Available online at www.sciencedirect.com
ScienceDirect
Energy Reports 8 (2022) 81–87
www.elsevier.com/locate/egyr
2021 The 2nd International Conference on Power Engineering (ICPE 2021), December 09–11, 2021, Nanning, Guangxi, China

An extended Kalman filter based SOC estimation method for Li-ion battery

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Received 26 January 2022; accepted 10 February 2022
Available online 24 February 2022

Abstract

In recent years, the global environmental pollution and energy crisis are becoming more and more serious. The Li-ion battery is widely used in vehicles due to long cycle life and high energy density. The state of charge (SOC) of Li-ion battery is an important indicator. The accurate estimation of SOC can ensure the safe operation of Li-ion battery. However, the traditional estimation method, the ampere-hour integration method, has a cumulative error and cannot maintain good results for a long time in an operating environment with the Gaussian noise. To this end, this paper firstly applies Thevenin equivalent circuit model of a battery to establish estimation model, and it can reflect the working state of the battery. Then, the extended Kalman filtering algorithm is employed to solve the estimation error caused by Gaussian noise. Finally, the test system is built in MATLAB/Simulink to investigate the performance of the proposed method. Simulation results show that the proposed method achieves better performance, and it has higher estimation accuracy in comparison with traditional methods under different working conditions.

Peer-review under responsibility of the scientific committee of the 2nd International Conference on Power Engineering, ICPE, 2021.

Keywords: Li-ion battery; State of charge; Estimation; Extended Kalman filtering algorithm

1. Introduction

Environment pollution and energy crisis are two severe problems of the world in recent years [1]. These problems are exacerbated by the dramatic increase in the number of fossil fuel vehicles. The large amount of carbon dioxide being released into the air leads to a series of economic and natural disasters such as global warming, reduced food production and rampant epidemic diseases. At the same time, some harmful gases are released into the air and affect human health, including nitrogen oxides and sulfides. Therefore, choosing low-carbon and efficient energy sources to replace fossil fuels to drive vehicles is an important part of sustainable development.

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https://doi.org/10.1016/j.egyr.2022.02.116

Peer-review under responsibility of the scientific committee of the 2nd International Conference on Power Engineering, ICPE, 2021.

Due to the features of long cycle life, high power endurance and high power density, Li-ion battery plays a significant role in advancing modern technology, for example, electric vehicles (EV) [2–4]. EV's mileage, safety and life of battery are performance criteria, which is of great interest to people. To meet these standards, the battery management system need be designed to monitor and control the states and performance of the battery during the operating process. Especially, state of charge (SOC) reflects the remaining capacity of the battery, and it is a very important indicator. The accurate estimation of SOC is an important part of the battery management system during charging and discharging process.

In recent years, a large amount of literatures has applied various methods to estimate SOC, including ampere-hour integration method (Ah) [5], Kalman filter method (KF) [6–8] and Deep Reinforcement Learning (DRL) [9–12]. Among them, the Ah is the most commonly method. During the operating process, this method can estimate the SOC of battery in real-time, and the measurement accuracy is less affected by the internal changes of the battery [13]. It makes that Ah method achieve a high measurement accuracy in a short period of time. However, Ah method is unable to correct the deviation of the initial value of SOC and has a cumulative error [14]. As time grows, the accuracy deteriorates.

To solve this problem, the extended Kalman filter (EKF) method has been introduced in this paper. This method can solve the interference caused by the white noise in the system and improve the cumulative error caused by the ampere-time integration method. It also has a good correction effect on the deviation of the initial value of SOC. The rest of this paper is summarized as follows. The Section 2 analyzes the model of Li-ion battery and establishes a state space model applicable to EKF. Then, the mechanism of EKF is analyzed in the discrete space and the EKF-based SOC estimation algorithm is established in Section 3. The estimated performance of Ah and EKF method are compared in Section 4. Section 5 concludes this paper.

2. State space model of SOC

2.1. Battery model

In this section, to estimate the SOC of the battery more effectively, the equivalent model should be established not only has higher accuracy, but also can fully represent the dynamic characteristics of the battery. Meanwhile, the estimation method of SOC needs to be applied to engineering, so it is also important to limit complexity of equivalent model. In general, the mainstream equivalent models of the Li-ion battery including the Rint model [15], Thevenin model [16], and Rngv model [17]. Among them, the Thevenin model can quickly reflect the operating state of the Li-ion battery without excessive delay to track the actual voltage, so the accuracy of the model can be ensured in a long simulation.

