of particle positions using a probability density function, which provides stronger global search capability and reduces the risk of being trapped in local optima. When the adaptive unscented Kalman filter (AUKF) estimates the state of charge (SOC) of lithium-ion batteries, the process noise covariance matrix (Q) and the observation noise covariance matrix (R) rely on empirically preset values. If the initial values deviate significantly from the actual operating conditions, this may result in a decrease in filtering accuracy or even filter divergence. The introduced QPSO algorithm models particle positions using a probability density function, eliminating the need to specify an inertia weight. It efficiently searches for the optimal values of the process noise covariance matrix Q and the observation noise covariance matrix R within the solution space, thereby improving the filter's adaptability and estimation accuracy under varying operating conditions. The basic position update equation for QPSO is presented in Equation (10).

$$x_i^{(t+1)} = p_i^{(t)} \pm \beta \left| m^{(t)} - x_i^{(t)} \right| \ln\left(\frac{1}{u}\right) \quad (10)$$

where $x_i^{(t)}$ is the position of the i -th particle at the t -th iteration, $p_i^{(t)}$ is the historical best position of the particle, β is the contraction-expansion coefficient used to balance global search and local convergence, u is a random number in the interval $(0, 1)$, the

symbol “ $\pm$ ” depends on the randomly selected direction, and $m^{(t)} = \frac{1}{N} \sum_{i=1}^N p_i^{(t)}$ is the global attraction center.

3.2. QPSO-Optimized AUKF Algorithm

3.2.1. Fundamentals of the Adaptive Unscented Kalman Filter

The Adaptive Unscented Kalman Filter (AUKF) is a recursive state estimation algorithm developed for nonlinear systems. The core concept involves introducing an adaptive update mechanism for the noise covariance matrices based on the standard Unscented Kalman Filter (UKF), thereby enhancing the algorithm's adaptability to modeling uncertainties and variations in measurement noise. The AUKF procedure is summarized as follows:

1. Initialization

The initial values for the subsequent filtering process are obtained by initializing the system state estimate and the associated covariance matrix. The system model is given in Equation (11).

$$\begin{cases} x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \\ y_k = h(x_k, u_k) + v_k \end{cases} \quad (11)$$

where x_k is the system state vector, y_k is the observation vector, u_k is the control input, $f(\cdot)$ is the state transition function, $h(\cdot)$ is the observation function, $w_k \sim N(0, Q_k)$ is the process noise, and $v_k \sim N(0, R_k)$ is the observation noise. The initial state estimate and its covariance matrix are given in Equation (12).

$$\begin{cases} \hat{x}_0 = E[x_0] \\ P_0 = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T] \end{cases} \quad (12)$$

where $\hat{x}_0$ is the initial state estimate and P_0 is the initial covariance matrix.

2. Calculation of Unscented Transform Parameters

In the Unscented Kalman Filter (UKF), a set of scaling parameters λ and corresponding weights are calculated to generate the sigma points. These parameters are subsequently used to propagate the sigma points through the state space. The scaling parameter λ and the sigma-point weights are computed as follows: $\lambda = \alpha^2(L + \kappa) - L$, where α is the scaling factor, L is the state dimension, κ is the secondary scaling parameter, and λ is the parameter that adjusts the distribution range of the sigma points.

$$\begin{cases} W_m^{(0)} = \frac{\lambda}{L + \lambda} \\ W_c^{(0)} = \frac{\lambda}{L + \lambda} + (1 - \alpha^2 + \beta) \\ W_m^{(i)} = W_c^{(i)} = \frac{1}{2(L + \lambda)}, i = 1, 2, \dots, 2L \end{cases} \quad (13)$$

where $W_m^{(i)}$ is the mean weight of the i -th Sigma point, $W_c^{(i)}$ is the mean square error weight of the i -th Sigma point, and β is the parameter used to adjust the weight calculation formula.

3. Generation of Sigma Points

Sigma points are employed to represent the state distribution and to propagate it through the state space. Through these sigma points, the uncertainty of the system state can be effectively captured. The sigma points are generated according to Equation (14).

$$X_{k-1}^{(i)} = \hat{x}_{k-1} \pm \sqrt{(L + \lambda)P_{k-1}}, i = 1, 2, \dots, 2L \quad (14)$$

where $X_{k-1}^{(i)}$ is the i -th generated Sigma point, $\hat{x}_{k-1}$ is the mean state estimate at the previous time step, P_{k-1} is the state estimation covariance matrix at the previous time step, and $\sqrt{(L + \lambda)P_{k-1}}$ is the square root of the covariance matrix.

4. Time Update

During the state transition, the predicted state estimate is obtained by propagating the sigma points. The sigma points are propagated according to Equation (15), which represents the state transition function.

$$\tilde{X}_{k|k-1}^{(i)} X_{k|k-1}^{(i)} = f(X_{k-1}^{(i)}, u_{k-1}), i = 0, 1, \dots, 2L \quad (15)$$

where $\tilde{X}_{k|k-1}^{(i)}$ is the i -th predicted Sigma point, and $f(\cdot)$ is the state transition function. The predicted state and its covariance matrix are given in Equation (16).

$$\begin{cases} \hat{x}_{k|k-1} = \sum_{i=0}^{2L} W_m^{(i)} \tilde{X}_{k|k-1}^{(i)} \\ P_{k|k-1} = \sum_{i=0}^{2L} W_c^{(i)} [\tilde{X}_{k|k-1}^{(i)} - \hat{x}_{k|k-1}] [\tilde{X}_{k|k-1}^{(i)} - \hat{x}_{k|k-1}]^T + Q_k \end{cases} \quad (16)$$

where $\hat{x}_{k|k-1}$ is the predicted state mean, $P_{k|k-1}$ is the predicted covariance matrix, and Q_k is the process noise covariance matrix.

5. Measurement Prediction

Measurement prediction is employed to transform the predicted state into the corresponding observation prediction. The sigma points are propagated through the observation model, as given in Equation (17).

$$\begin{cases} Y_{k|k-1}^{(i)} = h(\tilde{X}_{k|k-1}^{(i)}, u_{k-1}), i = 0, 1, \dots, 2L \\ \hat{y}_{k|k-1} = \sum_{i=0}^{2L} W_m^{(i)} Y_{k|k-1}^{(i)} \\ P_{yy,k} = \sum_{i=0}^{2L} W_c^{(i)} [Y_{k|k-1}^{(i)} - \hat{y}_{k|k-1}] [Y_{k|k-1}^{(i)} - \hat{y}_{k|k-1}]^T + R_k \\ P_{xy,k} = \sum_{i=0}^{2L} W_c^{(i)} [\tilde{X}_{k|k-1}^{(i)} - \hat{x}_{k|k-1}] [Y_{k|k-1}^{(i)} - \hat{y}_{k|k-1}]^T \end{cases} \quad (17)$$

where $Y_{k|k-1}^{(i)}$ is the i -th predicted observation Sigma point, $\hat{y}_{k|k-1}$ is the predicted observation mean, $P_{yy,k}$ is the observation prediction covariance matrix, $P_{xy,k}$ is the cross-covariance between the state and observation, and R_k is the observation noise covariance.

6. Measurement Update

Following the prediction step, the state is corrected using the actual measurements. During the measurement update, the state estimate is refined by combining the innovation (observation residual) with the Kalman gain, as shown in Equation (18).

$$\begin{cases} K_k = P_{xy,k} P_{yy,k}^{-1} \\ e_k = y_k - \hat{y}_{k|k-1} \\ \hat{x}_k = \hat{x}_{k|k-1} + K_k e_k \\ P_k = P_{k|k-1} - K_k P_{yy,k} K_k^T \end{cases} \quad (18)$$

where K_k is the Kalman gain matrix, e_k is the innovation (observation residual), $\hat{x}_k$ is the updated state estimate, and P_k is the updated covariance matrix.

7. Adaptive Noise Covariance Update

Through the innovation-based adaptive noise update, the covariances of the process noise (Q) and observation noise (R) are adaptively adjusted, as given in Equation (19).

$$\begin{cases} R_k = \alpha_R R_{k-1} + (1 - \alpha_R) e_k e_k^T \\ Q_k = \alpha_Q Q_{k-1} + (1 - \alpha_Q) K_k e_k e_k^T K_k^T \end{cases} \quad (19)$$

where α_Q and α_R are forgetting factors that control the smoothness of the noise update, Q_k is the adaptive estimate of the process noise covariance, R_k is the adaptive estimate of the observation noise covariance, and e_k is the observation residual (innovation).

The filtering process is carried out by iteratively repeating Steps 3–7. Based on the standard UKF, the AUKF incorporates an adaptive noise update mechanism that dynamically adjusts the process and measurement noise according to real-time observation errors. This mechanism enables the filter to better accommodate variations in system noise and modeling uncertainties. Furthermore, it enhances the stability and robustness of the algorithm under complex system conditions.

