Evaluation of Various Offline and Online ECM Parameter Identification Methods of Lithium-Ion Batteries in Underwater Vehicles

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ABSTRACT: For underwater vehicles, the state of charge (SOC) of battery is often used to guide the optimal allocation of energy. An accurate SOC estimation can improve work efficiency and reliability of underwater vehicles. Model-based SOC estimation methods are still mainstream routes used in practical applications. Hence, accurate battery models are highly desirable, which depends not only on the circuit structure but also on the circuit parameters. Four-parameter identification algorithms, offline mechanism-based and least squared (LS) methods, as well as online recursive least-squares with forget factor (FFRLS) and extended Kalman filter (EKF) methods were analyzed in terms of SOC estimation under three different conditions. The results revealed that in the case without any disturbance, the predicted SOCs based on four-parameter identification circuits fitted well with the reference. Moreover, it is remarkable that the LS offline methods work better than the FFRLS online routes. In addition, the robustness has also been accessed through the other two conditions, i.e., measurement data with disturbance and initial SOC value with deviation. The results showed that maximum errors of SOC estimation based on the EKF approach are significantly lower than those of the other methods, and the values are 0.51% and 0.20%, respectively. Thus, the circuit model based on the EKF parameter identification approach possessed a stronger anti-interference performance during the SOC estimation process. This research can provide corresponding theoretical support on ECM parameter identification for lithium-ion batteries in underwater vehicles.

1. INTRODUCTION

Underwater vehicles are a powerful tool that can promote the development of oceanic economy and military operations. With the advent of high-performance lithium-ion batteries, electric power has gradually become the most popular form of propulsion for underwater vehicles, which can reduce noise, weaken trails, and increase depth. The state of charge (SOC) reflects the current available capacity of battery, which is a critical indicator in the battery management system (BMS). Based on SOC, BMS efficiently and rationally allocates energy to ensure that underwater vehicles reliably complete the assigned task. Ouyang and Xiong et al. pointed out that the SOC estimation method based model was a research hotspot in practical applications for a long period of time, especially those based on an equivalent circuit model (ECM). Hence, establishing an accurate equivalent circuit model for SOC estimation is highly desirable. In general, the accurate circuit model depends not only on the circuit structure but also on circuit parameters.

Compared to other battery models, an ECM-based SOC observer can achieve a better balance between circuit structural complexity and prediction accuracy. The ECM is a circuit network to describe battery external characteristics. It is composed of some traditional electronic components, such as resistance, capacitance, and voltage source. Plett first proposed six ECMs, and then the lumped parameter ECMs with resistors and capacitors as the core were successively built to increase prediction accuracy, including the first-order RC model and second-order RC model. To avoid system failure caused by a single circuit structure, various circuit structure fusion methods based on the H Infinity Filter algorithm have been established by Lin et al. to improve the accuracy and reliability of the estimation results, whereas this method also enhances the computational complexity. Hu et al. systematically compared 12 ECM structures starting from complexity, accuracy, and robustness and found that the circuit...
structure can be generalized to adjacent cells. Also, the first-order RC model with one-state hysteresis was found to be more suitable for simulating LiFePO$_4$ cells. Berecibar et al. revealed that the first-order RC model was more suitable for LiPB and LMO by research of various battery systems. Lai et al. examined 11 widely used ECMs and concluded that the first-order and second-order RC models are optimal for LiNMC batteries with simultaneous accuracy and reliability. Xiong et al. and Gao et al. have also proposed the $n$-order RC model and established the mathematical expressions. They found the value of $n$ cannot increase indefinitely. Moreover, comparison results of $n$-order RC models showed that the accuracy of third-order was highest, while the first-order RC model was optimal based on the Akaike information evaluation criterion.

In addition to the circuit structure, the reliability of the battery model depends largely on the accuracy of model parameters. Two methods for circuit model parameters identification exist: (i) offline and (ii) online. The offline parameter identification method is usually used to search for optimal solutions of the ECM based on test data and various solutions. The hybrid pulse power characteristics (HPPC) test is often taken to support offline parameter identification. At present, a variety of parameter identification algorithms have also been proposed. Hu et al. used PSO and LS methods, and Xiong et al. adopted LS and GA approaches. The PSO algorithm has also been applied.

In practice, the circuit parameters change with battery state and ambient temperature, and it is not accurate or even convergent for battery state estimation to adopt offline parameter identification. Hence, the online methods adjusting parameters in real-time emerge gradually. Recursive Least Square (RLS) is a powerful online parameter identification method characterized by small calculation, high precision, and fast convergence. Hence, RLS has been widely used in circuit model parameters identification. However, this method may lead to data saturation in calculation. Xiong et al. introduced a forgetting factor into RLS, denoted Recursive Lease Square with Forgetting Factor (FFRLS), to increase the weight of current measurable data in the parameter identification process. Moreover, to solve the problem that RLS requires excitation all the time, Moving Window Least Square (MWLS) has been developed by Rahimi-Eichi et al. In addition to traditional online optimization algorithms, some filtering algorithms, such as extended Kalman filter (EKF), have also been adopted by Lin et al. and Malysz et al.

Overall, numerous studies dealing with parameter identification methods have been established, but they are only taken as the intermediate step of battery SOC estimation. Comparative studies of different parameter identification algorithms have rarely been reported, especially for comparison of offline and online methods. Therefore, four widely used ECM parameter identification methods were discussed, including the mechanism and LS offline methods, as well as RLS and EKF online approaches. To strictly evaluate the accuracy and robustness of different algorithms, the estimation results were analyzed under three different conditions, and the preferred method was extracted.