The structure of Thevenin model is shown in Fig. 1. It consists of different parts which are connected in series, including resistance R_0, voltage source U_{OC}, parallel structure of polarization resistance R_P, and polarization capacitor C_P. The resistive property of the Li-ion battery is expressed by the resistance R_0, which makes the terminal voltage of the model with suddenness. The capacitive characteristics of the battery are expressed by the part of the polarization resistance R_P in parallel with the polarization capacitance C_P, which makes the terminal voltage of the model change gradually. According to Kirchhoff's Voltage Laws and Kirchhoff's Current Law, the circuit equations of Thevenin model are shown below.

$$\begin{cases} \dot{U}_P = -\dfrac{U_P}{R_P C_P} + \dfrac{I_L}{C_P} \\ U_L = U_P + U_{OC} + I_L R_0 \end{cases} \tag{1}$$

where I_L is the current through the resistance R_0, U_L is terminal voltage of the equivalent circuit, U_P is the terminal voltage of polarization capacitor C_P, U_{OC} is open circuit voltage of equivalent circuit.

2.2. SOC estimation model

The SOC of Li-ion battery cannot be measured directly, and its calculation relies on the working condition of the battery and the characteristics of the battery. To describe the value of SOC, the definition of Ah is adopted and

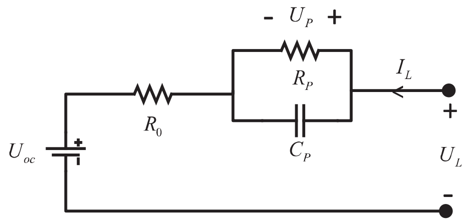

Fig. 1. Thevenin equivalent circuit model.

the equation is shown below.

$$SOC\left(t\right)=SOC\left(t_0\right)+\frac{\int_{t_0}^{t}k_Ti\left(\tau\right)d\tau}{Q_N} \tag{2}$$

where $SOC\left(t_0\right)$ is the SOC of Li-ion battery at moment t_0, k_T is the temperature correction factor for the Li-ion battery at temperature T. $i\left(\tau\right)$ is the current flowing through the battery at moment τ, Q_N is rated capacity of the battery.

The ampere-time integration method can be applied to calculate the variation of SOC. The variables of this method can be measured directly in the process of battery operating. Measurement accuracy is less affected by internal changes of battery and the results are very reliable in a short period of time, but the exact calculation of the initial value of SOC is not provided. To this end, model parameter identification experiments are usually employed to obtain the correspondence between SOC and the open circuit voltage of the battery. Then, the initial value of SOC can be obtained by calculating the open circuit voltage of the battery. The SOC estimation equation based on this method is shown below.

$$SOC\left(t\right)=SOC\left(OCV\right)+\frac{\int_{t_0}^{t}k_Ti\left(\tau\right)d\tau}{Q_N} \tag{3}$$

where OCV is the open circuit voltage value, $SOC\left(OCV\right)$ is the initial value of the corresponding SOC.

Combined (3) with Thevenin model, the discrete state space model of this estimation system is shown below.

$$\begin{bmatrix} SOC_k \\ U_{P,k} \end{bmatrix}=\begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{\Delta T}{R_PC_P}} \end{bmatrix}\begin{bmatrix} SOC_{k-1} \\ U_{P,k-1} \end{bmatrix}+\begin{bmatrix} \frac{\Delta T}{Q_N} \\ \left(1-e^{-\frac{\Delta T}{R_PC_P}}\right)R_P \end{bmatrix}I_{k-1}+w_{k-1} \tag{4}$$

$$U_{L,k}=OCV\left(SOC_k\right)+U_{P,k}+R_0I_k+v_k \tag{5}$$

where ΔT is discrete step size, w_{k-1} is the amount of process noise at moment $k-1$, v_k is the amount of observed noise at moment k.

