Food-Energy-Water Nexus
ISSN: 3105-0689 | E-ISSN: 3105-0697
Volume 1 , Issue 2

Article

SOC estimation of lithium battery based on EKF and UKF

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CITATION

Li CC. SOC estimation of lithium battery based on EKF and UKF. Food-Energy-Water Nexus. 2025; 1(2): 191.

https://doi.org/10.63808/fewn.v1i2.191

Abstract: Accurate SOC estimation plays a central role in lithium battery applications. It not only affects operational safety, but also determines energy utilization efficiency and battery life cycle length. Aiming at the lack of accuracy of the traditional SOC estimation method under dynamic working conditions, this paper adopts two algorithms, Extended Kalman Filter (EKF) and Untraceable Kalman Filter (UKF), based on the second-order RC equivalent circuit model of Li-ion battery to estimate the SOC of the battery. By comparing and analyzing the estimation error and convergence performance of the two filtering algorithms, the results show that both EKF and UKF have good dynamic response capability and high estimation accuracy, among which UKF performs better in terms of nonlinear processing and estimation stability. It provides theoretical basis and technical support for the precise control and optimization of battery management system (BMS).

Keywords: lithium battery; Charge of State; Equivalent circuit model; Kalman filtering

1. Introduction

With the global shift toward sustainable development and a circular carbon economy, lithium-ion batteries have emerged as pivotal enablers of clean energy transition, thanks to their high energy density, long lifespan, and minimal environmental footprint (Niu et al., 2024). These batteries play a vital role in electric vehicles, energy storage infrastructures, and portable electronics, where effective control and utilization strategies are essential to advancing sustainability. However, the accurate assessment of a battery's state of charge (SOC), which indicates the remaining capacity, is essential for maintaining operational safety and prolonging service life, and it remains a fundamental function of the battery management system (BMS) (Wu et al., 2024). Accurate SOC estimation not only prevents overcharging or over discharging and improves energy utilization efficiency, but also extends battery life, thereby reducing resource consumption and e-waste and contributing to green and low-carbon development (Nisama et al., 2024).

Currently, the SOC is commonly estimated using several established methods, including open-circuit voltage measurement, ampere-hour integration, machine learning-based data-driven techniques, and Kalman filtering schemes (Hassan et al., 2022). However, the complex electrochemical characteristics of lithium batteries make these methods have certain limitations in practical applications. Since the open-circuit voltage method relies on long resting periods to obtain accurate measurements, it becomes unsuitable for applications involving dynamic operating conditions(Pillai et al., 2022); the ampere-time integration method is susceptible to the accumulation of current measurement error and the difficulty of determining the initial value, which leads to a large estimation bias with the accumulation of time(Liu and Dai, 2022); and the data-driven method requires a higher quality of data and a larger amount of data, so there are still great difficulties in the practical application(Hossain et al., 2022). Kalman filtering is an efficient battery state estimation algorithm that achieves optimal estimation of the state of charge (SOC) through a unique prediction-correction mechanism (Cui et al., 2022). The algorithm is particularly suitable for dealing with dynamic systems with noise, and is able to provide continuous and accurate SOC estimation under the uncertainty conditions of the battery charging and discharging process. Kalman filtering (KF) is an efficient method for state estimation of linear systems, but has limitations when dealing with nonlinear systems. To solve this problem, researchers have developed two improved algorithms, EKF and UKF (Liu et al., 2023).

In this paper, a second-order RC equivalent circuit framework is initially established to describe the transient characteristics of lithium-ion batteries. The intrinsic parameters of the battery are extracted offline from pulse discharge test data using a curve-fitting strategy based on exponential functions. The resulting model and

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parameters are then comprehensively assessed to confirm the validity and consistency of the system. Building upon the second-order RC network, this study further integrates two estimation techniques, EKF and UKF, to assess the state of charge (SOC) of the lithium battery. The performance of these methods is evaluated through both empirical experiments and numerical simulations. The performance of the two methods under real working conditions is compared and analyzed to evaluate their potential application in battery management systems.