The overall arrangement of this manuscript is shown as follows. The test benches and schedules are described in section 2. The first-order equivalent circuit model and EKF-based SOC estimation algorithm are illustrated in section 3. Four-circuit model parameter identification methods are elaborated in section 4. The estimation results referring to accuracy and robustness of four parameter identification algorithms are analyzed and discussed in section 5. Finally, corresponding conclusions are summarized in section 6.

2. EXPERIMENTS

Here, the capacity test, specific hybrid pulse power characterization (SHPPC) test, incremental open-circuit voltage (IO) test, and dynamic stress test (DST) were performed to support and verify the proposed parameter identification approaches. Detailed introductions of test benches and test schedules were established.

2.1. Test Bench. Figure 1 shows the configuration of the battery test setup. It consisted of a battery test equipment to control cell charge/discharge, a thermal chamber to regulate the ambient temperature, a temperature test device to monitor the cell temperature, a computer to program and store the test results.
data, and tested cells LiFePO₄. The detailed specifications of LiFePO₄ are listed in Table 1.

### Table 1. Detailed Specifications of Sample Battery LiFePO₄

| Specifications                  | Values                  |
|---------------------------------|-------------------------|
| Nominal capacity                | 105 Ah                  |
| Nominal voltage                 | 3.2 V                   |
| Resistance (1 kHz)              | ≤0.5 mΩ                 |
| Standard charge/discharge rate  | 0.5C/0.5C               |
| Standard charge/discharge cutoff voltage | 3.65 V/2.50 V         |
| Charge/discharge temperature    | 0–55 °C/−20 to +45 °C   |
| Size (L × W × H), weight        | 130.0 mm × 36.7 mm × 200.0 mm, 1980 g |

#### 2.2. Test Schedule

The test schedule, including the capacity, SHPPC+IO, and DST, is provided in Figure 2. The capacity test was designed to obtain the battery maximum available capacity at the current state. Note that the current available capacity could disagree with the nominal value. In general, the capacity test required repeated measurements, and deviations between the three measurements were within 2%. The average of the three tests was then considered as the cell’s maximum available capacity in the current state. Otherwise, a new test was required. SHPPC, consisting of a series of the pulse charge/discharge currents shown in Figure 3a. The figure shows the current excitation during the 10% SOC increment including the pulse charge/discharge currents shown in Figure 3a. The flowchart figure depicts the current excitation during the 10% increment including the current load until 10% of the current maximum available capacity was reached, followed by resting for 1 h to remove the polarization. The terminal voltage regarded as $U_{ocv}$ then measured, and the above step of pulse sequence, nominal current discharging, and resting was repeated until the terminal voltage was reached. DST was used as a common dynamic test to load the synthetic current, and modeled the actual running schedule of electric vehicles. DST current load is shown in Figure 3b, where the inset shows the current curve during the whole test process and the main part represents the local enlargement view of one cycle. This test was employed to evaluate the robustness and reliability of SOC estimation.

To prevent overcharge, only discharging processes were carried out in both of the above tests for cells near the full state.

#### 3. BATTERY MODEL AND EKF-BASED SOC ESTIMATION ALGORITHM

##### 3.1. First-Order RC Equivalent Circuit Model

Battery research is often a one-way route based on external measurable data to reflect the internal state. Hence, building a scientific battery model is essential. As introduced above, ECM may reflect cell dynamic characteristics with fewer parameters in practical engineering. For instance, Gao et al. systematically analyzed the influence of RC network quantity on ECM performance and found ECM with first-order RC to achieve the best balance of accuracy and complexity. Hence, the first-order ECM was adopted in the present study with the specific schematic diagram depicted in Figure 4.

Based on Kirchhoff’s law, the state equation and output equation of the first-order RC ECM can be obtained according to eq 1

$$
\begin{align*}
U_p &= \frac{U_{ocv}}{R_p C_p} + \frac{i_p}{C_p} \\
U_t &= U_{ocv} - i_t R_i - U_p
\end{align*}
$$

where $U_{ocv}$ is the battery open-circuit voltage related to SOC, $U_p$ represents the potential difference across RC network, $U_t$ is the battery terminal voltage, $i_t$ refers to the battery current, $R_i$ represents the ohmic internal resistance of the battery, and $C_p$ and $R_p$ are the polarization resistance and polarization capacitance, respectively.
Following the solution rule of a differential equation, the linear discrete form of the state equation can be derived from eq 2

\[
U_p(t) = U_p(0)e^{-\Delta t/\tau} + (1 - e^{-\Delta t/\tau})i_L R_p
\]

where \(U_p(0)\) is the initial voltage across RC network, \(\tau = R_p C_p\) refers to the time constant, and \(\Delta t\) is the sampling time.

Finally, the discrete form of the state equation and output equation may be rewritten following eq 3

\[
\begin{align*}
U_{pk} &= e^{-\Delta t/\tau}U_{pk-1} + (1 - e^{-\Delta t/\tau})R_p i_{Lk-1} \\
U_{uk} &= U_{OCVk} - R_p i_{Lk} - U_{pk}
\end{align*}
\]

where \(k\) and \(k-1\) are the sampling steps.

