Sliding Mode Observer (SMO) using Aging Compensation based State-of-Charge(SOC) Estimation for Li-Ion Battery Pack

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ABSTRACT

This paper investigates a new approach for Li-Ion battery state-of-charge (SOC) estimation using sliding mode observer (SMO) technique including parameters aging compensation via recursive least squares (RLS). The main advantages of this approach would be low computational load, easiness of implementation along with the robustness of the method for internal battery model parameters estimation. The proposed algorithm was first tested on a set of acquired battery data using implementation in Simulink and later developed as C-code module for firmware application.

1. Introduction

An important purpose for battery management system (BMS) algorithm researchers is to have low SOC estimation error. Other purpose would be to have the BMS algorithm that requires little amount of initial parameters setup as well as low computational cost. Unfortunately, in order to acquire above purposes, high adaptive possibilities for battery aging and sudden changes in load as well as operational conditions is absolutely inevitable.

In this approach, a new method for Li-Ion battery state-of-charge (SOC) estimation using sliding mode observer (SMO) technique including parameters aging compensation using recursive least squares (RLS). Through proposed work, it is possible to implement an efficient SOC algorithm having easiness, low computational cost, and robustness of internal model parameters estimation. The approach has been validated by simulation and experimental results conducted on cylindrical $LiCoO_2$ cell that had a rated capacity of 1.5Ah produced by Samsung SDI.

2. Basic concept of sliding mode observer (SMO)

Sliding mode observer (SMO) is an outstanding method that provides an estimation of the internal state of a given real system, from measurements of the input and output of the real system using its model[1]. For determination of the real continuous-time nonlinear system model state-space representation is used. ($\dot{x} = Ax + Bu,\ y = Cx$)

The representative model of the Li-Ion battery is Fig. 1 with one resistance and one RC-ladder. This model is used for model's simplicity, reasonable accuracy, and possibility to update model parameters. Eqs (1) and (2) are used for the description of ECM model's state-space representation. For reference, C_n is the available capacity[2] under give C-rate of 0.5C.

$$S\dot{O}C = \frac{I_k}{C_n} \qquad \dot{V}_{Diff} = -\frac{V_{Diff}}{R_{Diff}\cdot C_{Diff}} + \frac{I_k}{C_n} \tag{1}$$

$$V_k = OCV + V_{Diff} + I_k R_i \tag{2}$$

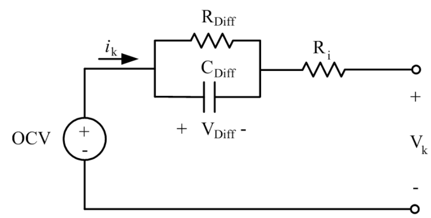

Fig. 1: Equivalent circuit model (ECM) of the battery.

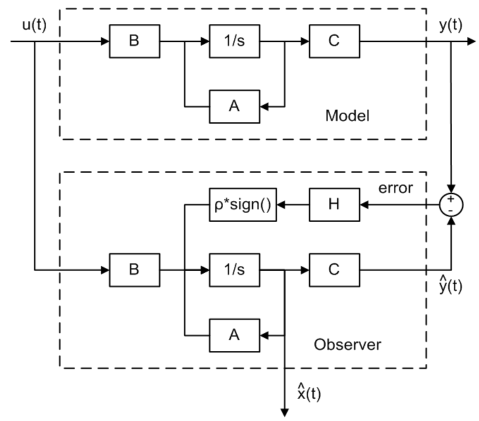

Fig. 2: Observer in conjunction with battery system structure.

The main advantages of the SMO are relatively simplicity in design, good dynamic response, and its robustness against a large class of perturbations. After conversion of the system into SMO, the continuous-time real nonlinear system model state-space representation is expressed in (3).

$$\begin{cases} \dot{\hat{x}} = A\hat{x} + Bu + H\rho f(y-\hat{y}) \\ \hat{y} = C\hat{x} \end{cases} \tag{3}$$

The feedback gain matrix H can be found using several ways - pole placing or LQ method. In case of LQ method, it is required to apply Riccati equation.

$$AP + PA^T - PC^T R^{-1} CP = -Q \qquad H^T = R^{-1}CP \tag{4}$$

There are two positive-definite and symmetric matrices P, R, and arbitrary semi-positive definite Q. Coefficient of matrix Q were chosen for reasons of optimal ratio between estmated system states (SOC and V_k) and the condition of the matrix Q (semi-positive). The value of matrix R were chosen after simulation in the reasons of optimal ratio with matrix Q to find the optimal speed of reducing error to zero, which is equivalent to the stability of A-HC. The switching law was chosen for the reasons of ensuring the stability condition for the system in sliding mode (Eq. (5)).

$$sign(y-\hat{y}) = \begin{cases} +1 (y-\hat{y}) > 0 \\ -1 (y-\hat{y}) < 0 \end{cases} \tag{5}$$

After developing mathematical description of the model, it is possible to add observer to the real system using Fig. 2.