3.2.2. QPSO-Based Noise Optimization Mechanism for AUKF

The performance of the AUKF strongly depends on the accuracy of the noise covariance matrices Q and R . Traditional methods typically rely on empirical settings, which makes it challenging to adapt to dynamic variations in operating conditions. To address this issue, the study introduces the Quantum-behaved Particle Swarm Optimization (QPSO) algorithm as an outer-layer optimizer to perform a global search for the optimal Q and R . Given a set of noise parameters (Q, R), the objective function of the AUKF is defined as the root mean square error (RMSE) of the residuals between the measured terminal voltage U_k^{meas} and the estimated terminal voltage $U_k^{est}(Q, R)$, as expressed in Equation (20). The objective function of the QPSO algorithm is based on the root mean square error (RMSE) of the terminal voltage rather than the SOC estimation error. The terminal voltage is directly measurable with high reliability, whereas the SOC reference value (typically derived from the ampere-hour (Ah) integration method) may accumulate drift during prolonged operation. Within the framework of the equivalent circuit model and Kalman filter, a strong coupling exists among the terminal voltage, SOC, and polarization states. Therefore, minimizing the RMSE of the terminal voltage residuals can effectively constrain SOC estimation accuracy while avoiding the introduction of potentially noisy or drifting SOC reference values into the optimization process. In this study, the QPSO algorithm is employed for global offline statistical calibration of the noise covariance matrices. The online correction of these matrices is achieved through the innovation sequence adaptation mechanism within the AUKF.

$$J(Q, R) = \sqrt{\frac{1}{N} \sum_{k=1}^N (U_k^{meas} - U_k^{est}(Q, R))^2} \quad (20)$$

where U_k^{meas} is the measured terminal voltage, $U_k^{est}(Q, R)$ is the estimated voltage calculated by the AUKF, and N is the sampling length. The optimization objective is shown in Equation (21).

$$(Q^*, R^*) = \operatorname{argmin}_{Q, R} J(Q, R) \quad (21)$$

Each particle in the QPSO represents a set of candidate parameters (Q_i, R_i). The outer-layer QPSO evaluates the performance of the particle swarm using the fitness function $J(Q_i, R_i)$, and updates the particle positions according to Equation (10). As the iterations

proceed, the Q^* and R^* corresponding to the global best particle g^t converge to the optimal noise matrices.

3.2.3. Dynamic Adjustment of Noise Matrices

After obtaining the initial optimal noise matrices via QPSO, and to balance global optimization with real-time adaptability, an online fine-tuning mechanism for the process noise matrix Q and measurement noise matrix R is incorporated within the inner layer of the AUKF. The noise matrices are adaptively updated using an exponential weighting method, as given in Equation (22).

$$\begin{cases} Q_k = \gamma Q_{k-1} + (1 - \gamma)(\epsilon_k \epsilon_k^T) \\ R_k = \delta R_{k-1} + (1 - \delta)(\nu_k \nu_k^T) \end{cases} \quad (22)$$

where Q_k is the current process noise covariance matrix, R_k is the current measurement noise covariance matrix, $\epsilon_k = \hat{x}_k - \hat{x}_{k|k-1}$ is the state prediction error (state innovation), $\nu_k = y_k - \hat{y}_{k|k-1}$ is the observation residual (measurement innovation), and $\gamma, \delta \in (0, 1)$ are smoothing factors that control the update rate. The adaptive factors γ and δ are dynamically adjusted based on the system innovation. During phases of drastic changes in operating conditions, their values are adaptively decreased to enhance the filter's ability to track state mutations; when the system tends towards a steady state, their values are correspondingly increased to effectively suppress measurement noise and improve estimation smoothness.

3.3. Online Parameter Identification and Joint Estimation

In the proposed QPSO-AUKF algorithm, the Forgetting Factor Recursive Least Squares (FFRLS) method is employed for online identification of the battery equivalent model parameters, aiming to enhance the filter model's accuracy and the system's robustness. Using the FFRLS algorithm, parameters such as resistances and capacitances in the battery's second-order RC equivalent circuit model can be identified in real time, allowing the model to dynamically reflect the battery's response under varying operating conditions. After initializing the second-order RC battery model, the FFRLS algorithm recursively updates the model parameters based on collected terminal voltage and current data, producing an optimal parameter vector that evolves over time. The updated parameters are then fed into the QPSO-AUKF algorithm in real time to correct the model-related terms in the state and observation equations, thereby enabling dynamic tracking of the battery state during filtering. To ensure filtering precision, QPSO is employed for global optimization of the noise covariance matrices Q and R , providing stable initial values. Once the initial parameters are determined, the AUKF performs online state estimation using real-time data and dynamically adjusts the noise covariance matrices to adapt to variations under different operating conditions. Simultaneously, FFRLS continuously updates the battery model parameters to maintain consistency between the model and actual operating conditions. This integrated strategy of "online parameter identification, real-time state estimation, and adaptive noise optimization" forms a closed-loop correction structure: QPSO performs global optimization of the noise covariance matrices in the outer layer; AUKF conducts SOC state estimation in the inner layer using the latest parameters; and FFRLS continuously adjusts the battery model parameters to match actual operating conditions. QPSO serves only as a one-time offline tuning step to provide robust initial values, while AUKF is responsible for online adaptive adjustment of the noise covariance matrices to accommodate changes in dynamic operating conditions. The flowchart of the algorithm is presented in Figure 3.

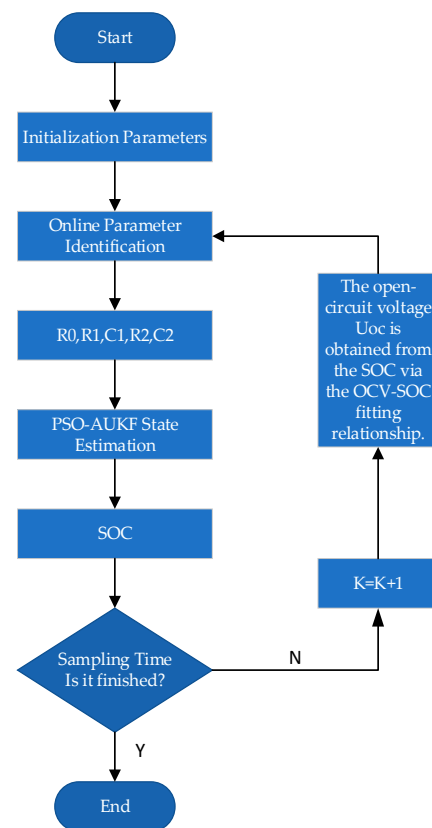


Figure 3. Online Identification and QPSO-AUKF for Battery SOC Estimation.

4. Experimental Verification and Analysis

4.1. Experimental Setup and Parameter Settings

This study employs the dataset published by the CALCE Battery Research Group to validate the accuracy of the proposed parameter identification method. The INR 18650-20R lithium-ion battery (Samsung SDI in Seoul, Republic of Korea) was selected as the test object, featuring a nominal voltage of 3.6 V, an operating voltage range of 2.5–4.2 V, and a rated capacity of 2000 mAh. The sampling interval for all experiments was set to 1 s. In this study, a second-order RC equivalent circuit model was adopted to characterize the dynamic behavior of the battery, with the state vector defined as $\mathbf{x} = [U_1, U_2, SOC]^T$. To account for the time-varying characteristics of the battery, the Forgetting Factor Recursive Least Squares (FFRLS) algorithm is employed for online identification of the model parameters R_0, R_1, R_2, C_1, C_2 . The forgetting factor is set to $\lambda = 0.98$. To prevent numerical instability caused by zero initial values, the parameters identified during the first three sampling instants are replaced with the values at the third instant. All resistance and capacitance parameters are expressed in ohms (Ω) and farads (F), respectively. The Quantum-behaved Particle Swarm Optimization (QPSO) algorithm is executed offline to determine the initial values of the process noise covariance matrix $\mathbf{Q}$ and the measurement noise covariance matrix $\mathbf{R}$ for the Adaptive Unscented Kalman Filter (AUKF). The optimization vector is defined as $\boldsymbol{\theta} = [q_1, q_2, q_3, r]^T$. Where $\mathbf{Q} = \text{diag}(q_1, q_2, q_3)$, The search ranges of all variables are set to $[10^{-12}, 10^{-1}]$. The QPSO population size is set to 30, and the maximum number of iterations is set to 50. The contraction–expansion coefficient decreases linearly with the iteration index. The optimization process terminates when the maximum number of iterations is reached. QPSO is executed offline to obtain the initial configuration of the noise covariance matrices, while SOC is estimated online using the AUKF. The AUKF is initialized with $\mathbf{x}_0 = [0, 0, 0.6]^T$, $\mathbf{P}_0 = \text{diag}(10^{-6}, 10^{-6}, 10^{-2})$. The UKF scaling parameters are selected as $L = 3$, $\alpha = 0.2$, $\kappa = 0$, and $\beta = 2$. An innovation-based adaptive mechanism is

incorporated, in which the innovation covariance is estimated using a sliding window of five samples, and the adaptive update is activated from the sixth sampling instant onward. To ensure a fair comparison, all algorithms were initialized with the same noise covariance matrices (Q and R) and parameter tuning ranges across all datasets.

