A practical and Accurate SOC Estimation System for Lithium-ion Batteries by EKF

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***Abstract*— In this paper, we propose a practical and accurate SOC (State of Charge) estimation system for Lithium-ion battery. The algorithm of SOC estimation uses the Extended Kalman filter, and estimates the SOC using OCV-SOC Curve, internal impedance, and the external current and voltage of a battery. It is constructed on a discrete-time system model of battery model using numerical analysis method, and employs a SOC-OCV curve using simple polynomial function. Also, it provides a noise tuning method by using test discharge experiments. The new EKF technique pulls essential power of EKF and implements more accurate and stable estimation. This means that the accurate SOC estimation can be executed with a larger time step and less complex computation. Consequently, the accurate calculation does not need expensive computer. It is sufficient by an inexpensive microcomputer. Computation time for each EKF time step (1 s) was 4 ms.**

Keywords*— *SOC estimation; Kalman filter; Noise tuning

I. Introduction

With the advent of big-scale popularization of Lithium-ion secondary batteries, the accuracy as well as the low cost should be indispensable for measurement systems. Particularly, the SOC (state of charge) estimation is essential for capturing the state of Lithium-ion secondary batteries. Generally, SOC estimation uses the external voltage and output current of battery. The self-discharge, the IR drop by internal resistance, and the battery degradation make the direct SOC estimation from the external voltage and current of battery very difficult.

In this paper, a precise SOC estimation system is devised by means of EKF (Extended Kalman Filter) run on a microcomputer. Compared with the conventional techniques, such as OCV[1], internal resistance method[2], current accumulation method[3], etc., EKF attains higher accuracy [4,5]

Our EKF approach is constructed on a discrete-time system model of battery model using numerical analysis method, and employs a SOC-OCV curve using simple polynomial function. Therefore, it is a practical estimation method that is easy to implement on microcontroller. Furthermore, it provides a noise tuning method by using test discharge experiments.

II. Battery Model

A. Battery Equivalent Circuit Model

To express the characteristics of the battery, we use the equivalent circuit model as Fig.1. The model consists of resistances, capacitors and a voltage source. The R_0 is solution resistance, two RC networks (R_1, C_1, R_2, C_2) represent the battery polarization[6].

Current i is the external current of the battery, u_L is terminal voltage of the storage battery, u_1 and u_2 are the voltages of the two RC networks. Equations (1) and (2) show the relationship of i, u_1 and u_2. Equation (3) shows relationship between u_L and i.

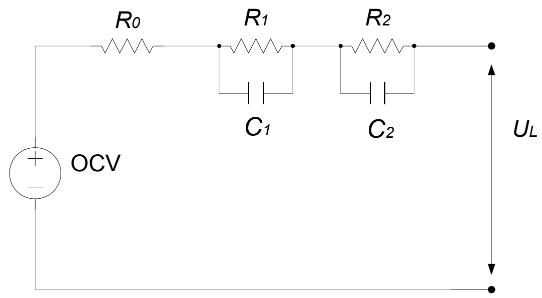

Fig. 1 Equivalent circuit model of a Li-ion battery.

$$C_1\frac{du_1}{dt}+\frac{u_1}{R_1}=i \quad (1)$$

$$C_2\frac{du_2}{dt}+\frac{u_2}{R_2}=i \quad (2)$$

$$u_L=u_1+u_2+iR_0+u_{OCV} \quad (3)$$

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B. Open Circuit Voltage Model

The voltage source represents the open circuit voltage (OCV). The OCV is the function related to SOC. We get the relationship between OCV and SOC by using experiment. We get the voltage curve of 0.02C discharge and the voltage curve of 0.02C charge. The average of 0.02C discharge and charge approximates the OCV. The result the 0.02C discharge - charge experiment is shown in Fig.2.