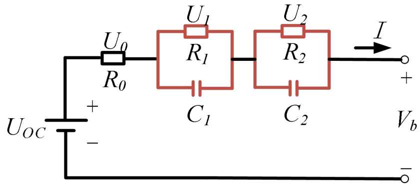
2. Lithium battery model establishment and parameter identification

2.1. Circuit Model Establishment

Accurate modeling of lithium-ion batteries is crucial for state analysis and management (Mehta et al., 2021). In this paper, the second-order RC equivalent circuit model is used, as shown in Figure 1, which can more accurately describe the dynamic characteristics of the battery by characterizing the polarization process on different time scales through two RC parallel networks (R1C1 and R2C2), respectively. Where Uoc denotes the open-circuit voltage, R0 is the ohmic internal resistance, U0 is the internal resistance voltage drop, and Vb is the terminal voltage. Compared with the first-order model, this structure significantly improves the simulation accuracy under fast charging and discharging conditions while maintaining the computational efficiency, providing a reliable basis for SOC estimation.

Figure 1

Second-order RC equivalent circuit model of lithium battery



It follows from Kirchhoff's Law:

$$V_b = U_{\mathrm{oc}} - U_1 - U_2 - IR_0 \tag{1}$$

$$C_1 \frac{dU_1}{dt} = I - \frac{U_1}{R_1} \tag{2}$$

$$C_2 \frac{dU_2}{dt} = I - \frac{U_2}{R_2} \tag{3}$$

The SOC of a lithium battery is defined as the ratio of its residual capacity to its rated capacity, and is calculated as follows:

$$\mathrm{SOC}(t) = \mathrm{SOC}(t_0) - \int_{t_0}^{t} \frac{\eta I}{Q_n} dt \tag{4}$$

2.2. Parameter Identification

2.2.1 SOC-OCV Relationship Curve

Before initiating the estimation process of lithium-ion battery state of charge (SOC), it is imperative to carry out model-oriented parameter extraction for the selected electrical representation. To ensure methodological robustness, this study adopts a well-documented open dataset from the University of Maryland as the experimental reference. The test subject is a single cylindrical 18650 Li-ion cell, characterized by a nominal energy capacity of 2000 mAh, an upper charge threshold of 4.2 V (corresponding to saturation), and a lower discharge cutoff at 2.5 V. This battery underwent systematic charge-discharge protocols under diverse operational profiles, thereby capturing detailed transient behavior and offering a dependable numerical foundation for both model calibration and SOC tracking verification. As presented in **Figure 2**, data from a hybrid pulse power characterization (HPPC) sequence are utilized to extract the functional dependency between SOC levels and the corresponding open-circuit potentials, which is subsequently approximated through sixth-order polynomial regression. as shown in **Figure3**.

Figure 2

HPPC data

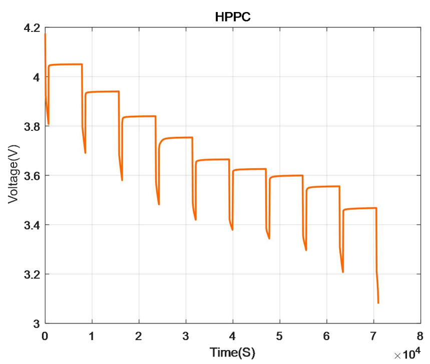
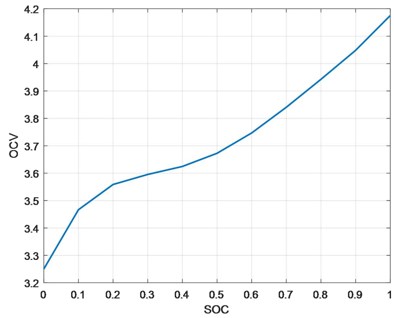