3. Li-ion battery SOC estimation based on EKF

In the operating process of battery, due to the random noise in the observation of current, voltage and other physical quantities, it will accumulate errors when adopting Ah method to calculate SOC, and the accuracy of the estimation results will decrease with time. Therefore the EKF algorithm can be applied to solve this nonlinear estimation problem. This algorithm is an optimal autoregressive data processing algorithm, and it implements minimum variance estimation by a recursive algorithm and can give the error of the estimate. The discrete nonlinear state space model is shown below.

$$\begin{cases} x_k=f\left(x_{k-1},u_{k-1},w_{k-1}\right) \\ y_k=h\left(x_k,u_k,v_k\right) \end{cases} \tag{6}$$

$$\begin{aligned} &w_k\sim\left(0,Q\right) \\ &v_k\sim\left(0,R\right) \end{aligned} \tag{7}$$

where w_{k-1} is process noise value at moment $k-1$, v_k is measurement noise value of moment k, Q is covariance of w_k, R is covariance of v_k.

To transform a nonlinear problem into a linear one, the system is linearized at an operating point. At this point $x_{k-1} = \hat{x}_{k-1|k-1}$, $w_{k-1} = 0$, the state equation is transformed into the Taylor expansion.

$$\begin{aligned} x_k &= f\left(\hat{x}_{k-1|k-1}, u_{k-1}, 0\right) + \frac{\partial f}{\partial x}|_{\hat{x}_{k-1|k-1}} \cdot \left(x_{k-1} - \hat{x}_{k-1|k-1}\right) + \frac{\partial f}{\partial w}|_{\hat{x}_{k-1|k-1}} \cdot w_{k-1} \\ &= \frac{\partial f}{\partial x}|_{\hat{x}_{k-1|k-1}} \cdot x_{k-1} + \left[f\left(\hat{x}_{k-1|k-1}, u_{k-1}, 0\right) - \frac{\partial f}{\partial x}|_{\hat{x}_{k-1|k-1}} \cdot \hat{x}_{k-1|k-1}\right] + \frac{\partial f}{\partial w}|_{\hat{x}_{k-1|k-1}} \cdot w_{k-1} \\ &= F_{k-1}x_{k-1} + \widetilde{u}_{k-1} + L_{k-1}w_{k-1} \\ &= F_{k-1}x_{k-1} + \widetilde{u}_{k-1} + \widetilde{w}_{k-1} \end{aligned} \tag{8}$$

$$\widetilde{w}_k \sim \left(0, L_k Q L_k^T\right) \tag{9}$$

where $\hat{x}_{k-1|k-1}$ is the posteriori estimation of state variables at moment $k-1$. $L_k Q L_k^T$ is covariance of $\widetilde{w}_k$.

At this point $x_{k-1} = \hat{x}_{k|k-1}$, $v_k = 0$, the output equation is transformed into the Taylor expansion.

$$\begin{aligned} y_k &= h\left(\hat{x}_{k|k-1}, u_k, 0\right) + \frac{\partial h}{\partial x}|_{\hat{x}_{k|k-1}} \cdot \left(x_k - \hat{x}_{k|k-1}\right) + \frac{\partial h}{\partial v}|_{\hat{x}_{k|k-1} \cdot v_k} \\ &= \frac{\partial h}{\partial x}|_{\hat{x}_{k|k-1}} \cdot x_k + \left[h\left(\hat{x}_{k|k-1}, u_k, 0\right) - \frac{\partial h}{\partial x}|_{\hat{x}_{k|k-1}} \cdot \hat{x}_{k|k-1}\right] + \frac{\partial h}{\partial v}|_{\hat{x}_{k|k-1} \cdot v_k} \\ &= H_k x_k + z_k + M_k v_k \\ &= H_k x_k + z_k + \widetilde{v}_k \end{aligned} \tag{10}$$

$$\widetilde{v}_k \sim \left(0, M_k R M_k^T\right) \tag{11}$$

where $\hat{x}_{k|k-1}$ is the priori estimation of state variables at moment k. And $M_k R M_k^T$ is covariance of $\widetilde{v}_k$.

According to (4), (5), (8), (10), the linearization results of SOC estimation model (12) are obtained, So the state variables and error covariance can be estimated by the standard EKF algorithm.

$$\begin{cases} F_{k-1} = \frac{\partial f}{\partial x}|_{\hat{x}_{k-1|k-1}} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{\Delta T}{R_P C_P}} \end{bmatrix} \\ L_{k-1} = \frac{\partial f}{\partial w}|_{\hat{x}_{k-1|k-1}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \\ H_{k=} \frac{\partial h}{\partial x}|_{\hat{x}_{k|k-1}} = \left[\, a_k \quad 1 \,\right] \\ M_{k=} \frac{\partial h}{\partial v}|_{\hat{x}_{k|k-1}} = 1 \end{cases} \tag{12}$$

where a_k is the derivative of $OCV\,(SOC_k)$ at point $SOC_{k|k-1}$.