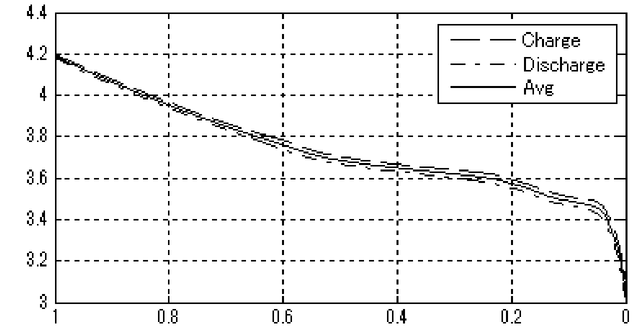


Fig. 2 OCV-SOC curve.

The voltage curve is complicated; we express the OCV-SOC using polynomial function. The fitting function is 12 squares polynomial as Equation (4), it is easier to calculate using computer than the method that use the logarithm function in [4,5].

$$OCV(SOC) = \sum_{i=0}^{12} a_i SOC^i \tag{4}$$

C. Battery Internal Impedance

In this section, we show how to extract the battery internal impedance as the equivalent circuit model using the least squares method. We get the Battery internal impedance parameters using battery recovery phenomenon. Using Equation (1, 2), the voltage of two RC network is as Equation (5, 6), when remove the constant current i. The τ_1 is R_1C_1, the τ_2 is R_2C_2.

$$u_1 = u_1(0)(1 - e^{-t/\tau_1}) \tag{5}$$

$$u_2 = u_2(0)(1 - e^{-t/\tau_2}) \tag{6}$$

When the time of discharge is considerably longer, iR_1 and iR_2 can approximate $u_1(0)$ and $u_2(0)$. Using Equation (3), the terminal voltage of the storage battery u_L is as Equation (7).

$$u_L = OCV(SOC) + iR_0 + u_1 + u_2 \tag{7}$$

The terminal voltage recovery amount Δu_L is as Eq. (8).

$$\Delta u_L = iR_1\left(1 - e^{-t/\tau_1}\right) + iR_2\left(1 - e^{-t/\tau_2}\right) + iR_0 \tag{8}$$

The battery internal impedance parameter can be identified using Equation (8) and the least squares method. Fig.3 shows a comparison of the measured values and fitting data using Equation (8) when SOC is 0.9.

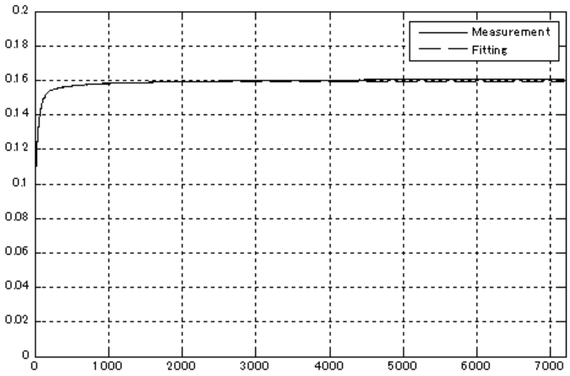


Fig. 3 Voltage recovery curve

III. SOC Estimation By EKF

The algorithm of SOC estimation uses the extended Kalman filter when the model is not linear. It is an adaptive filter, and can estimate the state parameters of discrete-time system that is including noise[7].

A. Battery's Discrete-time Model

Discrete-time system is as Equation (9) and (10). Equation (9) is state equation and Equation (10) is observation equation. $f(x_k)$ is the functional relationship of the state vector x_k and the next sample time x_{k+1}. $h(x_k)$ is the functional relationship of the state vector x_k and observation vector y_k. u_k is control vector, ω_k is the process noise, v_k is the observation noise. b_u and b are the process vector.

$$x_{k+1} = f(x_k) + \boldsymbol{b}_u u_k + \boldsymbol{b}\omega_k \tag{9}$$

$$y_k = h(x_k) + v_k \tag{10}$$

In battery model, we definite the battery's SOC, u_1, u_2 and $\mathrm{R_0}$ to the state vector as $x_k = [SOC(k) \quad u_1(k) \quad u_2(k) \quad R_0(k)]^T$, U_L to the observation vector as $y_k = U_L(k)$. From Equations (1) and (2), numerical solution of differential equation is as Equations (11) and (12) using the Forward Euler method. Δt is the sampling interval.