Figure 3

SOC-OCV curve



The equation describing the function of OCV versus SOC is obtained by fitting a sixth-degree polynomial to the SOC versus OCV curve:

$$\begin{aligned}\mathrm{OCV}&=4.4747*SOC^6-7.4769*SOC^5-4.0312*SOC^4+15.3296*SOC^3\\&-10.4296*SOC^2+3.0586*SOC+3.2501\end{aligned} \tag{5}$$

2.2.2 SOC-OCV Relationship Curve

Utilizing the experimental outputs from the Hybrid Pulse Power Characterization (HPPC) protocol, voltage measurements corresponding to the SOC interval between 100% and 90% were initially extracted and processed within the MATLAB environment. A dataset was then constructed with time mapped to the x-axis and terminal voltage to the y-axis, followed by appropriate data reduction to streamline subsequent modeling. Thereafter, MATLAB's curve fitting utilities were employed, where an exponential-type user-defined model was applied to perform parameter regression. The resulting estimated parameters are summarized in **Table 1**.

Table 1

Parameter identification results

SOC	R_0/Ω	R_1/Ω	C_1/F	R_2/Ω	C_2/F
0.1	0.341	0.0076	304329	0.0129	5797
0.2	0.238	0.0185	5695	0.0088	137434
0.3	0.231	0.02	3913	0.0096	134490
0.4	0.227	0.0145	5122	0.0063	292023
0.5	0.228	0.0165	2839	0.008	188724
0.6	0.2373	0.0089	203284	0.0288	14157

0.7	0.2445	0.0062	232372	0.026	2174
0.8	0.231	0.0059	223701	0.0225	1406
0.9	0.228	0.0052	11316	0.017	1713

2.3. Model Validation

To assess the fidelity of the constructed battery model and validate the extracted parameter set, a simulation framework was developed using the MATLAB/Simulink environment. The identified internal characteristics, derived from offline calibration, were embedded into the simulation structure. Model performance was then examined by aligning simulated output voltage with empirical voltage data obtained through experimentation. In this analysis, current profiles under HPPC testing conditions served as inputs, and the voltage comparison results between the numerical simulation and physical measurements are illustrated in **Figures 4** and **5**.

Figure 4

End Voltage Comparison

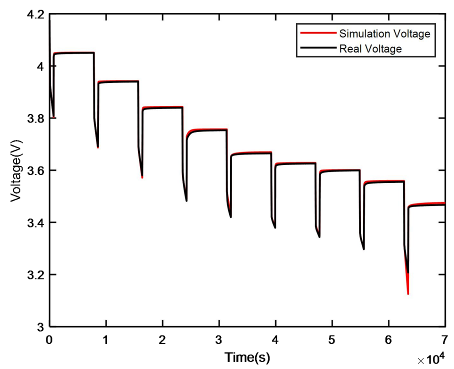
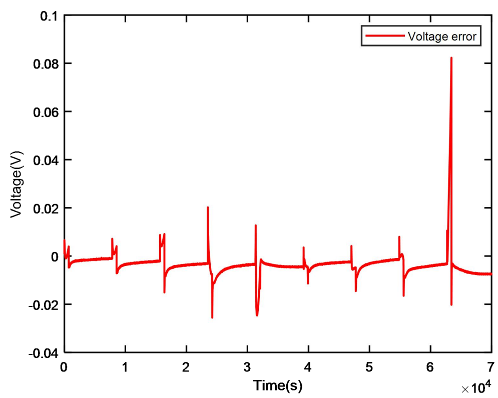


Figure 5

End voltage error



WISDOM ACADEMIC ISSN: 3105-0689 | E-ISSN: 3105-0697 Volume 1 , Issue 2

From the figure, it can be seen that the modeling error only increases significantly at the end of discharge, which is mainly attributed to the intensification of the internal chemical reaction of the battery in the low SOC stage. In the rest of the stages, the end-voltage error is always controlled within 0.03 V, which meets the requirement of battery modeling accuracy. It is verified that the constructed model has high accuracy and the validity of parameter identification, which lays a reliable foundation for the subsequent SOC estimation work.

