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State-of-Charge (SOC) Estimation of Lithium-Ion Battery Based on Unscented Kalman Filtering

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Abstract— **Real-time estimation of State of Charge (SOC) for lithium-ion batteries is one of the core technologies in Battery Management Systems (BMS). Accurate SOC estimation is fundamental for managing lithium-ion batteries. In this study, a second-order RC equivalent circuit model is established, and parameter identification methods are employed to determine the model parameters. The identified parameters are then incorporated back into the second-order RC model. The accuracy of these parameters and the model is validated through Hybrid Pulse Power Characteristic (HPPC) tests. Finally, the Unscented Kalman Filtering algorithm (UKF) is utilized to estimate battery SOC. Experimental results demonstrate that SOC estimation based on UKF exhibits high precision and stability.**

Keywords—lithium-ion battery; State of Charge (SOC); parameter identification; Unscented Kalman Filtering; HPPC

I. INTRODUCTION

The State of Charge (SOC) of a battery is an important parameter and a core technology of Battery Management Systems (BMS). Lithium-ion batteries, known for their high capacity, stable discharge, and safety performance, have been widely used in various energy storage systems, the new energy industry, aerospace, medical equipment, etc[1]. Accurate SOC estimation is essential for extending the battery's lifespan and preventing overcharging or over-discharging. However, SOC, unlike other battery parameters such as current, voltage, or temperature, cannot be directly measured. Moreover, due to the strong nonlinearity exhibited by lithium-ion batteries during operation, inaccurate estimation methods or models can result in low SOC estimation accuracy[2][3].

Common methods for estimating battery SOC include Coulomb counting, open-circuit voltage (OCV) method, Kalman filtering, improved algorithms, and neural networks[4]. Coulomb counting estimates SOC by integrating the current over time, but accumulated errors over time can lead to increasing SOC estimation errors. The OCV method involves plotting the OCV-SOC relationship curve and determining SOC through simple table lookup, but it requires long resting times. Estimating SOC using neural networks requires a large number of samples for data training and can be easily disturbed. Currently, the improved Kalman filtering algorithm is widely used for SOC estimation in nonlinear systems like lithium-ion batteries[6][7].

There are two main types of battery models commonly used: electrochemical models and equivalent circuit models[5]. Electrochemical models use computer numerical simulation techniques to comprehensively describe the chemical reactions occurring inside the battery during charging and discharging processes. However, these models are complex and often involve many differential equations and boundary conditions, making solving them challenging. In contrast, equivalent circuit models are widely adopted due to their simplicity, easy parameter identification, and intuitive nature. Typical equivalent circuit models include the resistance-capacitance (RC) model, Thevenin model, PNGV model, and GNL model[8].

Building upon this theoretical foundation, this study establishes a second-order RC physical model driven by a "mechanism + data + knowledge" multi-element fusion approach. Real-time data is used to identify model parameters and estimate SOC accordingly[9].

II. MODEL ESTABLISHMENT AND PARAMETER IDENTIFICATION

A. Battery Model Selection

Extensive experiments indicate that the accuracy of the second-order RC equivalent circuit model is sufficiently high and meets the requirements. It also has a lower computational burden compared to third-order or higher-order models. Additionally, it offers higher accuracy compared to Thevenin equivalent circuit models and reflects internal polarization reactions within the battery through two sets of RC networks. Therefore, this paper adopts the second-order RC model, as illustrated in Figure 1, as the research model.