$$u_1(k+1) = \left(1 - \frac{\Delta t}{R_1C_1}\right)u_1(k) + \frac{i}{C_1}\Delta t \tag{11}$$

$$u_2(k+1) = \left(1 - \frac{\Delta t}{R_2C_2}\right)u_2(k) + \frac{i}{C_2}\Delta t \tag{12}$$

From Equations (11) and (12), State Equation is as Equation (13). Observation equation is as follows Equation (14) using Equation (3). Because the variance of the internal impedance parameters, we process the variance of internal impedance parameters as the system noise in this Battery's Discrete-time stochastic model. v_k is processed as the measure error.

$$x(k+1)=\begin{bmatrix} SOC(k+1) \\ u_1(k+1) \\ u_2(k+1) \\ R_0(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \left(1-\frac{\Delta t}{R_1C_1}\right) & 0 & 0 \\ 0 & 0 & \left(1-\frac{\Delta t}{R_2C_2}\right) & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} SOC(k) \\ u_1(k) \\ u_2(k) \\ R_0(k) \end{bmatrix} + \begin{bmatrix} \frac{\Delta t}{C} \\ \frac{1}{C_1} \\ \frac{1}{C_2} \\ 0 \end{bmatrix} \times i(k) + \boldsymbol{b}\omega(k) \tag{13}$$

$$y(k) = U_L(k) = OCV(SOC) + i(k)R_0(k) + U_1(k) + U_2(k) + v_k \tag{14}$$

In this model, Equation (13) is linear equation, but the OCV(SOC) function is nonlinear equation in Equation (14). Therefore, the battery's Discrete-time stochastic model is a nonlinear model. The Kalman filter cannot process a nonlinear model, thence, linearized process method is necessary. Using partial differential, linearize this battery model as Equations (15) and (16). Because the state equation is linear equation, the partial differential of the state equation is a constant matrix as Equation (13).

$$\widehat{A_k} = \left.\frac{\partial f(x_k,u_k)}{\partial x_k}\right|_{x_k=\widehat{x_k}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \left(1-\frac{\Delta t}{R_1C_1}\right) & 0 & 0 \\ 0 & 0 & \left(1-\frac{\Delta t}{R_2C_2}\right) & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{15}$$

$$\widehat{C_k} = \left.\frac{\partial h(x_k,u_k)}{\partial x_k}\right|_{x_k=\widehat{x_k}} = \left[\left.\frac{dOCV}{dSOC}\right|_{SOC=\widehat{SOC}^-}, \quad 1, \quad 1, \quad i_k\right] \tag{16}$$

B. SOC Estimation Algorithm

The Extended Kalman filter flowchart is as Fig.4. In this flowchart, there are two steps and initial state estimation. In this SOC estimation, the initial state vector is not zero, we estimate the initial SOC as $f_{SOC-ocv}(U_L(0))$ using the initial external voltage. However, $U_1(k)$,$U_2(k)$ is internal state that cannot be observed, we set the initial state vector as 0. If the external voltage is stability, the initial SOC estimation will be precision. But the battery is at charge/discharge state or rest state; the initial SOC estimation error will be large. $P(0)$ is the initial error covariance matrix. In addition, $\hat{x}^-$ is the predicted estimate vector, $\hat{x}$ is the filtered estimate vector, P^- is the predicted covariance matrix, P is the filtered error covariance matrix.

$$x(0) = [f_{SOC-ocv}(U_L(0)), 0, 0, R_0(0)]^T \tag{17}$$

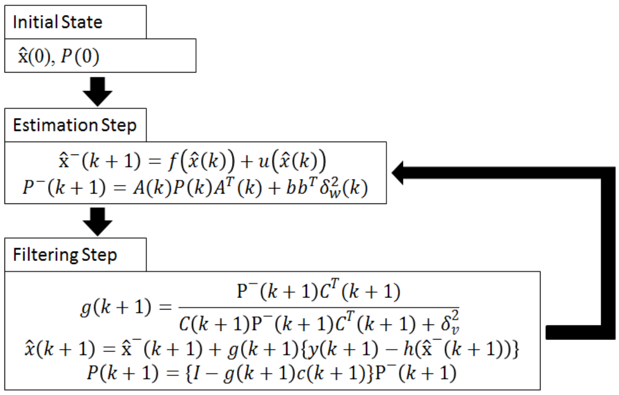


Fig. 4 Extended kalman filter flowchart.