As shown in Figure 4, the terminal voltage can be calculated following eq 3 after obtaining the parameters of ECM. Hence, four parameter identification methods can be evaluated based on the terminal voltage. The detailed introductions are provided in section 4.

### 3.2. EKF-Based SOC Estimation Algorithm

Parameter identification alone cannot be evaluated scientifically, so battery SOC usually needs to be further estimated to assess ECM with parameters identified by different algorithms. Accordingly, smaller errors between the predicted SOC and experimental values would induce a more accurate circuit model and a better corresponding model parameter identification algorithm.

SOC reflects the battery’s remaining capacity in percentage. The ampere-hour integral method was often used to obtain the current SOC following eq 4

\[
SOC_k = SOC_{k-1} - \frac{\eta i_{Lk-1} \Delta t}{C_n}
\]

where \(k\) and \(k-1\) are the time steps, \(i_L\) is discharge current value, \(\eta\) refers to the Coulombic efficiency considered here as 1, \(\Delta t\) denotes sample interval, and \(C_n\) is the maximum available capacity of the battery.

The ampere-hour integral method can only achieve open-loop control and cannot resist external disturbances. Hence, the mapping relationship between SOC and \(U_{OCV}\) was introduced to calibrate the estimation results of the ampere-hour integral method based on Kalman gain. The corresponding calculation flowchart is shown in Figure 5.

The complex internal structure and reactions resulted in a nonlinear battery system, making direct use of the traditional Kalman filter algorithm impossible. Hence, an improved method based on an extended Kalman filter (EKF) was developed. Other methods were not considered to reduce the interference in the estimation results. For a known nonlinear system, the state equation and observation equation can be expressed by eq 5, respectively

\[
\begin{align*}
x_k &= f(x_{k-1}, u_{k-1}) + \omega_{k-1} \\
y_k &= h(x_k, u_k) + \nu_k
\end{align*}
\]

where parameters \(k\) and \(k-1\) are the time steps, \(x\) refers to the system state vector, \(u\) is the system input vector, and \(y\) denotes the system observation vector. The error covariance matrix of the state estimation results is \(P_k\), \(\omega_k\) and \(\nu_k\) are system noise and observation noise, respectively, assumed to be Gaussian white noise with zero mean and covariance \(Q_k\) and \(R_k\). \(f(\cdot)\) and \(h(\cdot)\) are the state transition function and measurement function, respectively.
The first-order Taylor series expansion is performed in the EKF algorithm to approximate a nonlinear system. Correspondingly, the functions $f(x_k, u_k)$ and $h(x_k, u_k)$ can be processed following eq 6

$$
\begin{align*}
    f(x_k, u_k) &\approx f(\hat{x}_k, u_k) + \frac{\partial f(x_k, u_k)}{\partial x_k} |_{x_k=\hat{x}_k} (x_k - \hat{x}_k) \\
    h(x_k, u_k) &\approx h(\hat{x}_k, u_k) + \frac{\partial h(x_k, u_k)}{\partial x_k} |_{x_k=\hat{x}_k} (x_k - \hat{x}_k)
\end{align*}
$$

where $\hat{x}_k$ is the optimal estimation of $x_k$.

Moreover, the following definitions are given for clarity.

$$
\begin{align*}
    A &\triangleq \frac{\partial f(x_k, u_k)}{\partial x_k} |_{x_k=\hat{x}_k} \\
    C &\triangleq \frac{\partial h(x_k, u_k)}{\partial x_k} |_{x_k=\hat{x}_k}
\end{align*}
$$

Finally, the nonlinear system can be expressed in a linear form.

$$
\begin{align*}
    x_k &= A_{k-1}x_{k-1} + [f(\hat{x}_{k-1}, u_{k-1}) - A_{k-1}\hat{x}_{k-1}] + \omega_{k-1} \\
    y_k &= C_kx_k + [h(\hat{x}_{k}, u_k) - C_k\hat{x}_k] + \nu_k
\end{align*}
$$

Based on the above linearized discrete equations, the detailed implementation process of the EKF algorithm is described in Table 2.

### Table 2. Calculation Process of EKF

Step 1: Initialization

$x_0, P_0, Q, R$

Step 2: Time update $x_{k-1} \rightarrow \hat{x}_{k}^-$

System state update: $x^k = f(x_{k-1}, u_{k-1})$

Covariance of system state prediction error update: $P_k = A_kP_{k-1}A_k^T + Q_k$

Step 3: Measurement update $\hat{x}_{k}^+ \rightarrow \hat{x}_k^+$

Kalman gain: $K_k = P_kC_k^T(C_kP_kC_k^T + R) + 1$

System state update: $x^k = x^k - K_kC_k(y_k - h(x^k - \hat{x}_k))$

Covariance of system state prediction error update: $P_k = (I - K_kC_k)P_k$

Step 4: State prediction at time $k$ completed.

