Estimation of State of Charge of Lithium-ion battery using Kalman filtering and sensor bias

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ABSTRACT

The growing popularity of electric vehicles has resulted in significant improvements in battery technologies. Battery state of charge (SOC) is a vital performance indicator in a battery management system, which is crucial because it provides information on the remaining usable capacity and indicates charge and discharge strategies. As a result of non-uniformity in tuning and testing settings, measuring SOC estimation techniques' performances is challenging. This research study developed and evaluated the Extended Kalman filter(EKF) for estimating SOC in a range of situations including adding sensor noises and biases to terminal voltages and currents as well as altering the initialization for states and parameters. Furthermore, for SOC computation, a dual EKF was employed to predict the sensor voltage and current bias, which was then compared to the state EKF.

1. Introduction

Rechargeable lithium-ion batteries have seen a huge increase in demand recently since they are still the best option for many applications like electric vehicles (EVs) due to their ability to exhibit excellent properties compared to other battery-type technologies. However, lithium-ion battery is a highly intricate, time-varying non-linear electrochemical system that makes estimation of its states problematic[1]. Conventional approaches such as the coulomb counting method and open circuit voltage methods, machine learning-based techniques, and battery model-based techniques have been proposed in the quest for precise and accurate SOC estimation. When setting up an estimation problem, it is critical to include physical phenomena that occur in practical situations as much as feasible. One such prevalent circumstance is the use of inferior sensor readings as inputs into estimators[2]. The goal of this research is to create an algorithm to estimate SOC, sensor voltage/current bias, and to verify its performance under various operating scenarios.

2. Model description and analysis

This research adopts the second-order equivalent circuit model as shown in Fig.1 since it is able to precisely replicate the dynamic performance of the lithium-ion battery. According to Kirchhoff's law, Fig.1 can be expressed in the discrete form as shown in

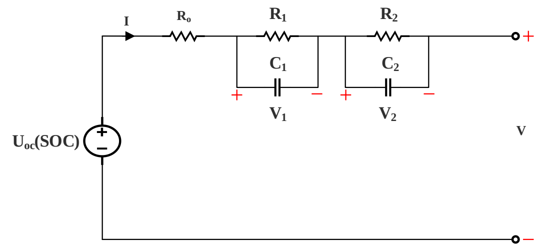


Fig. 1 Second-order battery equivalent circuit model

equations (2) and (3)

$$SOC_{k+1} = SOC_k - \frac{I_k \Delta t}{C_b} \tag{1}$$

$$V_{j,k+1} = e^{\frac{-\Delta t}{R_j C_j}} V_{j,k} + R_j \left(1 - e^{\frac{-\Delta t}{R_j C_j}}\right) \tag{2}$$

$$V_k = V_{OC}(SOC_k) - I_k R_o - \sum_{j}^{n} V_{j,k} \tag{3}$$

Eq. (1) computes the SOC based on coulomb counting where I stand for current, Δt is the sampling time, C_b is the capacity, and the subscript k connotes step time. The voltage and current biases are added as constant offsets in either the input current data or the terminal voltage measurement to produce biased data. V_b and I_b represent the current and voltage sensor bias, whereas V_m and I_m are the corresponding inaccurate measured signals, respectively.

$$I = I_m - I_b \;\; where \;\; \dot{I_b} \approx 0 \tag{4}$$

$$V = V_m - V_b \;\; where \;\; \dot{V_b} \approx 0 \tag{5}$$

From (6) the discrete-time model of the system with sensor bias is obtained with the output being the same terminal voltage V however the input signal now becomes the measured current I_m (current with bias) and I_b is the augmented current sensor bias. In the same vain the resulting augmented model system with voltage sensor bias is also obtained as shown in (8) with input current and output which is now the measured terminal voltage I and V_m respectively. V_b denotes the enhanced voltage sensor bias as a state.

$$\begin{bmatrix} SOC_{k+1} \\ V_{1,k+1} \\ V_{2,k+1} \\ I_{b\,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \frac{T}{C_{bat}} \\ 0 & e^{\left(\frac{-T}{R_1C_1}\right)} & 0 & -R_1(1-e^{\left(\frac{-T}{R_1C_1}\right)}) \\ 0 & 0 & e^{\left(\frac{-T}{R_2C_2}\right)} & -R_2(1-e^{\left(\frac{-T}{R_1C_1}\right)}) \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} SOC_k \\ V_{C1,k} \\ V_{C2,k} \\ I_{b\,k} \end{bmatrix} + \begin{bmatrix} \left(\frac{-T}{C_{bat}}\right) \\ R_1\left(1-e^{\left(\frac{T}{C_1R_1}\right)}\right) \\ R_2\left(1-e^{\left(\frac{T}{C_2R_2}\right)}\right) \\ 0 \end{bmatrix} I_m \tag{6}$$