IV. SOC Estimation Experiment

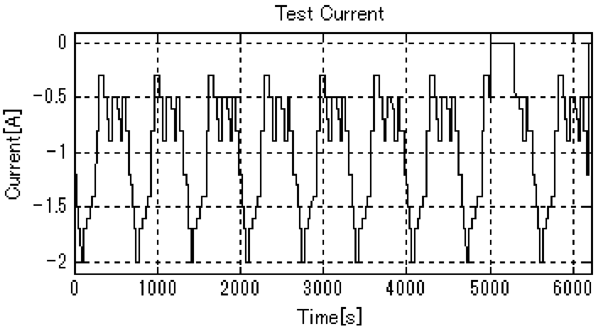
In order to verify the accuracy of SOC estimation, we compare the result of SOC estimation system to the Battery Test System (Kikusui_PFX2021S). In this section, we show the method that set the process noise and observation noise and the result of test experiment. We make 2 patterns in this estimation experiment to show the effectiveness using EKF. The current waveform of tow patterns is as Fig.5. Example 1 is proximate triangular waveform discharge and example 2 is proximate random discharge. The battery which is used in this experiment is type 18650. The specification is shown in Table I.

TABLE I. Specification of the Battery

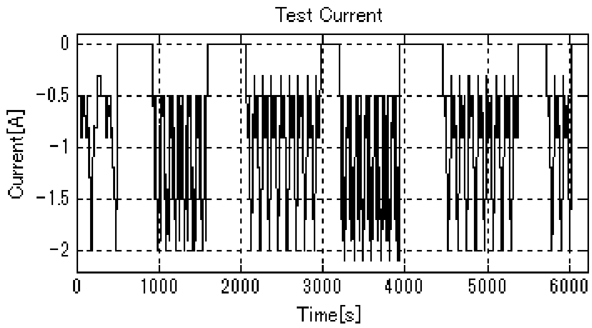
Nominal Voltage		3.6V
Nominal Capacity		2250mAh
Dimensions	Diameter	Max. 18.6mm
	Height	Max. 65.2mm
Weight		44g

A. The Noise Set Method

We used the MSE (Mean Square Error) to evaluate the set result using the result of the test experiment. Because of the real number's density is infinity, we use the logarithm format of the set noise to research the value of noise set at the minimum error. Variability region of the terminal voltage is at 0.2[V], the research region of the observation noise σ_{v_k} is at 0.001 to 0.2[V]. The SOC variability region in 1 [Sec] is at $I_{max}/3600$ as 0.01. The I_{max} is the maximum of output current. The research region of the process noise σ_{ω_k} is at 1×10^{-7} to 0.01[V]. The research result is as Fig.6. In the Fig.6, the minimum region is at σ_{ω_k}=[10^{-5} , 10^{-6}] σ_{v_k}=[10^{-1}, 3×10^{-1}]. The enlarged view of minimum region is as Fig.7. In the Fig.7, the minimum set value, σ_{ω_k}=10^{-5}, σ_{v_k}=0.2.



(a)



(b)

Fig. 5 Current waveforms of the test discharge experiment, (a) example 1, and (b) example 2.