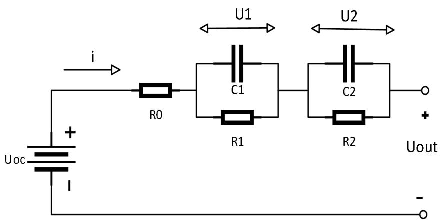

Fig.1 Second-Order RC Equivalent Circuit Model

Where U_{oc} represents the open-circuit voltage; R_0 denotes the Ohmic resistance, representing the current in the loop; U_{out} signifies the terminal voltage; C_1 and C_2 stand for two polarization capacitors; R_1 and R_2 represent two polarization resistances. The mathematical expressions related to these parameters are derived from Kirchhoff's voltage law.According to Kirchhoff's voltage law, the relevant mathematical expressions are derived as follows:

$$i = C_1 dU_1/dt + U_1/R_1 \tag{1}$$

$$i = C_2 dU_2/dt + U_2/R_2 \tag{2}$$

$$U_{out} = U_{oc} - U_1 - U_2 - R_0 i \tag{3}$$

The definition of State of Charge (SOC) obtained from the Ampere-hour integration method is:

$$SOC(k+1) = SOC(k) - \frac{\eta \int i\mathrm{d}t}{Q} \tag{4}$$

To discretize the above equation, we obtain the state equation of the system as follows:

$$\begin{bmatrix} \mathrm{SOC}(k+1) \\ U_1(k+1) \\ U_2(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^a & 0 \\ 0 & 0 & e^b \end{bmatrix} \begin{bmatrix} \mathrm{SOC}(k) \\ U_1(k) \\ U_2(k) \end{bmatrix} + \begin{bmatrix} \frac{\eta T}{c_n} \\ R_1(1-e^a) \\ R_2(1-e^b) \end{bmatrix} i(k) + \omega(k) \tag{5}$$

$$a = -T/R_1 C_1 \tag{6}$$

$$b = -T/R_2 C_2 \tag{7}$$

Where T is the sampling period, which in this experiment is 1 second, and k is the discharge time.

The observation equation of the system is:

$$u_{out}(k+1) = U_{oc}\big(SOC(k+1)\big) - U_1(k+1) - U_2(k+1) - i(k+1)R_0 + v(\mathrm{k}) \tag{8}$$

Where $U_{oc}\big(SOC(k+1)\big)$ is a function of open-circuit voltage and SOC, and $\omega(k)$ and $v(\mathrm{k})$ are stochastic process noise and stochastic observation noise, respectively.

B. Battery Model Parameter Identification

For the second-order RC equivalent circuit model depicted in Figure 1, the model parameters to be identified are R_0,R_1,R_2,C_1, and C_2. The experimental procedure is as follows:

1. Charge the battery at a 1C nominal current until it reaches the charge termination voltage, and then allow it to rest for a sufficient amount of time to reach a steady state internally.

2. Conduct Hybrid Pulse Power Characterization (HPPC) tests on the battery:

Discharge the battery at a 0.5C current for 12 minutes, reducing the SOC from 100% to 90%. After adjusting, allow for sufficient rest to reach a steady state internally, and record the terminal voltage after each rest period.

Repeat the above step ten times, discharging the battery to the cutoff voltage.

3. Use the terminal voltages obtained during each discharge to perform a sixth-order polynomial fit using the cftool tool in MATLAB, resulting in the OCV-SOC curve, as shown in Figure 2. The relationship between OCV and SOC during the discharge process is represented by Equation (9).

$$f(SOC) = -7.78 \times SOC^6 + 38.29 \times SOC^5 - 69.09 \times SOC^4 + 58.58 \times SOC^3 - 24.10 SOC^2 + 5.13 \times SOC + 3.13 \tag{9}$$

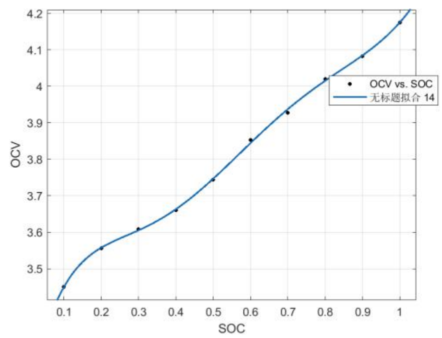

Fig.2 OCV-SOC Curve

Based on the voltage graph obtained through HPPC discharge and analysis using the established second-order equivalent RC circuit model, since there is no sudden change in voltage across the capacitor, it can be concluded that the sudden change in battery terminal voltage during discharge is caused by the ohmic resistance R_0. Therefore, the sudden change in voltage is given by:

$$\Delta u = R_0 i \tag{10}$$

After the pulse discharge of the battery, during a period of rest, the voltage undergoes a slow rise, which can be considered as the battery's zero-input response, caused by polarization reactions within the battery. The expression for the terminal voltage during this process is given by:

$$U_{out} = U_{oc} - iR_1 e^{-t/(R_1 C_1)} - iR_2 e^{-t/(R_2 C_2)} \quad (11)$$

Following this, various parameters will be fitted using Origin software, as shown in Table 1.