$(x^k = x^k + P_k = P_k +)$

Step 5: From time $k$ to time $k+1$

According to the EKF calculation pattern, the state equation and observation equation of the battery system can be expressed by eqs 9 and 10:

$$
\begin{align*}
    U_{p,k} &= e^{-\Delta t/\tau}U_{p,k-1} + (1 - e^{-\Delta t/\tau})R_{p,k-1} \\
    \text{SOC}_k &= \text{SOC}_{k-1} - \frac{m_{i,k-1}\Delta t}{C_n} \\
    U_{j,k} &= U_{OCV,k} - R_{j,k} - U_{p,k}
\end{align*}
$$

Accordingly, the state transfer matrix and observation matrix can be retrieved by eq 11

$$
\begin{align*}
    A_k &= \begin{pmatrix}
        e^{-\Delta t/\tau} & 0 \\
        0 & 1
    \end{pmatrix} \\
    C_k &= \begin{pmatrix}
        -1 & dU_{OCV} \over d\text{SOC}
    \end{pmatrix}
\end{align*}
$$

where the intrinsic relationship between $U_{OCV}$ and SOC was fitted based on incremental open circuit voltage test data and the calculation model was described by eq 12

$$
U_{OCV} = k_0 + k_1\text{SOC} + k_2\text{SOC}^2 + k_3\text{SOC}^3 + k_4/\text{SOC} + k_5\log(\text{SOC}) + k_6(1 - \log(\text{SOC}))
$$

where $k$ is the polynomial parameters that should be fitted.

### 4. Model Parameter Identification Methods

Every parameter identification method possesses certain characteristics. Compared to offline methods, the online algorithms are more adaptable to the external environment but suffer from a larger computational burden, whereas the conclusion mainly stays at the qualitative stage and a detailed quantitative comparison is lacking. Hence, the mechanism-based method with a clearer physics significance and simple LS approach was established to recognize circuit parameters offline. Meanwhile, the most widely used algorithms FFRLS and EKF were selected as online circuit parameter identification means.

#### 4.1. Mechanism-Based Method

The mechanism-based parameter identification method calculates the parameters in ECM and relies on the voltage response curve in the SHPPC test. Figure 6 shows the current and voltage response profiles of the SHPPC test at SOC = 100%. The voltage clearly showed a response curve composed of four stages in one pulse discharge period, namely section A–B, section B–C, section C–D, and section D–E.

In section A–B, a voltage drop appeared abruptly when a pulse discharge current was loaded, and the battery turned from an open-circuit state to discharged state. Based on the characteristics of the capacitor, the voltage of the R–C network $U_p$ cannot change immediately. Hence, the abrupt drop in the terminal voltage of sections A–B was caused by the ohmic internal resistance $R_i$.

In section B–C, the voltage dropped slowly. This stage represented a continuous discharge process with the battery in a working state. The coupling of electrochemical polarization and concentration polarization dropped the voltage exponent
tially. Since \( U_p = 0 \) at point B, section B–C can be treated as a zero-state response.

In section C–D, a voltage increase appeared abruptly, reflecting the moment when the pulse discharge current was removed, and the battery translated from a discharged state to an open circuit state. Similarly, the sudden change of terminal voltage was caused by the ohmic internal resistance \( R_i \).

In section D–E, the battery is in the open-circuit state, and the polarization led to a slow rise in terminal voltage. In absence of excitation current, Section D–E can be regarded as zero input response state.

Accordingly, the ohmic internal resistance can be calculated through sections A–B and C–D

\[
R_i = \frac{(U_A - U_B) + (U_D - U_C)}{2I}
\]

where \( U_A, U_B, U_C, \) and \( U_D \) represent the battery terminal voltage at time A, B, C, and D. \( I \) is the battery discharge current.

As analyzed above, section D–E corresponded to a zero-input response. Taking point D as the initial moment, the equation of zero input respond state can be derived from eq 2 to yield eq 14:

\[
U_p(t) = U_p(0)e^{-t/\tau}
\]

Corresponding, the terminal voltage response equation can be derived at section D–E:

\[
U(t) = U_{OCV}(SOC) - U_p(0)e^{-t/\tau}
\]

By taking eq 15 as a fitting function, as well as test data in section D–E as fitting data and Python as a fitting tool, the fitting operation can be performed based on least-squares to yield the value of time constant \( \tau \).

Starting from point B, a zero-state response equation can be derived:

\[
U_p(t) = (1 - e^{-t/\tau})i_lR_p
\]

Accordingly, the output voltage response expression in segment B–C might be obtained as eq 17. In terms of test data on section B–C, the polarization resistance \( R_p \) can be fitted. Next, the polarization capacitance \( C_p \) can be calculated based on the relationship of \( \tau = R_pC_p \):

\[
U(t) = U_{OCV}(SOC) - i_lR_i - (1 - e^{-t/\tau})i_lR_p
\]

### 4.2. LS-Based Method

LS-based parameter identification method calculates the ECM parameters by mathematically deducing the output equation of battery system based on reasonable assumptions. eq 18 can be obtained using eq 3:

\[
R_{j,k-1}
\]

Here, \( E_{i,k} = U_{i,k} - U_{OCV,k} \) and eq 18 can be expressed following eq 19:

\[
E_{i,k} = e^{-\Delta t/\tau}U_{i,k-1} - R_{j,k-1} \left( 1 - e^{-\Delta t/\tau} \right) R_{p,k-1}
\]

Moreover, \( E_{i,k-1} \) can also be derived by the output equation at step \( k-1 \) to yield eq 20:

\[
E_{i,k-1} = -U_{i,k-1} - R_{j,k-1}
\]

The relationship of \( E_i \) between adjacent sampling points can be obtained:

\[
E_{i,k} = e^{-\Delta t/\tau}E_{i,k-1} - R_{j,k-1} \left[ e^{-\Delta t/\tau}R_i - (1 - e^{-\Delta t/\tau})R_p \right] i_{l,k-1}
\]

Owing to the slow time-varying characteristics of the battery system, some assumptions were made.

\[
U_{OCV,k} = U_{OCV,k-1}
\]