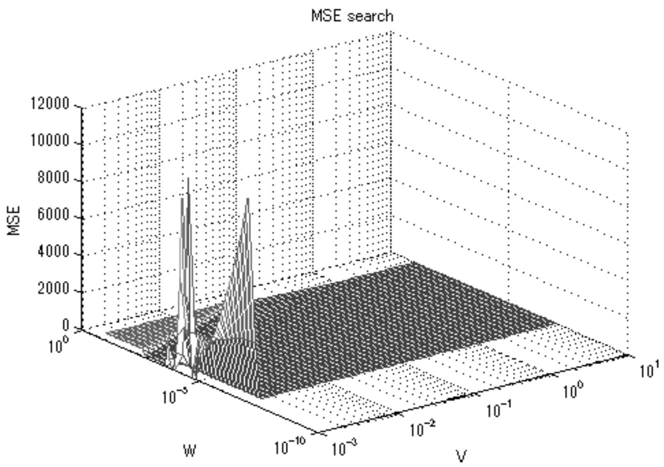


Fig. 6 Estimation error vs. σ_{ω_k} and σ_{υ_k}

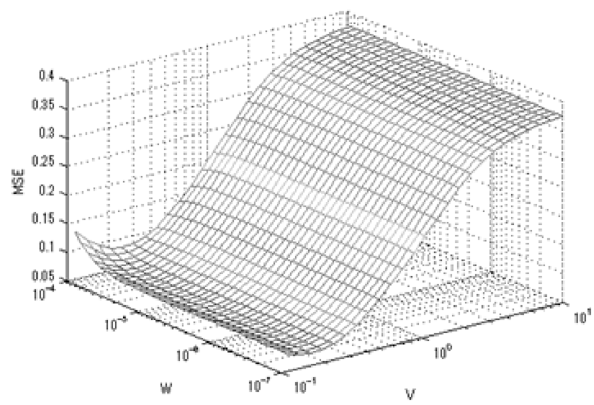
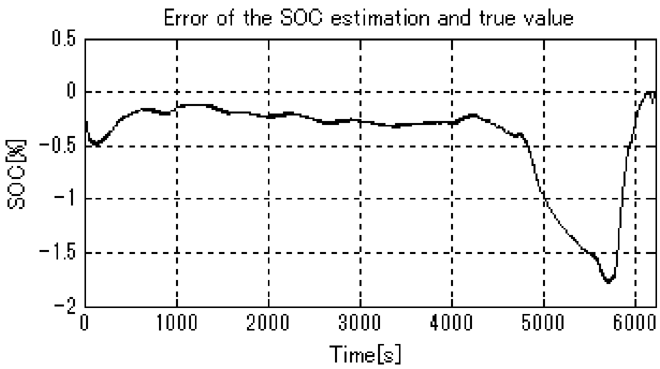


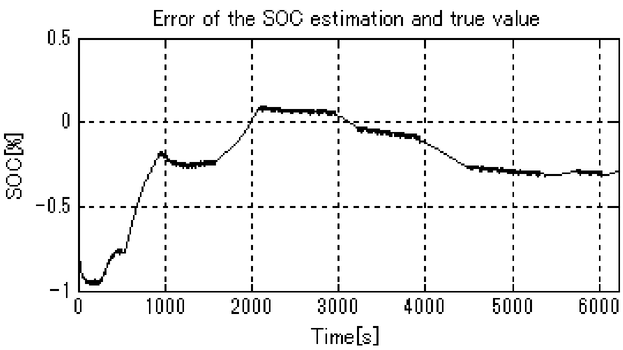
Fig. 7 Enlarged view of Fig.6

B. The Result of The Test Experiment

To compare the noise set, we show the 2 noise set results of the test experiment. One is the minimum noise set value as the research result ($\sigma_{\omega_k} = 10^{-5}$, σ_{v_k} =0.2), the other is σ_{ω_k}=0.0002, σ_{v_k}=0.02. Compare the Fig.8 and Fig.9, the maximum SOC error is smaller than 2% in Fig.8, the maximum SOC error is bigger than 4% in Fig.9. The efficacy is notable using the research result.