The main idea of EKF is to use the state equation to predict the state quantity of the system at the next moment. Specifically, adopting the difference between actual observations and predicted output values to calculate the minimum variance estimate to update the Kalman gain coefficient. Then, using this coefficient to correct the weights of the observed and predicted values in the calculation of state variable estimation. The details of the EKF is shown below.

$$\begin{cases} \hat{x}_{k|k-1} = f\left(\hat{x}_{k-1|k-1}, u_{k-1}, 0\right) \\ P_{k|k-1} = F_{k-1} P_{k-1|k-1} F_{k-1}^T + L_{k-1} Q L_{k-1}^T \\ K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + M_k R M_k^T\right)^{-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left[y_k - h\left(\hat{x}_{k|k-1}, u_k, 0\right)\right] \\ P_{k|k} = \left(I - K_k H_k\right) P_{k|k-1} \end{cases} \tag{13}$$

where P_k is error covariance, K_k is Kalman gain coefficient.

In each sampling cycle, the EKF algorithm has to estimate the P_k and x_k in two different ways, including priori estimation and posteriori estimation. Between the two stages, the Kalman gain coefficient K_k is calculated by the priori estimate.

4. Simulation and analysis

In this paper, a simulation model is built in MATLAB/Simulink to investigate the effectiveness of the proposed method, and the parameters of the simulated battery are shown in Table 1. Moreover, the traditional Ah integration method are employed to act as comparison example.

Table 1. Parameters of Li-ion battery.

Quantity	Parameter	Unit
Battery rated capacity	5	Ah
Battery rated voltage	3.4	V
Max. continuous discharge	20	A
Resistance	1.445	mΩ
Polarization resistance	3.506	mΩ
Polarization capacitor	14.6	kF

To reflect the performance of the battery under real working conditions, this paper adopts both step constant current discharge (SCCD) and dynamic stress test discharge (DSTD) as current inputs, as shown in Fig. 2. The discharge current of SCCD is 5 A. Moreover, in order to better simulate the interference present in the actual sampling numbers, a certain degree of white noise is added to the current data and voltage data. The SOC estimation and errors of the two methods under these two conditions are shown in Figs. 3–4.

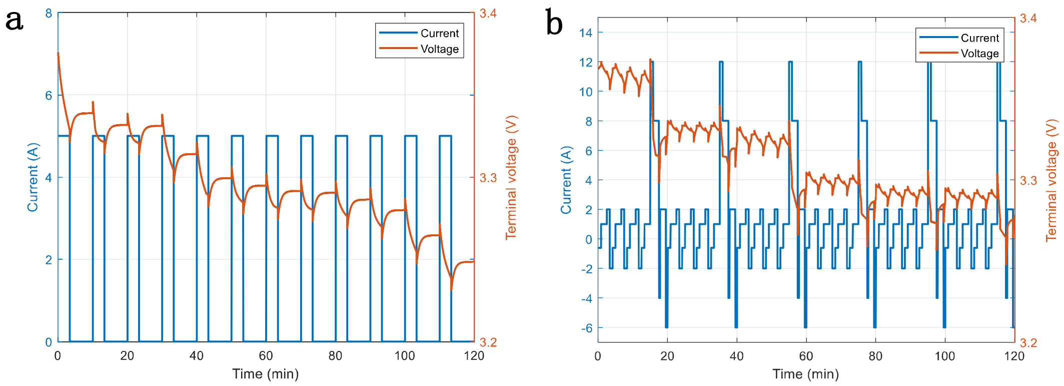

Fig. 2. Operating conditions of Li-ion battery (a) SCCD; (b) DSTD.

It can be seen from Fig. 3 that both two methods are able to track SOC in the initial time. However, as time grows, the estimation error of SOC gradually becomes larger. It means that the Ah method cannot suppress the estimation error caused by white noise. In contrast, the EKF method has smaller estimation error in comparison with Ah method, and it has an estimation error of less than 0.5%. Fig. 4 shows that this conclusion still holds for more complex operating condition. To compare the estimation performance of these methods intuitively, the estimation results of SOC were analyzed by Mean Error (ME), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). As shown in Tables 2 and 3.