Equation 21 can further be rewritten following eq 23.

\[
U_{i,k} = e^{-\Delta t/\tau}U_{i,k-1} + (1 - e^{-\Delta t/\tau})U_{OCV,k} - R_{j,k-1} + \left[ e^{-\Delta t/\tau}R_i - (1 - e^{-\Delta t/\tau})R_p \right] i_{l,k-1}
\]

To produce a more intuitive expression, the following definitions were considered:

\[
\begin{align*}
& d_1 = e^{-\Delta t/\tau} \\
& d_2 = -R_i \\
& d_3 = e^{-\Delta t/\tau}R_i - (1 - e^{-\Delta t/\tau})R_p
\end{align*}
\]

Correspondingly, eq 23 can be rewritten as eq 25.

\[
U_{i,k} = d_1U_{i,k-1} + (1 - d_1)U_{OCV,k} + d_2i_{l,k-1} + d_3i_{l,k-1}
\]

According to the computational requirements of LS, eq 25 can further be converted into a matrix calculation:

\[
Y = \Phi \theta
\]

Here, \( \Phi \) represents the data matrix and \( \theta \) is the parameter matrix.

Based on eq 25, the corresponding definitions were collected:

\[
\Phi = 
\]

\[
\theta = [d_1(1 - d_1)U_{OCV,d}d_1I]^T
\]

According to the solution of LS, the parameter matrix \( \theta \) can be derived following eq 28:

\[
\theta = (\Phi^T\Phi)^{-1}\Phi^TY
\]

\( R_i, R_p, \) and \( C_p \) can be derived from eq 24:

\[
\begin{align*}
& R_i = -d_2 \\
& R_p = \frac{d_3 + d_1}{d_1 - 1} \\
& C_p = \frac{\Delta t(1 - d_1)}{\ln(d_1)(d_1 + d_3d_2)}
\end{align*}
\]

### 4.3. FFRLS-Based Method

Based on the adaptive filtering theory, RLS is a common online parameter identification
algorithm used to change the overall data operating of LS to real-time data processing for adapting better to different working conditions. However, for slow time-varying systems, the traditional RLS can cause data saturation, affecting the precision and stability of identification results. Hence, a forgetting factor was introduced into the original RLS algorithm to increase the weight of the current measurement data and improve the reliability of parameter identification.

Based on the above LS, the RLS algorithm updated the model parameters at every sampling moment, and the output equation (eq 25) can be rewritten at every test point k using eq 30:

\[ U_{k} = \phi_{k} \theta_{k} \]  
(30)

Here, the data matrix \( \phi_{k} \) and parameter matrix \( \theta_{k} \) changed over time and can be given as

\[
\begin{align*}
\phi_{k} &= [U_{k-1}1i_{k-1i_{k-1}}1] \\
\theta_{k} &= [d_{1,k}(1 - d_{1,k})U_{O C V}d_{2,k}d_{3,k}]^T
\end{align*}
\]
(31)

The specific calculation process of RLS is shown in Table 3.

**Table 3. Calculation Process of RLS**

| Step | Initialization \( \theta_{R L S,0} \), PRLS,0 |
|------|-------------------------------------------|
| 2    | Update the gain matrix and error covariance matrix |
| 3    | Update the parameter vector \( \theta_{k} = \theta_{k-1} + \text{GRSL},k(\text{yk} - \phi_{k} \theta_{k-1}) \) |
| 4    | From time k to time k+1 |

Here, \( \lambda \) is the forgetting factor, and it is considered as 0.98 here. Similarly, the model parameters in steps k, \( R_{L}, R_{P,k} \) and \( C_{P,k} \) can be derived following eq 32:

\[
\begin{align*}
R_{L,k} &= -d_{2,k} \\
R_{P,k} &= \frac{d_{3,k} + d_{1,k}d_{2,k}}{d_{1,k} - 1} \\
C_{P,k} &= \frac{\Delta t(1 - d_{1,k})}{\ln(d_{1,k})(d_{3,k} + d_{1,k}d_{2,k})}
\end{align*}
\]
(32)

Here, \( \Delta t \) is the sampling interval.

### 4.4. EKF-Based Method.

The Kalman filter series algorithm could be employed to identify the states and parameters in complex systems. The extended Kalman Filter can well balance the calculation accuracy and complexity, making it preferred for battery systems. To identify parameters based on EKF, the assumption of constant parameters at adjacent sampling points is taken into consideration. For the EKF-based parameter identification method, \([U_{O C V}, U_{P}, R_{P}, R_{P}, e^{-\Delta t/\tau}]^T\) and \([U_{k}]\) were considered as state vectors and observation vectors, respectively. The corresponding state equations and observation equations can be obtained as follows:

\[
\begin{align*}
U_{O C V,k} &= U_{O C V,k-1} \\
U_{P,k} &= U_{P,k-1}e^{-\Delta t/\tau} + i_{k-1}R_{P,k-1}[1 - e^{-\Delta t/\tau}] \\
R_{L,k} &= R_{L,k-1} \\
R_{P,k} &= R_{P,k-1} \\
e^{-\Delta t/\tau} &= e^{-\Delta t/\tau}
\end{align*}
\]
(33)

\[
U_{t,k} = U_{O C V,k} - U_{P,k} - i_{k}R_{L,k}
\]
(34)

The state transfer matrix \( A \) and observation matrix \( C \) can further be derived by eq 35:

\[
A_{\theta} =
\begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & e^{-\Delta t/\tau} & 0 & i_{k-1}[1 - e^{-\Delta t/\tau}] \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{pmatrix}
\]

\[
C_{\theta} = (1 - 1 - i_{k-1} 0 0)
\]
(35)

The detailed calculation process could refer to the introduction of EKF-based SOC estimation.