SOC	R_0/Ω	R_1/Ω	R_2/Ω	C_1/KF	C_2/KF
0.9	0.0032	0.0657	0.0020	507.908	572.917
0.8	0.0033	0.1746	0.0286	733.970	522.184
0.7	0.0032	0.0876	0.0147	819.216	514.183
0.6	0.0033	0.1181	0.0522	593.988	519.915
0.5	0.0033	0.1209	0.0175	622.571	499.268
0.4	0.0032	0.1049	0.0187	477.027	373506
0.3	0.0032	0.0631	0.0108	697.018	518.579
0.2	0.0032	0.0451	0.0116	592.994	907.744
0.1	0.0035	0.0327	0.0348	504.172	338.975
0	0.0252	0.0142	0.1574	50.342	589.643

Table.I Offline Identification Results of Battery Model Parameters

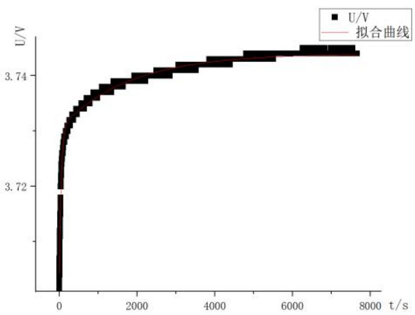

Fig.3 "Origin Fitted Curve"

Figure 3 shows the actual recovery curve and the fitted curve of terminal voltage during the rest period when the battery SOC is 50%. The R-squared value of the fitted curve is 0.996. A higher R-squared value indicates better fitting performance. Subsequently, the identified parameters will be substituted into the second-order RC model constructed in Simulink. A comparison will then be made with the current-voltage obtained from the experiment to assess the accuracy.

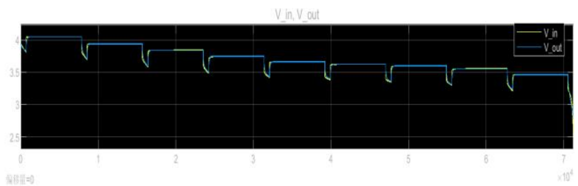

Fig.4 Comparison of Simulation and Experimental Results

From Figure 4 and Figure 5, it can be observed that the simulated voltage and the actual voltage fit almost perfectly, indicating high accuracy in error estimation. This suggests that the parameters of the second-order RC model obtained from offline identification can effectively simulate the battery's operating characteristics.

III. STATE OF CHARGE ESTIMATION

Kalman Filtering (KF) is an algorithm that utilizes the state equation of a linear system and input-output observation data to optimally estimate the system state. Based on this, many improved algorithms have been proposed, such as Extended Kalman Filtering (EKF) and Unscented Kalman Filtering (UKF), among others. The EKF algorithm estimates by linearizing nonlinear problems, but this process ignores higher-order terms, leading to increased computational errors and a higher computational load. In contrast, the UKF algorithm transforms the generated Sigma points through the Unscented Transform (UT), making all calculations nonlinear. This approach can avoid errors introduced during linearization, improve estimation accuracy, and greatly reduce computational load as it does not use Taylor series expansion for linearization. Lithium-ion batteries can be viewed as nonlinear systems during discharge. The state equation and observation equation of a general nonlinear system can be expressed as:

$$\begin{cases} x_k = f(x_{k-1}, u_k) + \omega_k \\ y_k = g(x_k, u_k) + v_k \end{cases} \quad (12)$$

Where u_k is the input variable of the system, x_k and x_{k+1} are the state variables of the system at time steps k and $k+1$ respectively, y_k is the output value at time step k, and ω_k and v_k are independent Gaussian-distributed random noises added to the system.