It can be seen from Table 2 that the ME index of EKF method is 62.95% lower than Ah method. The MAE and RMSE indexes of EKF are half as low as Ah method in the SCCD condition. It can be concluded that EKF method has better estimation performance in this condition. When in the DSTD condition, all three indicators of EKF method are 60% lower than Ah method. Therefore, compared with the Ah method, the EKF method works better under both SCCD and DESD conditions.

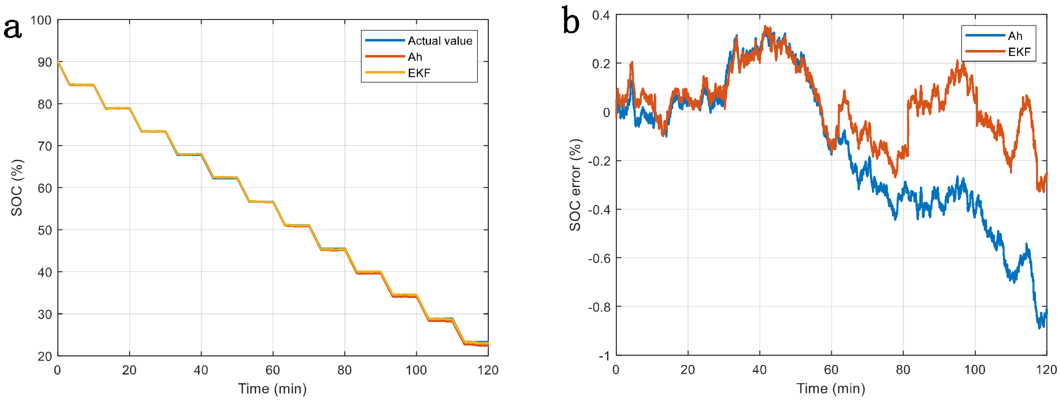

Fig. 3. Operating in the SCCD condition (a) SOC results; (b) SOC error.

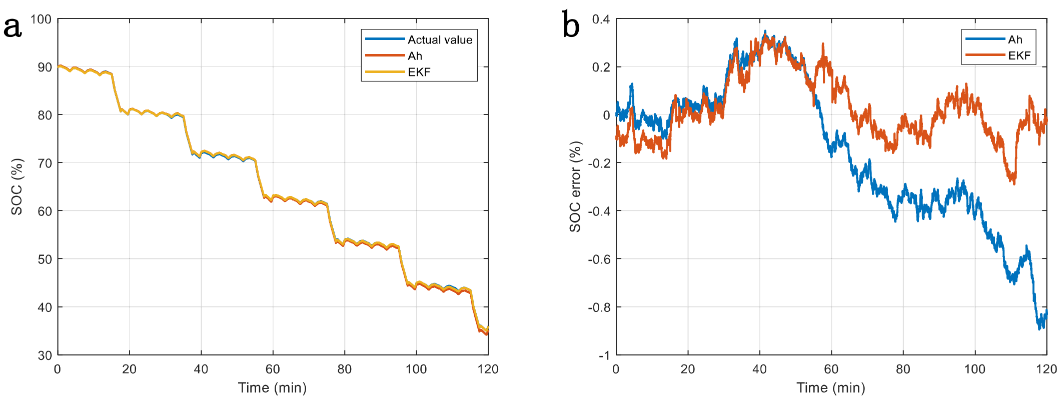

Fig. 4. Operating in the DSTD condition (a) SOC results; (b) SOC error.

Table 2. Comparison of ME, MAE, and RMSE in SCCD.

Method	ME	MAE	RMSE
Ah	0.8905	0.2660	0.3350
EKF	0.3300	0.1190	0.1460
Performance enhancement	62.95%	55.26%	56.42%

Table 3. Comparison of ME, MAE, and RMSE in DSTD.

Method	ME	MAE	RMSE
Ah	0.8949	0.2673	0.3366
EKF	0.3349	0.1074	0.1367
Performance enhancement	62.58%	59.82%	59.39%

5. Conclusion

In this paper, the Thevenin equivalent circuit model is used to quickly reflect the operating state of the Li-ion battery without excessive delay to track the actual voltage. Based on it, an EKF estimation algorithm is designed for SOC estimation of Li-ion batteries. The simulation results show that the SOC estimation accuracy of EKF under both SCCD and DSTD conditions is better than that of the conventional Ah algorithm.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This work was supported by the Science and Technology Support Program of Sichuan Province, China (19ZDYF1887).

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