3. Battery SOC estimation based on Kalman filtering

3.1 EKF serves as a widely adopted technique for estimating internal states in systems exhibiting nonlinear behavior. Within the context of lithium-ion battery SOC prediction, the inherent nonlinearity between SOC, voltage, and current poses modeling challenges. To address this, EKF applies a local linear approximation to the nonlinear dynamics via first-order Taylor series expansion, enabling more accurate state tracking and improved adaptability to the time-varying characteristics of battery operation.

The basic working mechanism of EKF can be divided into two main phases:

1. Prediction step: Based on the predefined state-space representation of the battery system, the SOC at the subsequent time step is forecasted. This mathematical model is typically derived from the lithium batteries equivalent circuit, in which the current is treated as the system excitation, the terminal voltage serves as the observable output, and SOC functions as the core internal state. The future state is inferred by utilizing the present state information along with the corresponding input signal.

Prediction Equation:

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1}, u_{k-1}) + w_{k-1} \tag{6}$$

2. Correction step: During this stage, the EKF algorithm incorporates real-time voltage observations to refine the previously predicted SOC by adjusting the estimate based on the discrepancy between observed and simulated outputs. This adjustment is achieved by computing the estimation error covariance, which is then used to correct the SOC value, thereby enhancing its consistency with the actual system behavior.

Updating the equation:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - h(\hat{x}_{k|k-1}, u_k)) \tag{7}$$

3.2 Traceless Kalman Based on the traceless (UT) transform, the battery condition can be estimated more accurately. The basic principle of UT transform is given below.

The UT transform is the key step of UKF, and 2n+1 Sigma points can be obtained by sampling according to the symmetric distribution. The formula is shown in the following equation.

$$\begin{cases} X^i = \hat{x}\,, i = 0 \\ X^i = \hat{x} + (\sqrt{(n+\lambda)P})_i \;\;, i = 1,2,3,\ldots,n \\ X^i = \hat{x} - (\sqrt{(n+\lambda)P})_{i-n}\,, i = n+1, n+2, \ldots, 2n \end{cases} \tag{8}$$

The corresponding weights are:

$$\begin{cases} w_m^0 = \lambda/(n+\lambda) \\ w_c^0 = \dfrac{\lambda}{n+\lambda} + (1 - \alpha^2 + \beta) \\ w_m^i = w_c^i = \dfrac{\lambda}{2(n+\lambda)}, i = 0,2\ldots,2n \end{cases} \tag{9}$$

4. Simulation Verification and Analysis

The SOC estimation procedures based on EKF and UKF are implemented within the MATLAB/Simulink framework. To validate the effectiveness of both methods, simulations are carried out under the Hybrid Pulse Power Characterization (HPPC) profile, where the initial SOC is set to 0.9 for convergence evaluation. The ampere-hour accumulation technique is employed as a benchmark reference to assess the estimation accuracy of both filters, and the corresponding comparison results are presented in **Figures 6** and **7**. Calculate the errors of the two algorithms, as shown in **Table 2**.