$$V = V_{OC}(soc) \;\; - V_{1,k} - V_{2,k} \;\; - R_o I_m \tag{7}$$

$$\begin{bmatrix} SOC_{k+1} \\ V_{1,k+1} \\ V_{2,k+1} \\ V_{b,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & e^{\left(\frac{-T}{R_1C_1}\right)} & 0 & 0 \\ 0 & 0 & e^{\left(\frac{-T}{R_2C_2}\right)} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} SOC_k \\ V_{1,k} \\ V_{2,k} \\ V_{b,k} \end{bmatrix} + \begin{bmatrix} \left(\frac{-T}{C_{bat}}\right) \\ R_1\left(1-e^{\left(\frac{T}{C_1R_1}\right)}\right) \\ R_2\left(1-e^{\left(\frac{T}{C_2R_2}\right)}\right) \\ 0 \end{bmatrix} I \tag{8}$$

$$V_m = V_{OC}(soc) \; - V_{1,k} - V_{2,k} \; - R_s I + V_b \qquad (9)$$

3. Algorithm implementation

In this research both EKF and the DEKF are implemented since the battery is a nonlinear system to predict the terminal voltage and current bias as well as the SOC, utilizing an enhanced state space model. For a non-linear system the EKF algorithm can be derived as follows;

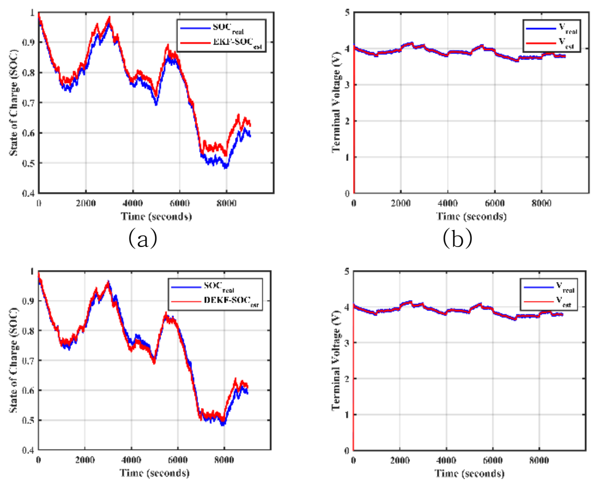
$$x_{k+1} = f(x_k, u_k) + d_k \qquad (10)$$
$$y_k = g(x_k, u_k) + s_k$$

Where, $f(x_k, u_k)$ and $g(x_k, u_k)$ are nonlinear state transition and measurement functions, respectively. The nonlinear functions are linearized at every time step by Taylor's first-order series expansion. The DEKF algorithm is as follows;

$$x_{k+1} = f(x_k, u_k, \theta_k) + d_k \; and \; \theta_{k+1} = \theta_k + r_k \qquad (11)$$
$$y_k = g(x_k, u_k, \theta_k) + s_k \; and \; h_k = g(x_k, u_k, \theta_k) + e_k$$

Where w_k, v_k, r_k and e_k are independent zero mean Gaussian noise processes. To evaluate estimate methods under varying sensor qualities, noise and bias are supplied to both current and terminal voltage data. The bias level is set at 20mV for voltage and 12.5mA for current. Parameters used for simulation

R_o = 0.001Ω, R_1 =0.013Ω, R_2=0.0013Ω C_1 =2.0kF and C_2 = 3.5kF.



(a) (b)

(c) (d)

Fig. 2 Voltage bias scenario estimations (a) EKF-SOC; (b) EKF-voltage (c) DEKF-SOC (d) DEKF-voltage

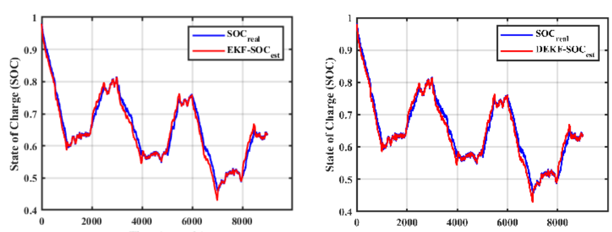


Fig.3 (a) EKF-SOC (b) DEKF-SOC with input current bias respectively

4. Simulation Results

Matlab is used to simulate the EKF and DEKF algorithms in this study. The SOC prediction performance for both algorithms is compared in the presence of sensor bias as shown in fig 2 and 3. In the presence of voltage bias, DEKF performs better in calculating SOC. Results demonstrate that the utilization of DEKF results in an approximate enhancement of about 1.64% in estimating SOC when evaluating the root mean square values. However, both algorithms show identical performance under a constant current bias.

5. Conclusion

This work presented a SOC estimation algorithm (EKF and DEKF) considering the addition of sensor bias and noise using a second-order ECM. The simulation results show DEKF performs quite better performance compared to EKF in SOC estimation. Based on sensor bias situations, it can be concluded that sensor bias modeling, filter type, and tuning are critical for the performance of SOC estimation.

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References

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