The specific steps to implement the UKF algorithm are as follows:

(1) Initialize the mean x and covariance p of the state variables.

$$\begin{cases} \overline{x}_0 = E(x_0) \\ p_0 = E[(x_0 - \overline{x}_0)(x_0 - \overline{x}_0)^T] \end{cases} \quad (13)$$

(2) Perform the Unscented Transform (UT) to obtain $2n$+1 sigma sampling points.

$$X_{k-1}^0 = \hat{x}_{k-1} \quad (14)$$

$$X_{k-1}^i = \hat{\chi}_{k-1} + \left(\sqrt{(n+\lambda)P_x}\right)_i, i = 1,2,\cdots,n \quad (15)$$

$$X_{k-1}^{i}=\hat{x}_{k-1}-\left(\sqrt{(n+\lambda)P_x}\right)_i, i = n+1,\cdots 2n \tag{16}$$

Where n is the number of state variables, and for this system, n is taken as 3; λ is the scaling factor, and its expression is given by:

$$\lambda=a^2(n+h)-n \tag{17}$$

Where typically it is a small positive number, in this paper it is taken as 1.Where h is a tunable parameter, calculated as shown in equation (18), and in this paper, it is taken as 0.

$$\lambda=3-n \tag{18}$$

(3) Determine the weighting coefficients.

$$\begin{cases}\omega_0^m &= \dfrac{\lambda}{\lambda+n} \\ \omega_0^c &= \dfrac{\lambda}{\lambda+n}+(1+\beta-a^2) \\ \omega_{\mathrm{i}}^m &= \omega_{\mathrm{i}}^c=\dfrac{\lambda}{2(\lambda+n)}, i=1,2,\cdots,2\end{cases} \tag{19}$$

Where ω^m and ω^c are the weight factors; for Gaussian white noise systems, they are generally taken as 2.

(4) Calculate the state covariance matrix of the state variables.

$$X_{k/k-1}^{i}=f\left(X_{k-1}^{i},u_{k-1}\right) \tag{20}$$

$$\hat{x}_{k/k-1}=\sum_{i=0}^{2n}\omega_{\mathrm{m}}^{i}X_{k/k-1}^{i}+q_k \tag{21}$$

$$P_{k/k-1} = \sum_{i=0}^{2n}\omega_c^i\left[X_{k/k-1}^{i}-\hat{x}_{k/k-1}\right] \times\left[X_{k/k-1}^{i}-\hat{x}_{k/k-1}\right]^{\mathrm{T}}+Q_k \tag{22}$$

Where $i=1,2,\cdots,2n$; q_k is the mean of the process noise; Q_k is the covariance of the process noise.

(5) Calculate the mean of the system observation.

$$y_{k/k-1}^{i} = g\left(X_{k-1}^{i},u_{k-1}\right) \tag{23}$$

$$\hat{y}_{k/k-1} = \sum_{i=0}^{2n}W_{\mathrm{m}}^{i}y_{k/k-1}^{i}+r_k \tag{24}$$

Where r_k is the mean of the observation noise.

(6) Calculate the cross-covariance matrix and covariance matrix of the system observation.

$$P_{x_k,y_k}=\sum_{i=0}^{2n}W_c^i\left[X_{k/k-1}^{i}-\hat{x}_{k/k-1}\right] \times\left[y_{k/k-1}^{i}-\hat{y}_{k/k-1}\right]^{\mathrm{T}} \tag{25}$$

$$P_{y_k,y_k} = \sum_{i=0}^{2n}W_c^i\left[y_{k/k-1}^{i}-\hat{y}_{k/k-1}\right] \times\left[y_{k/k-1}^{i}-\hat{y}_{k/k-1}\right]^{\mathrm{T}}+R_k \tag{26}$$

Where R_k is the covariance matrix of the observation noise.