4.2. Parameter Identification Results Under Different Operating Conditions

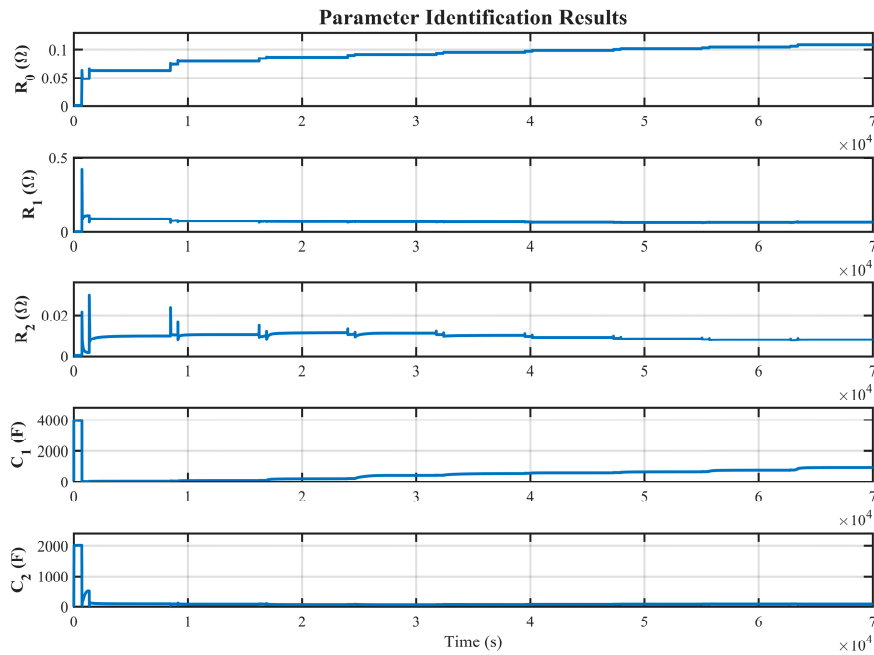
Experiments were conducted under constant-current pulse discharge, dynamic stress test (DST), and federal urban driving schedule (FUDS) conditions at three different temperatures (0 °C, 25 °C, and 45 °C) to obtain online parameter identification results. The identified parameters were substituted into the state-space equations, and the simulated terminal voltage was compared with the experimentally measured data, producing terminal voltage comparison results and the corresponding error curves. Figure 4, Figure 5, and Figure 6 illustrate the battery parameter identification results under constant-current pulse discharge, DST, and FUDS conditions, respectively, at the three tested temperatures.

Simulation results show that across three temperatures (0 °C, 25 °C, and 45 °C), the simulated terminal voltage closely matches the measured terminal voltage under constant-current pulse discharge, DST, and FUDS conditions, indicating high overall accuracy of the online-identified second-order RC equivalent circuit model. Among the three profiles, DST generally exhibits the largest voltage deviation due to its more aggressive dynamic excitation, while the pulse discharge and FUDS profiles maintain satisfactory accuracy. These results demonstrate that the proposed online parameter identification strategy can robustly support SOC estimation across a wide temperature range. In particular, by introducing a forgetting factor and exponential weighting to gradually reduce the influence of historical data, the FFRLS algorithm can dynamically track temperature- and condition-dependent parameter variations, thereby providing a reliable foundation for subsequent high-accuracy SOC estimation.

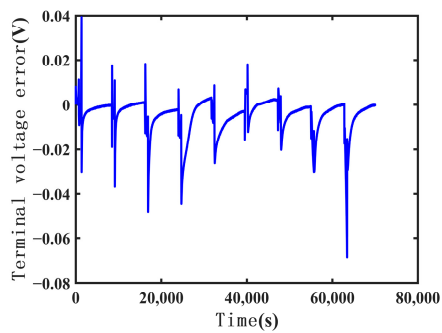
4.3. Comparison of SOC Estimation Results Under Multiple Operating Conditions

To verify the accuracy and reliability of the QPSO-AUKF algorithm for battery SOC estimation, real-time SOC estimation is conducted under pulse discharge, DST, and FUDS operating conditions. The actual SOC value, calculated using the ampere-hour integration method, is used as the reference standard. Meanwhile, the SOC estimation results obtained using the QPSO-AUKF algorithm are compared with those of the UKF, AUKF, and PSO-AUKF algorithms to comprehensively evaluate the performance differences and applicability of each algorithm under different operating conditions.

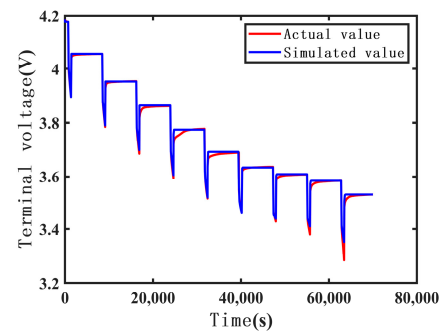
First, the simulation results under the HPPC operating condition at 0 °C, 25 °C, and 45 °C are presented in Figure 7. As shown in Figure 7, the UKF, AUKF, PSO-AUKF, and QPSO-AUKF algorithms are all capable of estimating the battery SOC with reasonable accuracy. However, the SOC estimation obtained using QPSO-AUKF is the closest to the reference value across all three temperatures. This performance can be attributed to several factors. The UKF is highly dependent on the initialization of parameters and noise covariance matrices. Although the adaptive mechanism of the AUKF improves performance, its response may still lag under highly nonlinear or rapidly varying conditions in the HPPC test. Moreover, the PSO-AUKF algorithm exhibits slow convergence and a tendency to become trapped in local optima during the optimization process, particularly under temperature variations. In contrast, the QPSO-AUKF algorithm employs QPSO for global parameter optimization, providing a broader search range, faster convergence, and reduced susceptibility to local optima. These results indicate that incorporating QPSO significantly enhances the accuracy and robustness of SOC estimation under HPPC conditions across different temperatures.



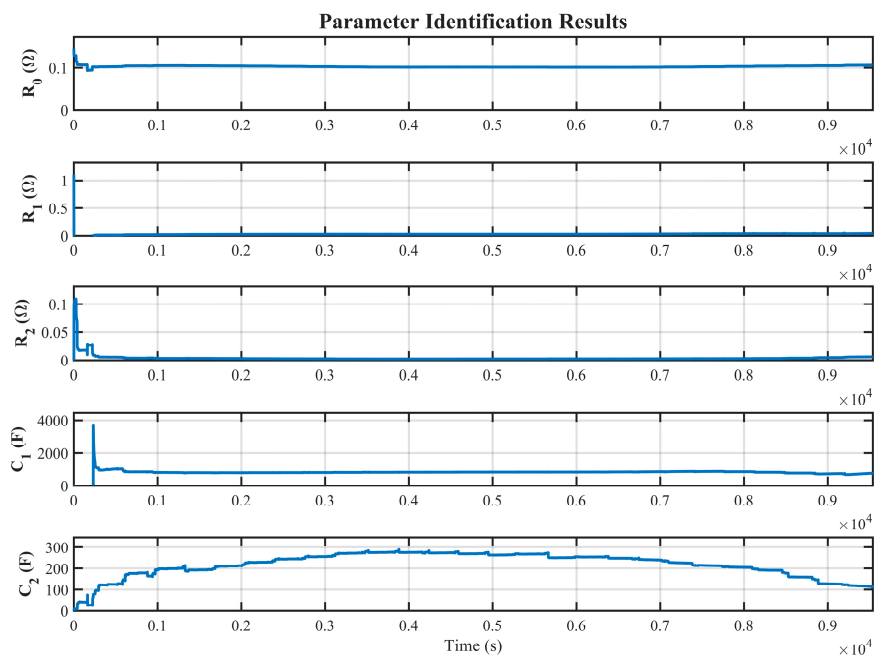
(a) Parameter identification results under HPPC condition



(b) Terminal voltage error under HPPC condition

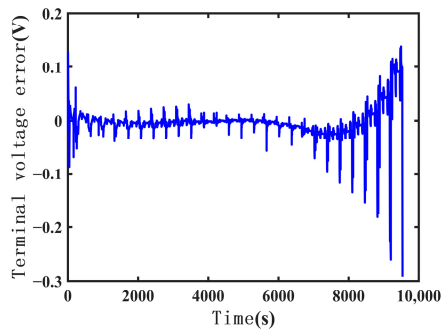


(c) Terminal voltage comparison under HPPC condition

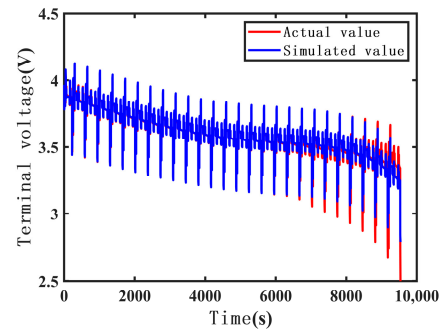


(d) Parameter identification results under DST condition

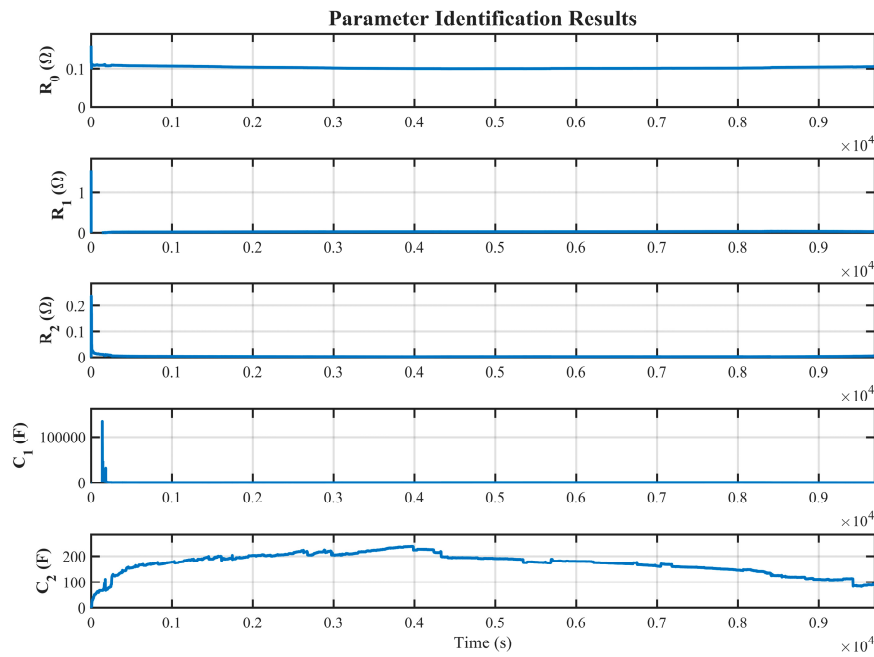
Figure 4. Cont.