### 5. RESULTS AND DISCUSSION

#### 5.1. Parameter Identification Results.

The identified parameters of the equivalent circuit model consisted of coefficient \( k \) of function between SOC and \( U_{O C V} \), ohmic resistance \( R_{P} \), and dynamic voltage performance parameters \( R_{P} \) and \( C_{p} \). The polynomial coefficient \( k \) in eq 12 was fitted based on IO test data. The results are listed in Table 4, and the fitted function is shown in Figure 7. Good agreement between the experimental and fitted data was recorded with an error band between ±13 mV.

The identified parameters based on the above four-circuit parameter identification means are gathered in Figure 8. Note that Figure 8a,b represent the mechanism-based and LS-based offline identification results and Figure 8c,d are the FFRLS-based and EKF-based online recognition results. As shown in Figure 8a, \( R_{L} \) stayed between 0.5 mΩ and 0.6 mΩ in the whole range of SOC, while \( R_{P} \) maintained 1.0 mΩ except SOC = 1. Thus, the battery state had little effect on resistance relating on the mechanism-based method. The polarization capacitances \( C_{p} \) fluctuated randomly between 10 and 25 kF. In Figure 8b, \( R_{P} \) increased with the depth of discharge while maintaining values between 0.5 and 0.6 mΩ except at the end of the discharge. For \( R_{P} \) a float from 0.5 to 1.0 mΩ without SOC = 0.1 was employed. Compared to the mechanism-based method, the resistances obtained here were more sensitive to SOC and \( C_{p} \) varied irregularly with SOC. Since FFRLS and EKF were online algorithms, the SHPPC data supporting the offline

| Table 4. Fitted Coefficients of SOC-U_{O C V} Function |
|----------|----------|----------|----------|----------|----------|----------|----------|
| \( k_{0} \) | \( k_{1} \) | \( k_{2} \) | \( k_{3} \) | \( k_{4} \) | \( k_{5} \) | \( k_{6} \) |
| 3.3000 | 0.0800 | -0.0900 | 0.0300 | -0.0002 | 0.0400 | -0.0025 |
methods were replaced by DST. Correspondingly, the relationship between parameters versus SOC was changed into parameters versus time. In Figure 8c, the identified parameters jumped largely at the start of the prediction, especially when compared to the EKF method, indicating an FFRLS-based algorithm sensitive to the initial values. The identified parameters quickly converged to a reasonable range with iterative calculation. Overall, $R_i$ jittered irregularly and increased slightly with discharging. $R_p$ varied significantly within the range of 0.25–0.75 mΩ. $C_p$ fluctuated slightly between 10 and 35 kF, with an insignificant effect of discharge depth. The results identified by the EKF algorithm in Figure 8d still showed disorder jitters, mainly due to the online algorithm that required adjusting the identified parameters according to evaluation error in real-time. However, the results converged gradually toward a constant range along with the iteration. For $R_i$, the values ranged mainly between 0.50 and 0.75 mΩ, and the jitter amplitudes looked larger in the middle of discharge. $R_p$ gradually stabilized between 0.25 and 0.75 mΩ, and the overall trend rose while bouncing widened in the middle. $C_p$ fell sharply during the initial stage, gradually converging to the range between 20 and 40 kF. In sum, the parameters obtained by the four algorithms were all within a reasonable range of magnitude.

Figure 7. SOC-U_{OCV} function accuracy.

Figure 8. Identified circuit parameters. (a, b) Offline identification results based on SHPPC test data. (c, d) Recognized parameters by online algorithms under DST test.
The terminal voltage of the first-order RC equivalent circuit can further be obtained according to eq 1 and the above parameters. The corresponding experimental data are compared in Figure 9. Note that Figure 9a, c, e, g are terminal voltage comparison results, while Figure 9b, d, f, h are errors between the experimental and calculated results. The terminal voltages derived from the equivalent circuit model with parameters identified by four algorithms are all confirmed well with the experiment results. However, the online identification algorithm was superior in terms of voltage response as obviously depicted in local enlargement and terminal voltage error. The reason for that had to do with the parameters calculated by offline methods, which were constant. By comparison, the online algorithm could timely adjust parameters according to the error between the test and estimated data. For the mechanism-based method, the voltage response range looked wider at the position with the high pulse loading. In other words, the terminal voltage was over-

Figure 9. Terminal voltage prediction results and errors: (a, b) mechanism-based; (c) and (d) LS-based; (e, f) FFRLS-based; (g, h) EKF-based.
Figure 10. SOC estimation results and errors without any interference: (a, b) mechanism-based; (c, d) LS-based; (e, f) FFRLS-based; (g, h) EKF-based.