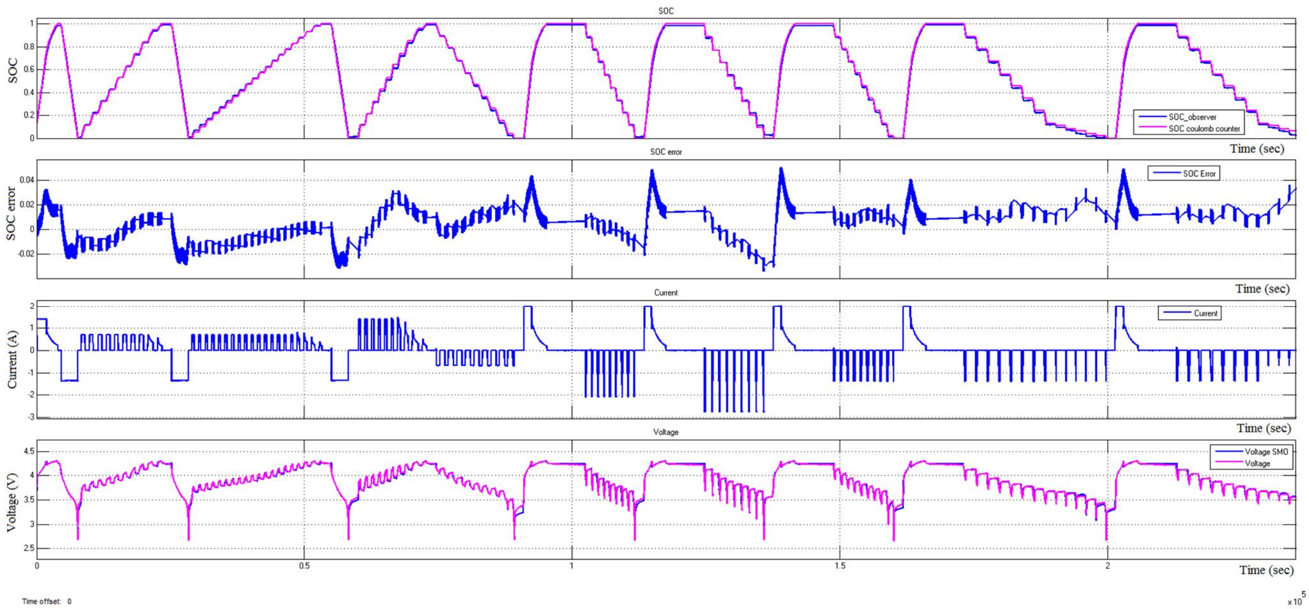

Fig. 3: Experimental results with fully discharging and charging on different C-rates.

3. Proposed approach

There are four parameters that tend to change with time and degradation; R_i, R_{Diff}, C_{Diff}, and available capacity C_n. In this work, two separate techniques for above parameters estimation are used.

3.1. Estimation of available capacity C_n

It is needed to have some correction describing available capacity change with time. As expressed in (6), the change of available capacity is similar with that of maximum battery capacity Q_{max}[2]. Therefore, in this work, maximum battery capacity Q_{max} is used for capacity aging compensation.

$$\frac{C_n}{C_{n\_aged}} = \frac{Q_{max}}{Q_{max\_aged}} = k_{correction} \tag{6}$$

For reference, the principle for Q_{max} relies on updates after the relaxation modes, using open-circuit voltage (OCV) me-asurements[2]. If two relaxation modes separated by charge or discharge are present, it is possible to use following Eq. (7) for capacity correction coefficient calculation.

$$Q_{max} = \frac{Q_{passed}}{SOC_1(OCV_1) - SOC_2(OCV_2)} \quad Q_{passed} = \sum_{SOC_1}^{SOC_2} I_k \Delta t \tag{7}$$

3.2. Estimation of other model parameters

One of the most obvious estimation for online model para-meters estimation would be least squares approach. In this approach, recursive least squares (RLS) is used for the benefits such as robustness, quick convergence, and no need of inverting large matrices on each calculation step. The equations for least squares estimation are presented as:

$$\begin{cases} V_{ls} = V_p + R_s I_k, \quad V_{ls} = V_k - OCV \\ \dot{V}_{Diff} = -\dfrac{V_{Diff}}{R_{Diff} \cdot C_{Diff}} + \dfrac{I_k}{C_n} \end{cases} \tag{8}$$

After applying Laplace transform (s-transform) to (8) and converting it to transfer function representation, Eq. (9) can be obtained. In order to use in real firmware, s-transform is required to convert intro z-transform in discrete time domain expressed in Eqs (10) and (11).

$$\frac{V_{ls}(s)}{I_k(s)} = \frac{1}{C_{Diff}\left(s + \dfrac{1}{R_{Diff} \cdot C_{Diff}}\right)} + R_s = H(s) \tag{9}$$

$$s \rightarrow \frac{2}{T}\frac{(1-z^{-1})}{(1+z^{-1})} \tag{10}$$

$$H(z) = \frac{z^{-1}\left(T - 2R_{Diff} \cdot C_{Diff} + \dfrac{TR_s}{R_{Diff}}\right) + \left(T + 2R_{Diff} \cdot C_{Diff} + \dfrac{TR_s}{R_{Diff}}\right)}{z^{-1}\left(-2C_{Diff} + \dfrac{T}{R_{Diff}}\right) + \left(2C_{Diff} + \dfrac{T}{R_{Diff}}\right)} \tag{11}$$

It is possible to calculate parameters of numerator and denominator and use them for least squares estimation with the help of discrete time equation.

3.3. *Verification*

The experimental results of SMO algorithm working on different pulses and constant CC-CV currents are presented in Fig. 3. The SOC estimation error between SOC coulomb counting and SMO SOC exists within ±5% for new battery. For reference, in case of aged 1.5Ah battery, SOC error exists within ±7%, however after updating SOC error can be reduced within ±5%

4. Conclusion

This paper investigates a new approach for Li-Ion battery SOC estimation using SMO technique including parameters aging compensation via recursive least squares.

This research was supported by Chosun University and Samsung SDI.

Reference

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