Figure 6

SOC estimation curve

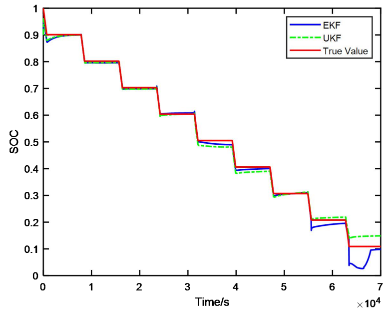


Figure 7

SOC error curves

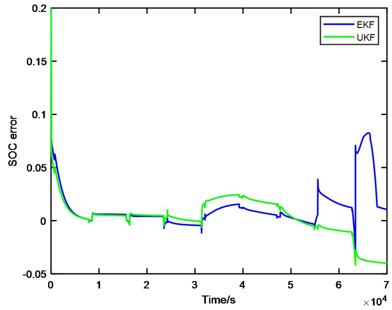


Table 2

Comparison of EKF and UKF errors

algorithm	MAE	RMSE
EKF	1.304%	2.22%
UKF	1.301%	1.80%

Under conditions where the initial SOC estimate deviates from the true value, both EKF and UKF demonstrate strong convergence performance, enabling rapid alignment between estimated and actual SOC. Experimental evaluation reveals that the mean estimation error for both algorithms remain within 2%, confirming their high prediction accuracy. Nevertheless, in the later stages of the simulation, UKF exhibits a noticeably superior performance compared to EKF, primarily because EKF relies on linearization and thus neglects higher-order nonlinear dynamics during state updates.

5. Conclusion

In this study, a second-order resistor–capacitor equivalent model was developed to represent the electrical characteristics of a lithium-ion battery, and its parameters were determined through exponential function fitting. Building on this foundation, a corresponding simulation framework was implemented within the MATLAB/Simulink environment to evaluate model accuracy. Furthermore, the extended Kalman filter and the unscented Kalman filter were applied independently to perform estimation of the battery's state of charge. By comparing the estimated SOC values from both filtering techniques with reference values, the analysis confirms that Kalman-based approaches offer reliable accuracy and robustness, with the unscented Kalman filter exhibiting superior performance compared to the extended Kalman filter.

Conflict of interest: The author declares no conflict of interest.

Funding: This research received no external funding.

References

[1] Cui, Z., Hu, W., Zhang, G., Zhang, Z., & Chen, Z. (2022). An extended Kalman filter based SOC estimation method for Li-ion battery. *Energy Reports*, 8, 81–87.

[2] Hassan, M. U., Saha, S., Haque, M. E., Islam, S., Mahmud, A., & Mendis, N. (2022). A comprehensive review of battery state of charge estimation techniques. *Sustainable Energy Technologies and Assessments*, 54, 102801.

[3] Hossain, M., Haque, M. E., & Arif, M. T. (2022). Kalman filtering techniques for the online model parameters and state of charge estimation of the Li-ion batteries: A comparative analysis. *Journal of Energy Storage*, 51, 104174.

[4] Liu, X., & Dai, Y. (2022, February). Energy storage battery SOC estimate based on improved BP neural network. In *Journal of Physics: Conference Series* (Vol. 2187, No. 1, p. 012042). IOP Publishing.

[5] Liu, S., Deng, D., Wang, S., Luo, W., Takyi-Aninakwa, P., Qiao, J., ... & Hu, C. (2023). Dynamic adaptive square-root unscented Kalman filter and rectangular window recursive least square method for the accurate state of charge estimation of lithium-ion batteries. *Journal of Energy Storage*, 67, 107603.

[6] Mehta, C., Sant, A. V., & Sharma, P. (2021). Selection of three RC branches in equivalent circuit model of lithium-ion batteries for improved accuracy. *Turkish Journal of Computer and Mathematics Education*, 12(14), 1478–1489.

[7] Njema, G. G., Ouma, R. B. O., & Kibet, J. K. (2024). A review on the recent advances in battery development and energy storage technologies. *Journal of Renewable Energy*, 2024(1), 2329261.

[8] Niu, H., Zhang, N., Lu, Y., Zhang, Z., Li, M., Liu, J., ... & Miao, Z. (2024). Strategies toward the development of high-energy-density lithium batteries. *Journal of Energy Storage*, 88, 111666.

[9] Pillai, P., Sundaresan, S., Kumar, P., Pattipati, K. R., & Balasingam, B. (2022). Open-circuit voltage models for battery management systems: A review. *Energies*, 15(18), 6803.

[10] Wu, L., Lyu, Z., Huang, Z., Zhang, C., & Wei, C. (2024). Physics-based battery SOC estimation methods: Recent advances and future perspectives. *Journal of Energy Chemistry*, 89, 27–40.