Table 5. Statistical Results of Predicted SOC by Four-Parameter Identification Methods under the Working Conditions without Any Interference

| Method          | MAE (%) | RMSE (%) |
|-----------------|---------|----------|
| Mechanism-based | 0.090   | 0.108    |
| LS-based        | 0.062   | 0.062    |
| FFRLS-based     | 0.390   | 0.390    |
| EKF-based       | 0.060   | 0.060    |

discharged when loading larger pulse charging currents, while the terminal voltage was underestimated under large pulse discharging currents. In Figure 9b, the terminal voltage errors looked more scattered and the error band ranged from −15 to +20 mV. Nonetheless, the terminal voltage deviations mainly ranged from −5 to 10 mV as seen from the depth of shade in the error figure. The circuit based on LS parameter identification means still over responded for terminal voltage known from Figure 9c, while terminal voltage errors were more concentrated as shown in Figure 9d. The errors varied from −15 to +15 mV, but the main error ranged from −5 to +4 mV. Depictions in Figure 9e,f revealed that estimation terminal voltages can greatly follow the experiments with errors band
only between ±1 mV, indicating a significant increase in accuracy of the circuit model based on FFRLS algorithm. In Figure 9g,h, a cusp of the prediction value at the position with a large pulse charge load was observed, leading to a deviation of a few error points from the zero-reference position.

However, the overall estimation performance of EKF-based method was good with the main error band between ±2 mV.

5.2. Accuracy Evaluation of Four-Model Parameter Identification Methods. To more accurately evaluate the reasonableness of the equivalent circuit model built by four algorithms, the battery SOC was further calculated based on
the above-identified parameters. The estimation results and experimental data in line with DST dynamic conditions are provided in Figure 10a,c,e,g. The corresponding errors are exhibited in Figure 10b,d,f,h. As shown in Figure 10a, the values of SOC looked underestimated in the whole process. In Figure 10b, although the errors between the estimation and reference increased in the middle, it tended to be stable at the end, with errors ranging between 0.00% and 0.20%. The estimation results based on the LS method in Figure 10c showed a great agreement between the prediction and experimental data. In Figure 10d, the SOC deviations decreased with iterations, and errors varied from −0.10% to 0.00%. According to the results based on the FFRLS algorithm in Figure 10e, the SOC looked overstated, especially clear in the local enlarged figure. The error band ranged between −0.42% and +0.15%. The SOC prediction values derived by the EKF-based model in Figure 10f were well in line with the experimental values. The error established in Figure 10h revealed SOC to be slightly overestimated, resulting in errors all below the zero-reference line and floating between −0.09% and −0.02%. Overall, the assessment accuracy based on FFRLS algorithm was the worst among all four methods, but the estimation performances were all satisfactory.

To quantitatively confirm the estimation accuracy, the corresponding statistical values were further calculated and the data are listed in Table 5. These included the mean absolute error (MAE) and root mean squared error (RMSE). The calculation equations can be described as below

\[
\text{MAE} = \frac{\sum_{i=1}^{N} |\text{SOC}_{\text{exp},i} - \text{SOC}_{\text{est},i}|}{N}
\]

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (\text{SOC}_{\text{exp},i} - \text{SOC}_{\text{est},i})^2}{N}}
\]

where SOC_{exp} and SOC_{est} are the reference and estimation SOC, respectively. N represents the total number of samples.

As shown in Table 5, the equivalent circuit models based on four algorithms all demonstrated high accuracy for SOC estimation in absence of external interference. The MAE and RMSE of LS and EKF algorithms were similar and significantly lower than those of the other two methods. The result indicates the offline methods may work better than online routes under the working conditions without measurement noise and initial deviations.

### 5.3. Robustness Evaluation of Four-Model Parameter Identification Methods

In actual engineering, inevitable measurement interruptions may occur. Therefore, it is critical that the equivalent circuit model has satisfactory anti-interference ability. Accordingly, the robustness of the circuit model with parameters identified by the mechanism, LS, FFRLS, and EKF algorithms was evaluated based on SOC estimation accuracy. Two aspects were discussed according to the actual situation under measurement data with disturbance and initial SOC value with deviation.

#### 5.3.1. Measurement Data with Disturbance

To assess the antinoise capability of the four parameter identification algorithms, random noise was applied to the measurement data. Here, the normal distribution noise with mean 0 and variance 0.1 times the nominal value (0.32 V for voltage and 5.25A for current) was selected. The SOC results estimated by four algorithms were further studied based on the inaccurate current and voltage data. Figure 11a,b shows SOC comparisons and the SOC errors between the experiment and the estimation based on the mechanism method. As shown in Figure 11a, the SOC estimation results were significantly higher than the experimental data. The errors ranged from −1.15% to −0.70%, markedly larger than the condition with accurate measurement data. However, the errors converged toward the zero-reference axis as an iteration. Figure 11c,d depicts the estimation results obtained by LS method. In Figure 11c, the SOC was still overestimated with an error band between −0.90% and −0.40%. Also, the error values dramatically increased when compared to the results under accurate current and voltage. The SOC identification value by FFRLS algorithm in Figure 11e,f indicated that prediction SOC results mostly confirmed the experimental data, while a jump in the estimation curve near the end of calculation was noticed with an error reaching −1.10%. This could mainly be attributed to FFRLS method, which identified the parameters based on real-time test data. However, the error in Figure 11f was adjusted toward the zero-reference axis. In Figure 11g, the SOC estimation values by EKF way looked slightly lower than the reference values while showing good consistency in the whole. The maximum deviation was estimated to less than 0.51%.

According to the statistical results in Table 6, the MAE and RMSE of the offline or online methods were basically the same. By comparison, the MAE and RMSE of the offline-based methods were twice as high as those of online-based routes. Hence, SOC prediction values derived by the online parameter identification circuit model were more accurate. Compared to FFRLS algorithm, the MAE and RMSE statistical results of EKF-based method were slightly higher but showed stronger anti-interference performance.