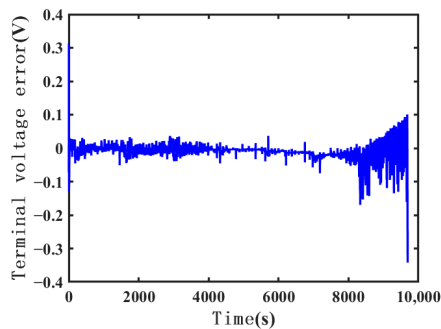
(e) Terminal voltage error under DST condition



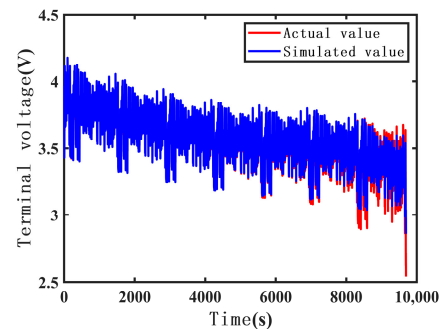
(f) Terminal voltage comparison under DST condition



(g) Parameter identification results under FUDS condition

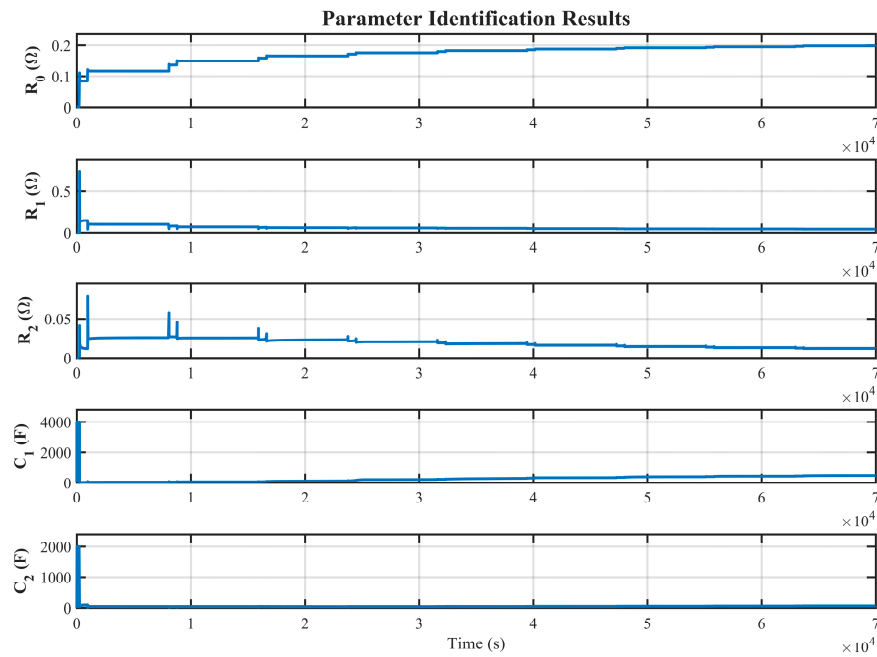


(h) Terminal voltage error under FUDS condition

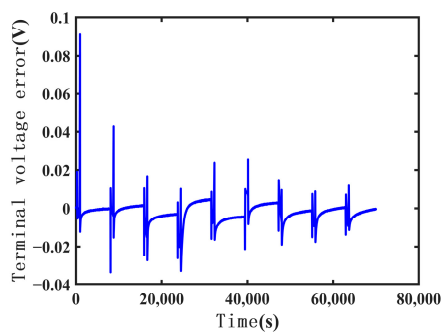


(i) Terminal voltage comparison under FUDS condition

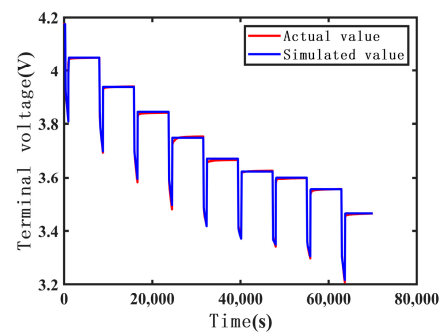
Figure 4. Comparison of identified parameters and voltage errors at 0 °C.



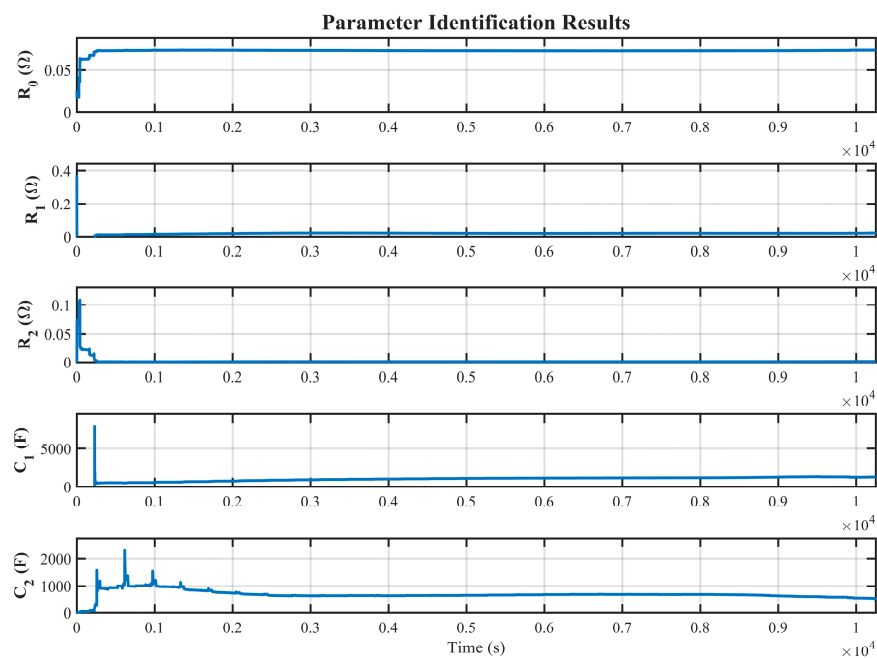
(a) Parameter identification results under HPPC condition



(b) Terminal voltage error under HPPC condition

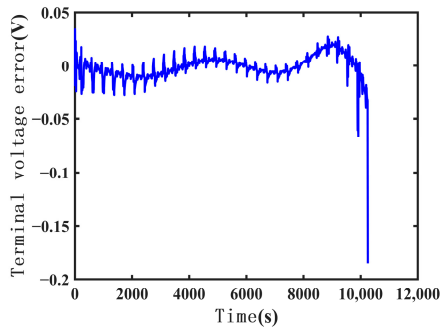


(c) Terminal voltage comparison under HPPC condition

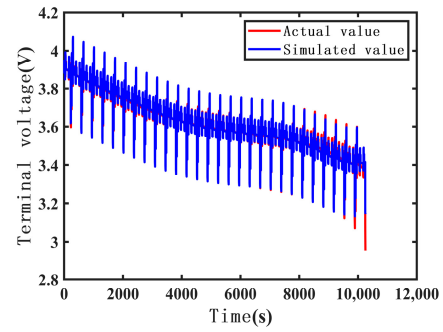


(d) Parameter identification results under DST condition

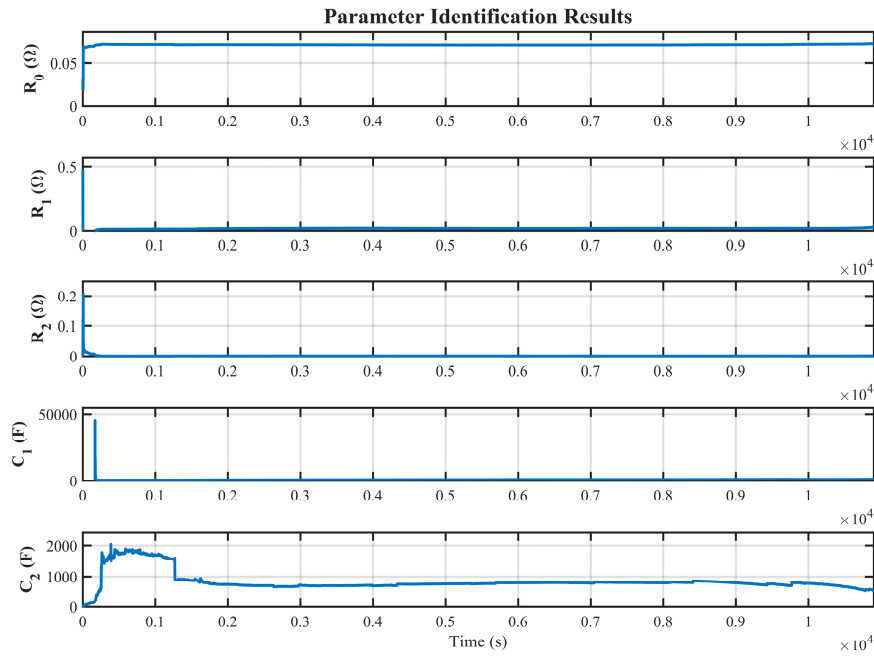
Figure 5. Cont.