(7) Calculate the Kalman gain K.

$$K=P_{x_k,y_k}P_{y_k,y_k}^{-1} \tag{27}$$

(8) Update the state matrix and error covariace matrix of the system.

$$\begin{cases}\hat{x}_k &= \hat{x}_{k/k-1}+K_k\left(y_k-\hat{y}_{k/k-1}\right) \\ P_k &= P_{k/k-1}-K_kP_{y_k,y_k}K_k^T\end{cases} \tag{28}$$

EKF has several drawbacks: (1) The Taylor series expansion formula, due to the omission of its higher-order terms, may cause the Kalman filtering algorithm to diverge in highly nonlinear systems. (2) EKF requires the computation of cumbersome Jacobian matrices. (3) EKF can only converge to the global optimum when both the state and observation equations are close to linear continuously. Compared to EKF, the UKF algorithm does not require the linearization of nonlinear functions. By approximating the linearization of the probability density distribution of the system state variables, it conducts SOC estimation, reducing the estimation error of the system and improving the accuracy of the algorithm.

IV. Experimental Results

Using the UKF algorithm to estimate lithium-ion batteries, verify the performance of the algorithm. The lithium-ion battery, fully charged, is left standing for a sufficiently long time, with the initial SOC set to 1. HPPC tests are conducted with a discharge current of 0.50C, i.e., 1.4A, and a sampling period of T=1s. The experimentally measured SOC is used as the reference value (obtained through Coulomb counting with the known initial SOC). Then, the SOC of the battery is estimated using the UKF and EKF algorithms, and the results are shown in Figure 4, with errors depicted in Figure 5.

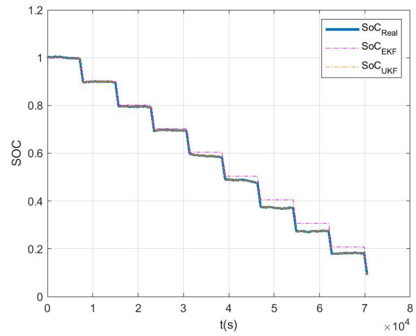

Fig.5 Estimation results when the initial SOC is 1

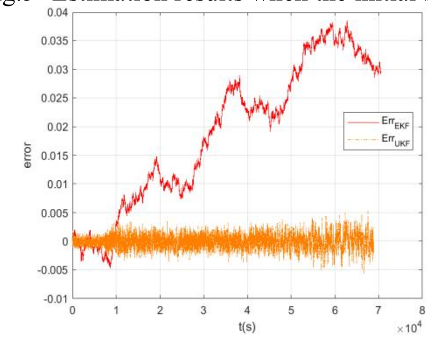

Fig.6 Comparison of estimation errors between the EKF and UKF algorithms

From the graph, it can be observed that the EKF estimates the battery SOC quite effectively until around 31000s, after which the error gradually increases with time accumulation, reaching a maximum of about 0.04. On the other hand, the UKF algorithm maintains an error absolute value of around 0.005 throughout the estimation process. It is evident that the UKF algorithm exhibits higher precision.

V. Conclusion

In this study, we first established a second-order equivalent RC model of the battery and conducted HPPC tests on the battery to obtain its discharge terminal voltage curve. Subsequently, we employed an offline identification method to identify the parameters of the battery model. We then constructed a second-order RC simulation model to verify the accuracy of the parameters. Furthermore, we used the UKF and EKF algorithms to estimate the SOC of the battery. The simulation results showed that the accuracy of offline parameter identification was high and met the requirements. The overall error of SOC estimation by the UKF algorithm was around 0.5%, while the maximum error of SOC estimation by the EKF algorithm reached 4%. This indicates that the UKF algorithm can better meet the needs of battery SOC estimation. In the actual operation process of batteries combined with other electrical appliances, it is necessary to address issues such as the idealization of mechanism model conditions for operational state monitoring and the lack of objective physical constraints in data models. Additionally, by studying adaptive fusion strategies for mapping mechanisms and data, as well as parameter dynamic optimization iterative methods, the estimation of battery state can be further improved.

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