#### 5.3.2. Inaccurate SOC Initial

In general, obtaining the exact initial SOC is difficult, so a good initial value fault tolerance degree of circuit model is required during SOC evaluation. Hence, the SOC estimation results obtained by the four-parameter identification methods under an initial SOC value with 20% deviation (SOC_{error} = 0.8) were analyzed (Table 7). Figure 12a,c,e,g compares the SOC of prediction and reference, while Figure 12b,d,f,h displays errors between the test and estimation. The SOC tracking accuracy based on the mechanism parameter identification circuit was the worst. The estimation value rises to reduce the initial deviation, but the

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**Table 6. Statistical Results of SOC Estimation Obtained by Four Parameter Identification Methods under DST Data with Random Noise**

| Method       | MAE (%) | RMSE (%) |
|--------------|---------|----------|
| Mechanism-based | 0.881   | 0.883    |
| LS-based      | 0.686   | 0.690    |
| FFRLS-based  | 0.218   | 0.353    |
| EKF-based    | 0.396   | 0.401    |

**Table 7. Statistical Results of SOC Estimation Values Based on Four Parameter Identification Algorithms under the Initial SOC with 20% Offset**

| Method       | MAE (%) | RMSE (%) |
|--------------|---------|----------|
| Mechanism-based | 7.087   | 7.438    |
| LS-based      | 2.227   | 2.604    |
| FFRLS-based  | 0.838   | 3.031    |
| EKF-based    | 0.133   | 0.471    |
The increase is too small to converge to the real value. The maximum error reached 11.0% except for the initial moment, an unacceptable value for practical applications. The SOC prediction accuracy by LS parameter identification circuit was relatively acceptable, and the estimation SOC converged to the reference value after certain sampling intervals. The decline rate of prediction values was faster than the true values, resulting in increase of deviations as calculation. Nonetheless, Figure 12(d) revealed errors gradually tending to stabilize with a range of $-1.0\%$ to $5.0\%$, apparently higher than the SOC error based on the accurate initial SOC. As shown in Figure 12(e),(g), the SOC estimation results based on online parameter identification methods followed well the reference curve, especially for EKF. In the prediction SOC curve derived by FFRLS (Figure 12(e)), the estimation values increased significantly in the initial calculation stage and quickly traced to the vicinity of the experimental value. The error margin in Figure 12(f) ranged between $\pm 2.5\%$ with errors leveling off at the end of discharge. In Figure 12(g),(h), the SOC estimation based on EKF parameter identification circuit looked very insensitive to the initial SOC value and can quickly converge to the reference value after just a few iterations. Moreover, errors

Figure 12. SOC estimation results and errors under the initial SOC with 20% offset. (a, b) Mechanism-based; (c, d) LS-based; (e, f) FFRLS-based; (g, h) EKF-based.
shown in (h) varied from −0.2% to 0.0%, with values convergent during the whole calculation process. Meanwhile, the MAE and RMSE of SOC estimation by EKF-based parameter identification circuit were significantly lower than those of other algorithms. Hence, the equivalent circuit model identified by EKF method was the most appropriate for SOC estimation with inaccurate initial SOC.

6. CONCLUSIONS

Accurate ECM depends not only on the circuit structure but also on circuit parameters. Hence, four ECM parameter identification methods with different characteristics were evaluated here. These were mechanism-based and LS-based offline means, as well as FFRLS-based and EKF-based online algorithms. Based on the terminal voltage and SOC estimation results derived by the first-order ECM, the accuracy of each parameter identification method was analyzed. Moreover, two additional working conditions with measurement noise and initial SOC offset were systematically studied to evaluate the robustness. The following conclusions can be drawn:

(1) The terminal voltages derived from ECM with online parameter identification algorithms preferably overlapped with the experimental values. Compared to EKF-based way, terminal voltage calculation errors based on the FFRLS were smaller and more concentrated.

(2) Under accurate measurement data and exact initial SOC, the SOC estimation results derived by four parameter identification methods were the same, and all prediction SOCs confirmed well the reference curves. The performances of LS-base and EKF-based methods were superior, and the maximum deviations were all less than 0.1%. However, estimation errors based FFRLS online parameter identification algorithm was relatively significant. Therefore, the offline methods may work better than the online routes under the working conditions without any disturbance.

(3) Under measurement noise and accurate initial SOC, the SOC estimation errors increased to some extent when compared to the case with accurate test data. SOC estimation results based on the online parameter identification circuit model agreed better with the experiment data. Also, MAE and RMSE of the offline-based methods were twice as high as those of the online-based method. For the online route, a bounce was noticed in FFRLS-based SOC estimation graph near the end. The maximum SOC errors are −1.1% and 0.51% for the FFRLS-based and the EKF-based methods, respectively. Thus, EKF-based parameter identification circuit model possesses stronger anti-interference performance for SOC estimation.

(4) For the case with accurate test data and 20% initial SOC offset, the SOC estimation values calculated by LS-based, FFRLS-based, and EKF-based circuit models converged to the reference after certain sampling intervals. Moreover, MAE and RMSE of SOC estimation based EKF algorithm were significantly lower than those of other means with a maximum error lower than 0.5%, indicating an approach insensitive to the initial SOC. Hence, the EKF-based parameter identification circuit model was most appropriate for SOC prediction under imprecise initial SOC.

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Notes
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