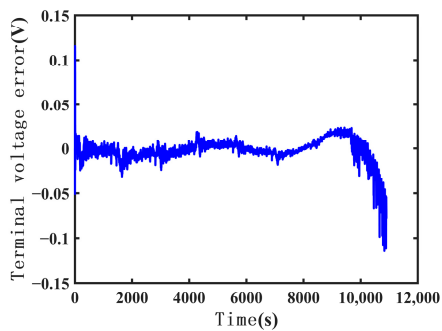
(e) Terminal voltage error under DST condition



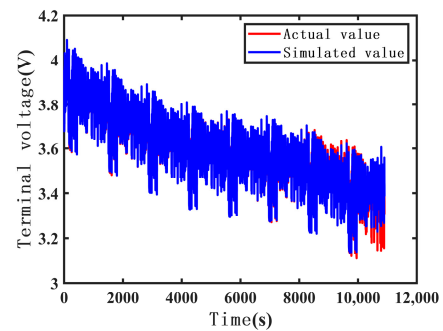
(f) Terminal voltage comparison under DST condition



(g) Parameter identification results under FUDS condition

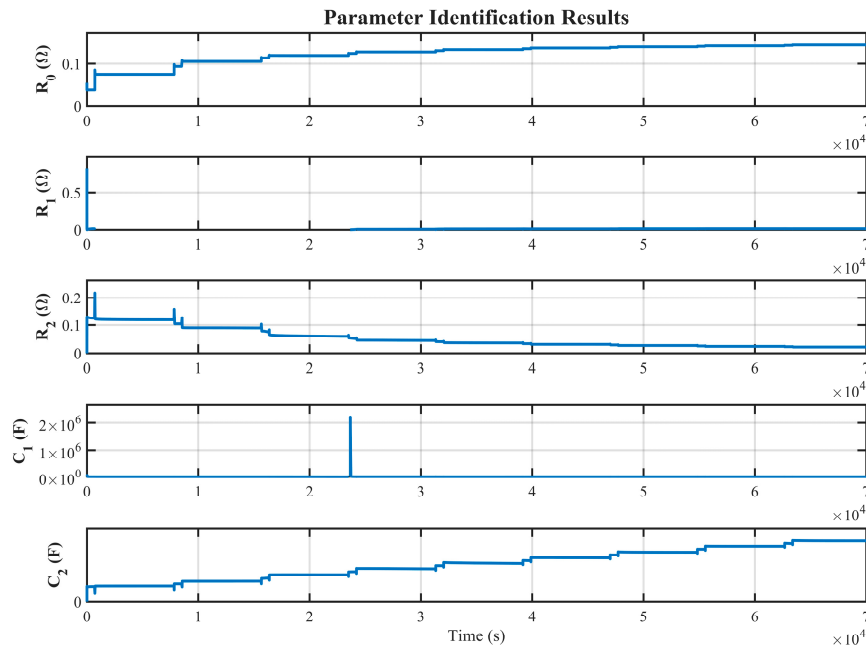


(h) Terminal voltage error under FUDS condition

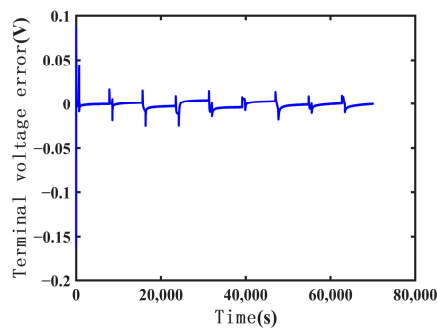


(i) Terminal voltage comparison under FUDS condition

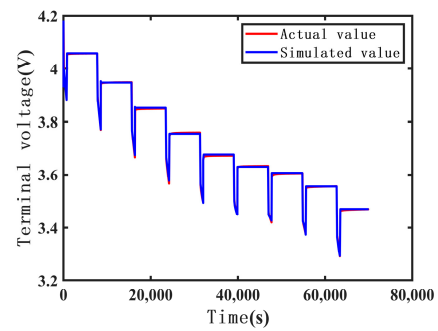
Figure 5. Comparison of identified parameters and voltage errors at 25 °C.



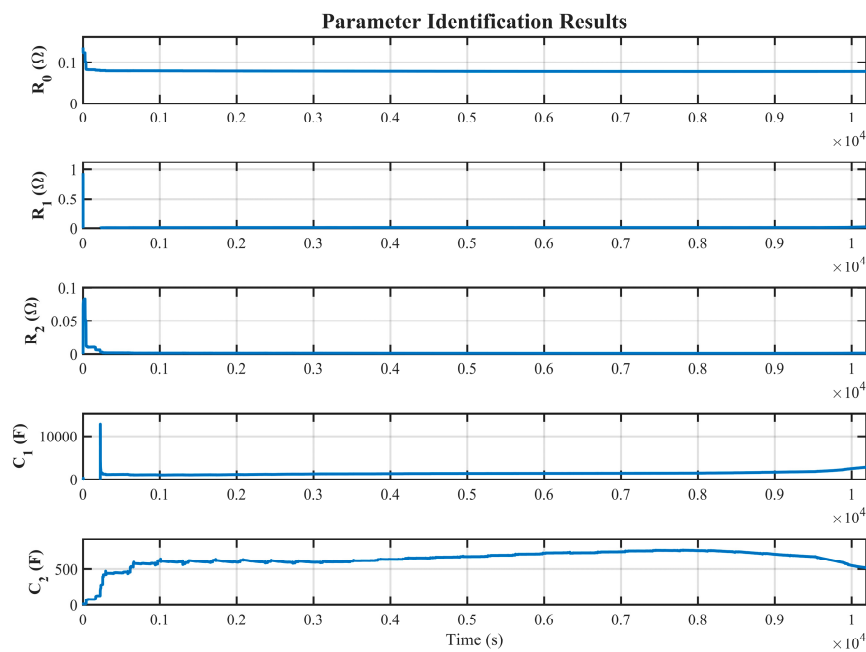
(a) Parameter identification results under HPPC condition



(b) Terminal voltage error under HPPC condition

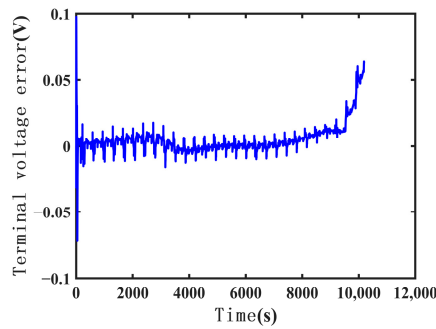


(c) Terminal voltage comparison under HPPC condition

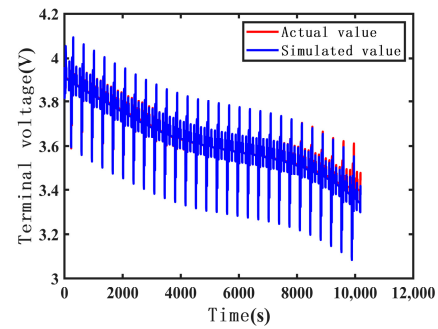


(d) Parameter identification results under DST condition

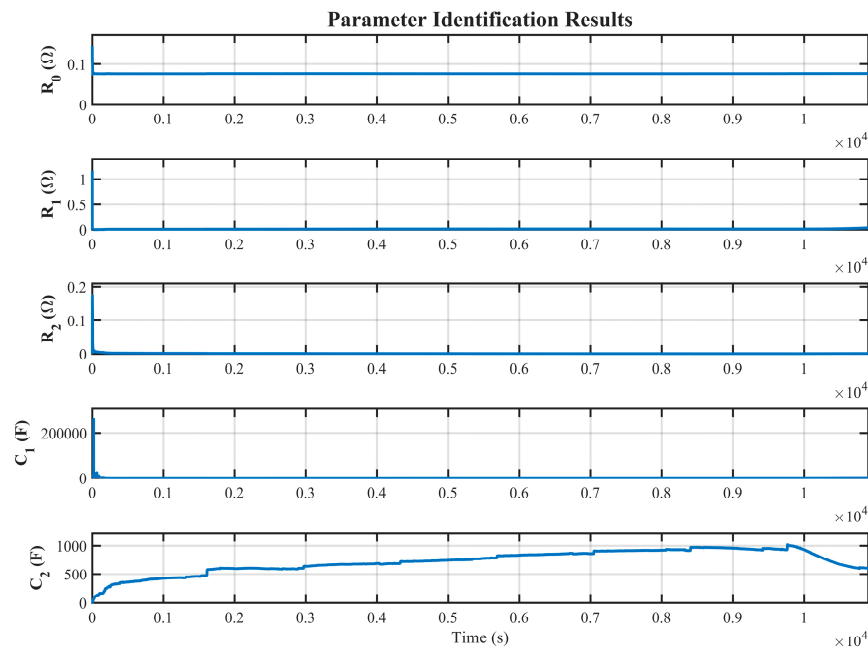
Figure 6. Cont.



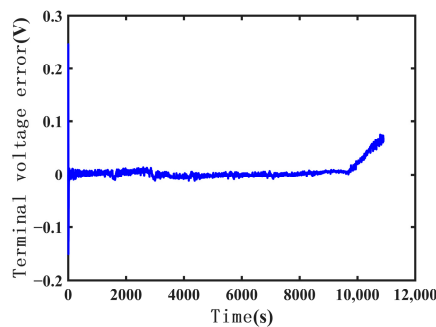
(e) Terminal voltage error under DST condition



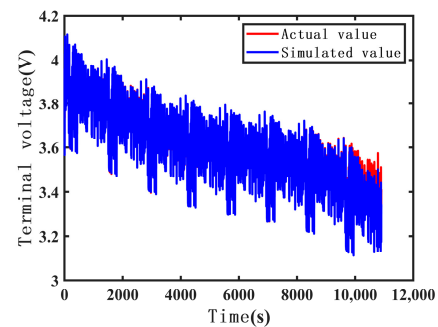
(f) Terminal voltage comparison under DST condition



(g) Parameter identification results under DST condition



(h) Terminal voltage error under DST condition



(i) Terminal voltage comparison under DST condition

Figure 6. Comparison of identified parameters and voltage errors at 45 °C.

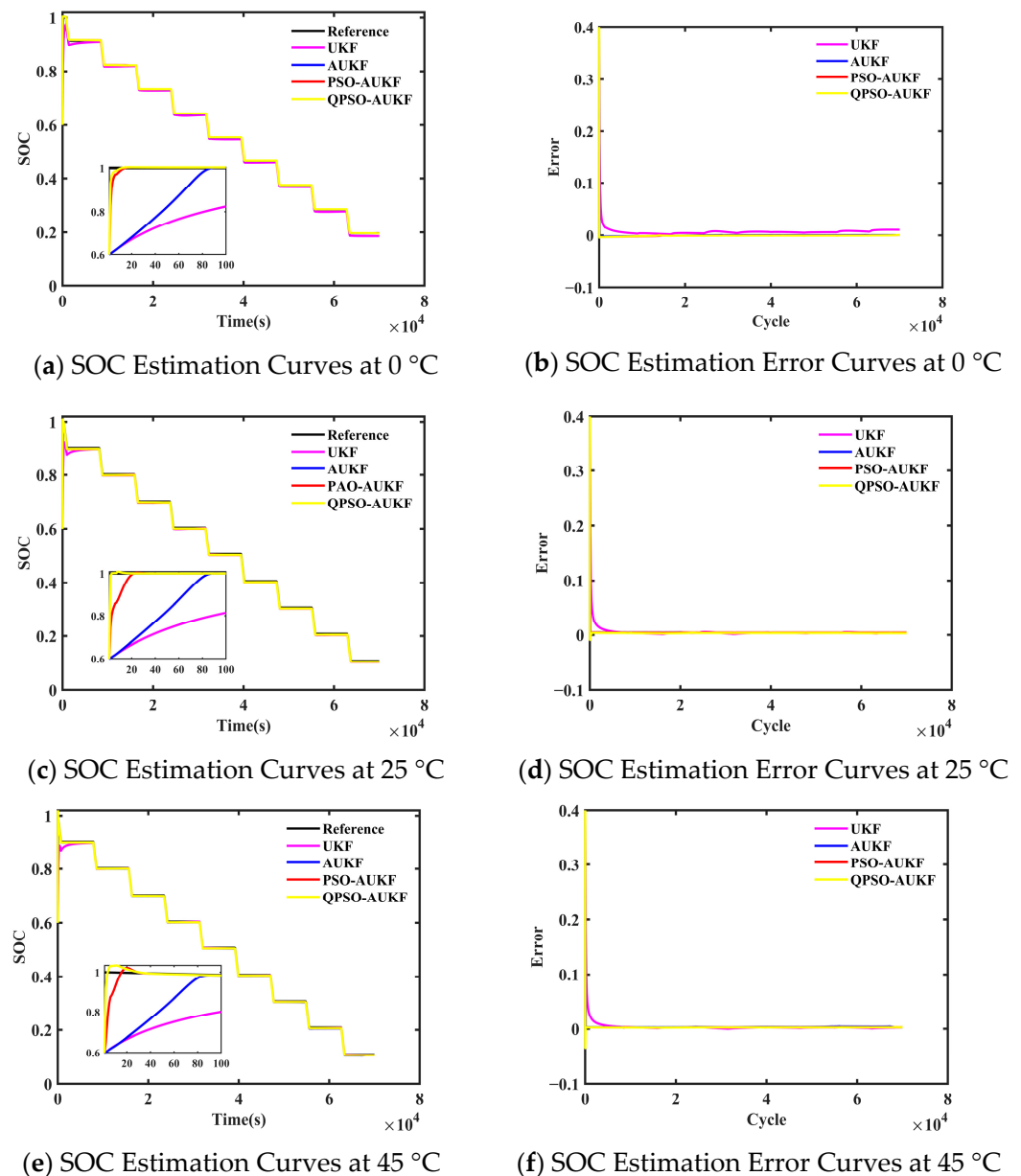


Figure 7. SOC estimation comparison under HPPC conditions.

Second, the simulation results under DST conditions at 0 °C, 25 °C, and 45 °C are presented in Figure 8. Compared with the HPPC condition, differences in the responses of the various algorithms to frequent and severe current disturbances are more pronounced under DST conditions. Although all methods capture the overall SOC variation trend, the QPSO-AUKF algorithm exhibits smaller fluctuations and more stable tracking performance throughout the dynamic process across all three temperatures. This phenomenon primarily results from the higher demands imposed by DST conditions on the adaptive capability of model parameters and noise estimation. The conventional UKF, due to its reliance on fixed noise statistics, is prone to significant overshoot during large current step changes, particularly under temperature variations. Although the AUKF mitigates part of the overshoot through online adjustment, its adaptive response still lags under continuous and strong dynamic disturbances. The PSO-AUKF demonstrates improved parameter optimization performance; however, particle swarm optimization may become trapped in local optima, resulting in intermittent error increases during complex dynamic processes across different temperatures. The results demonstrate that the QPSO-AUKF, benefiting

from its stronger global search capability, provides more robust parameter configurations for the filter. Consequently, it maintains superior estimation accuracy and stability under demanding DST operating conditions across different temperatures.

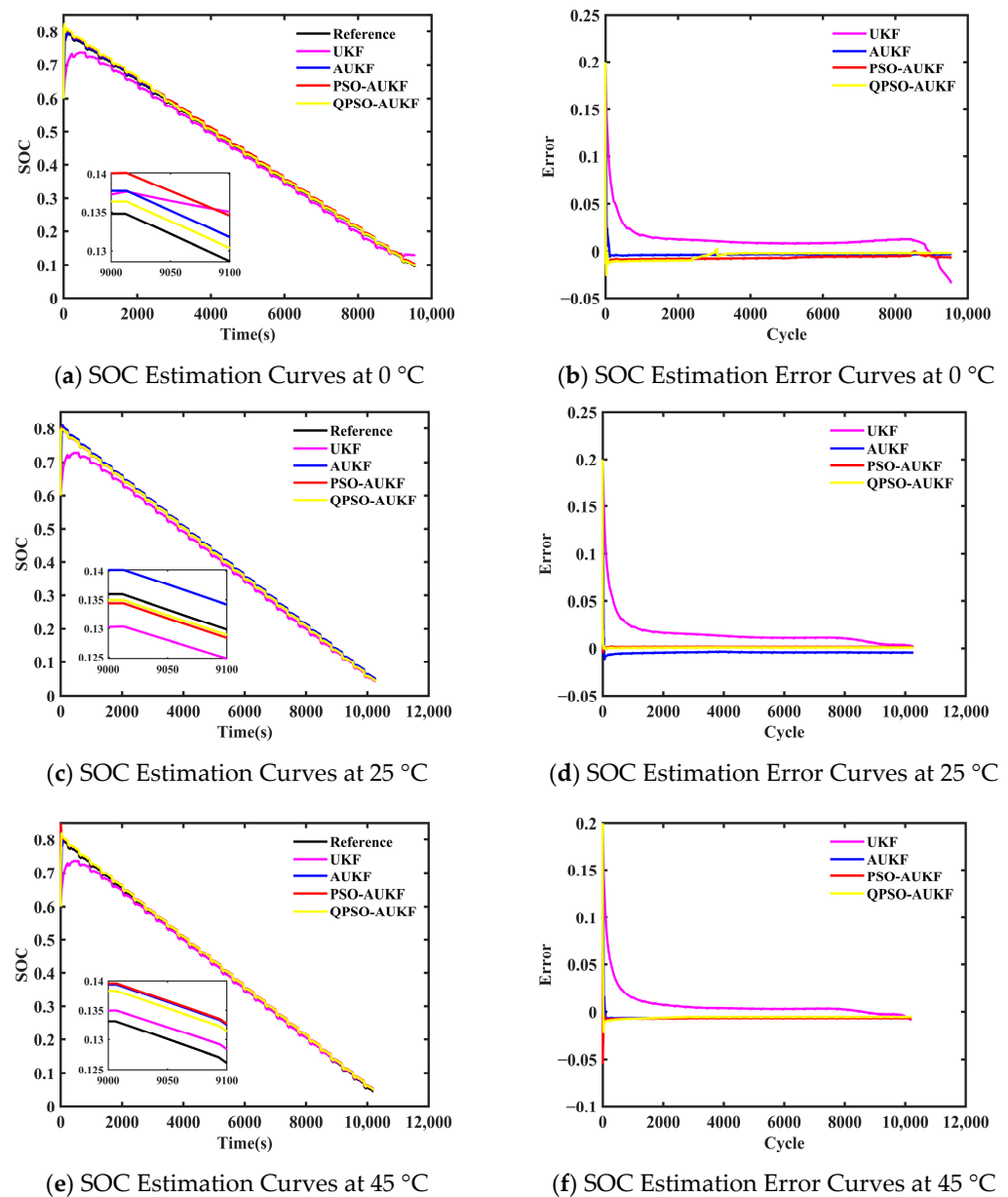


Figure 8. SOC estimation comparison under DST conditions.

Finally, under FUDS conditions at 0 °C, 25 °C, and 45 °C, the SOC estimation comparison and error distribution are presented in Figure 9. FUDS conditions simulate continuous and slowly varying current loads typical of urban traffic, providing a persistent test of the algorithm's long-term tracking accuracy and cumulative error control capability. Under these operating conditions, the advantage of QPSO-AUKF is demonstrated by its extremely low steady-state error and non-divergent trend tracking behavior across all three temperatures. The analysis suggests that the UKF exhibits a cumulative error trend during long-term operation. The AUKF improves long-term performance but shows limited adaptability to the slowly time-varying characteristics of model parameters, particularly under temperature variations. Moreover, the statically optimized parameters of PSO-AUKF may lead to performance degradation toward the end of long-duration operating conditions across different temperatures. In contrast, QPSO-AUKF, through its quantum-behavior

mechanism, ensures that the optimized parameter set not only achieves excellent initial performance but also effectively adapts to changes in system characteristics throughout the entire operating process, thereby guaranteeing high-precision estimation from start to finish across different temperature conditions.

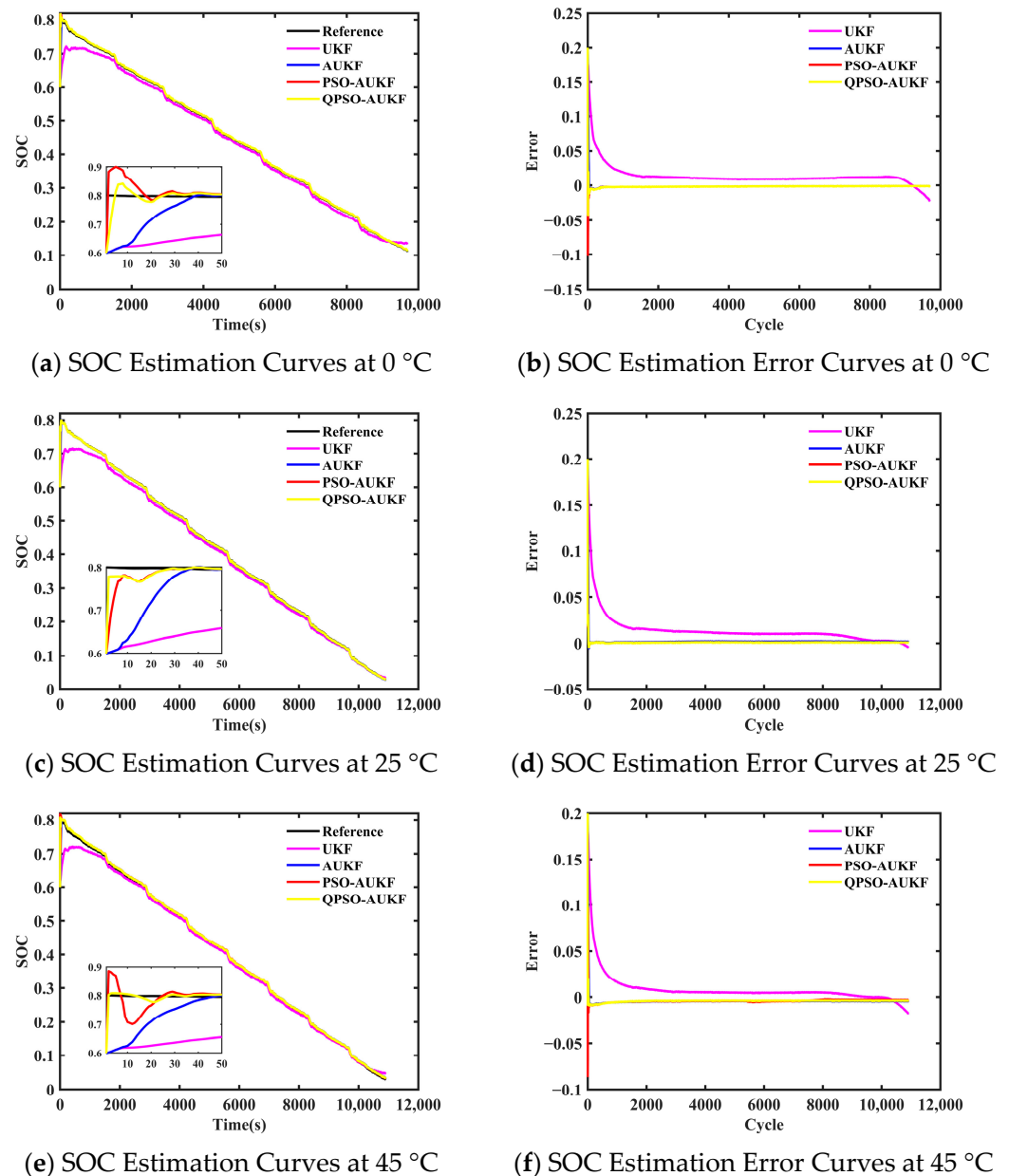


Figure 9. SOC estimation comparison under FUDS conditions.

This study employs the mean absolute error (MAE) and root mean square error (RMSE) as evaluation metrics for SOC estimation performance. Lower values of these metrics indicate higher estimation accuracy. A quantitative comparison of SOC estimation performance among the UKF, AUKF, PSO-AUKF, and QPSO-AUKF algorithms is presented in Table 1, Table 2, and Table 3 for different temperatures, respectively.

As shown in Tables 1–3, the QPSO-AUKF algorithm achieves the lowest values for both MAE and RMSE metrics. Its MAE and RMSE are not only significantly lower than those of the UKF and AUKF algorithms but also outperform those of the PSO-AUKF algorithm. These results indicate that, among the evaluated algorithms, QPSO-AUKF

demonstrates superior estimation accuracy and stability, thereby enhancing the reliability of battery SOC estimation.

Table 1. MAE and RMSE of SOC Estimation by Different Algorithms and Test Cycles at 0 °C.

Test Cycle	Estimation Method	MAE	RMSE
HPPC	UKF	0.73%	1.41%
	AUKF	0.088%	0.84%
	PSO-AUKF	0.093%	0.21%
	QPSO-AUKF	0.089%	0.19%
DST	UKF	1.40%	2.09%
	AUKF	0.38%	0.84%
	PSO-AUKF	0.65%	0.72%
	QPSO-AUKF	0.41%	0.60%
FUDS	UKF	1.45%	2.17%
	AUKF	0.22%	0.76%
	PSO-AUKF	0.20%	0.41%
	QPSO-AUKF	0.19%	0.35%

Table 2. MAE and RMSE of SOC Estimation by Different Algorithms and Test Cycles at 25 °C.

Test Cycle	Estimation Method	MAE	RMSE
HPPC	UKF	0.5%	1.37%
	AUKF	0.42%	0.92%
	PSO-AUKF	0.4%	0.47%
	QPSO-AUKF	0.32%	0.36%
DST	UKF	1.56%	2.3%
	AUKF	0.47%	0.84%
	PSO-AUKF	0.15%	0.28%
	QPSO-AUKF	0.09%	0.22%
FUDS	UKF	1.37%	2.17%
	AUKF	0.2%	0.71%
	PSO-AUKF	0.10%	0.31%
	QPSO-AUKF	0.097%	0.24%

Table 3. MAE and RMSE of SOC Estimation by Different Algorithms and Test Cycles at 45 °C.

Test Cycle	Estimation Method	MAE	RMSE
HPPC	UKF	0.36%	1.34%
	AUKF	0.32%	0.89%
	PSO-AUKF	0.25%	0.36%
	QPSO-AUKF	0.24%	0.29%
DST	UKF	0.81%	1.86%
	AUKF	0.67%	0.97%
	PSO-AUKF	0.66%	0.81%
	QPSO-AUKF	0.58%	0.68%
FUDS	UKF	0.91%	1.92%
	AUKF	0.46%	0.83%
	PSO-AUKF	0.41%	0.54%
	QPSO-AUKF	0.39%	0.45%

4.4. Validation on an Independent Wisconsin Dataset

To further assess the effectiveness and robustness of the proposed QPSO-AUKF algorithm, an additional experiment was conducted using the independent Wisconsin dataset, which provides a diverse set of test cycles under varying operational conditions. The dataset contains data collected from the Panasonic 18650PF Li-ion battery (Panasonic Corporation, Osaka, Japan), which has a nominal voltage of 3.6 V, an operating voltage range of 2.5–4.2 V, and a rated capacity of 2.9 Ah. This experiment was conducted under the standard temperature condition of 25 °C to evaluate the algorithm's performance in a real-world scenario. The SOC estimation results under HWFET, LA92, and UDDS conditions are presented in Figures 10–12, respectively, and the corresponding error metrics, including MAE and RMSE, are summarized in Table 4.

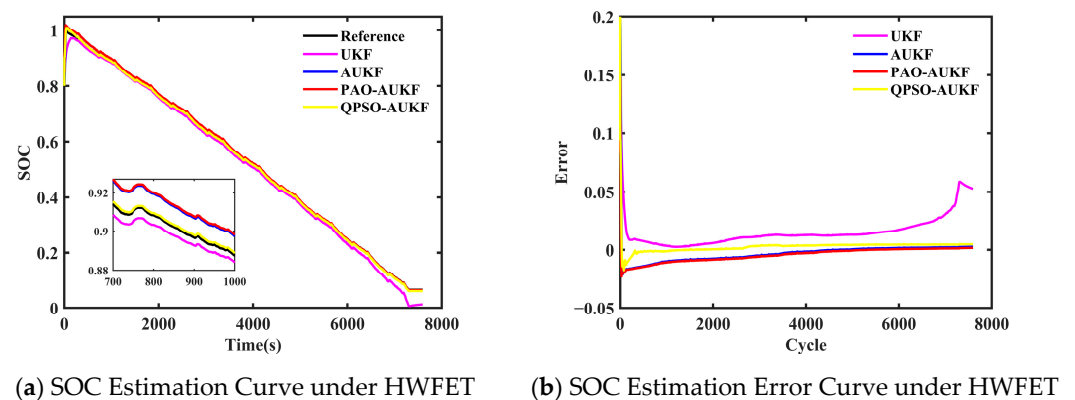


Figure 10. SOC Estimation and Error Curves under HWFET Condition.

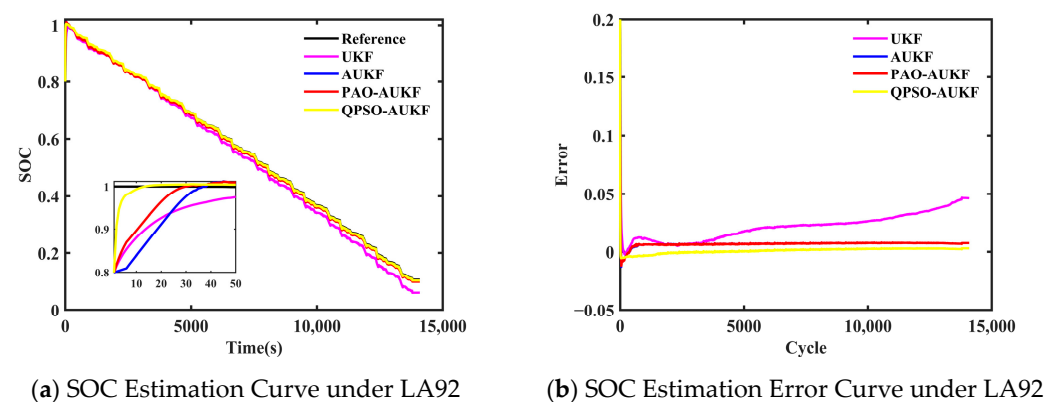


Figure 11. SOC Estimation and Error Curves under LA92 Condition.

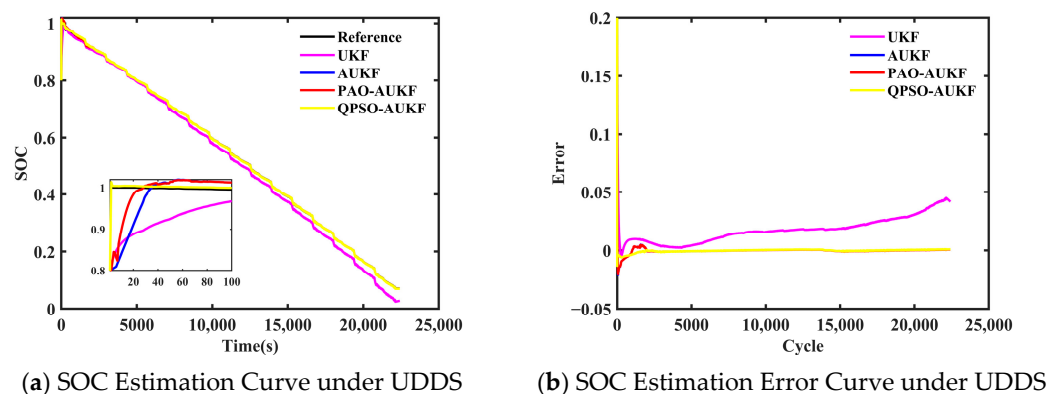


Figure 12. SOC Estimation and Error Curves under UDDS Condition.

The experimental results demonstrate that the QPSO-AUKF algorithm consistently outperforms the UKF, AUKF, and PSO-AUKF algorithms across all three test cycles (HWFET, UDDS, and LA92). The algorithm maintains superior accuracy and stability in SOC estimation, even when applied to the independent Wisconsin dataset at 25 °C. These results further confirm the robustness and reliability of the QPSO-AUKF method, demonstrating its strong potential for real-world applications in battery management systems.

Table 4. MAE and RMSE of SOC Estimation by Different Algorithms and Test Cycles.

Test Cycle	Estimation Method	MAE	RMSE
HWFET	UKF	1.54%	2.08%
	AUKF	0.52%	1.05%
	PSO-AUKF	0.52%	0.83%
	QPSO-AUKF	0.35%	0.61%
LA92	UKF	2.16%	2.46%
	AUKF	0.70%	0.92%
	PSO-AUKF	0.69%	0.81%
	QPSO-AUKF	0.19%	0.29%
UDDS	UKF	1.79%	2.11%
	AUKF	0.11%	0.53%
	PSO-AUKF	0.099%	0.41%
	QPSO-AUKF	0.075%	0.18%

5. Conclusions and Outlook

In battery management systems (BMSs), accurate state-of-charge (SOC) estimation for lithium-ion batteries is essential for ensuring system safety and optimizing energy utilization. To enhance SOC estimation performance, this study employs the FFRLS algorithm for online identification of model parameters and adopts a second-order RC equivalent circuit model to characterize the battery's dynamic behavior, thereby improving the model's representational accuracy under various dynamic operating conditions. Furthermore, to address the dependence on empirical settings of the noise covariance matrices Q and R in the AUKF algorithm, as well as potential numerical instability during iterations, a fused estimation algorithm integrating QPSO and AUKF is proposed. Comparative validation was conducted against traditional UKF, AUKF, and PSO-AUKF algorithms under various operating conditions, including HPPC, DST, and FUDS. Simulation results demonstrate that introducing the quantum-behaved particle swarm optimization (QPSO) algorithm for global optimization of the noise covariance matrices significantly enhances both SOC estimation accuracy and algorithm robustness.

In summary, future work could incorporate additional practical factors, such as battery aging and temperature, into SOC estimation to further enhance the algorithm's adaptability over the entire battery lifecycle. Simultaneously, exploring the integration of advanced optimization strategies could further improve estimation accuracy and computational efficiency, thereby enhancing algorithm stability under complex load conditions. Extending such methods to embedded battery management systems would enable real-time SOC monitoring and joint optimization with battery health management, providing reliable support for electric vehicles and energy storage systems. Achieving synergistic integration with functions such as battery fault monitoring, state-of-health assessment, and online SOC calibration could further enhance the practical engineering utility of these systems.

6. Patents

The authors plan to file a patent application based on the work described in this manuscript.

Author Contributions: Conceptualization, H.G. and Z.L.; methodology, Z.L.; software, H.G.; validation, H.G. and J.L.; formal analysis, H.G.; investigation, H.G.; resources, Z.L.; data curation, H.G.; writing—original draft preparation, H.G.; writing—review and editing, H.G.; visualization, Z.L.; supervision, Z.L.; project administration, H.X.; funding acquisition, Z.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding author.

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

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