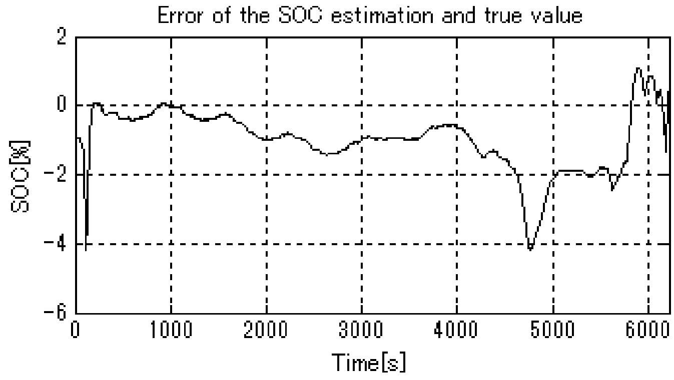


(a)

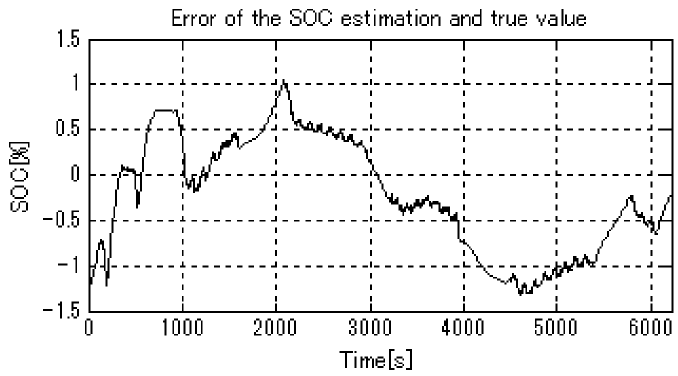


(b)

Fig. 8 Result of σ_{ω_k}=10^{-5}, σ_{v_k}=0.2, for (a) example 1, and (b) example 2.



(a)



(b)

Fig. 9 Result of σ_{ω_k}=0.002, σ_{v_k}=0.02, for (a) example 1, and (b) example 2.

C. Implementation of the System on a Micro-computer

An implementation of the microcomputer of the SOC estimation algorithm described above is shown. Microcomputer used in implementation is mbed, it is the same as the battery monitoring system. We also use the mbed evaluation board with modules such as LCD and SD (Fig.7). Basic characteristics such as voltage and current of the battery are required for EKF processing, so we create an amplification circuit of each. Each amplification values enter the 12bit analog input pin of the mbed.

Then, the operation flow of the SOC estimation system is showed. Fig.8 is a representation schematically the operation flow. The beginning of the operation flow measures the voltage of the target cell. Battery initial parameters are determined based on measurement voltage values from tables. Initial SOC is determined from the relationship table of OCV-SOC. Performing low-pass filtering when the voltage and current values measured.

Above mentioned steps is finished, flow moves to the loop processing of SOC estimation. After measuring the cell parameters necessary for processing EKF, EKF estimates SOC. The estimation results of the SOC output to the LCD and SD are a module mbed evaluation board. This loop step repeat until the battery SOC becomes zero. The sampling interval is adjusted using the mbed Timer library. SOC estimation accuracy and the sampling interval is a trade-off, therefore SOC estimation accuracy increases as the sampling interval decreases.

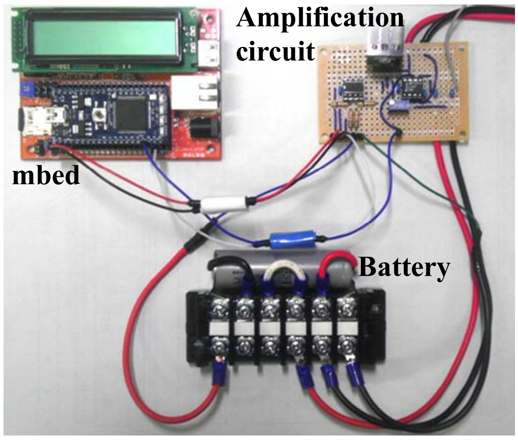


Fig. 10 SOC Estimation System

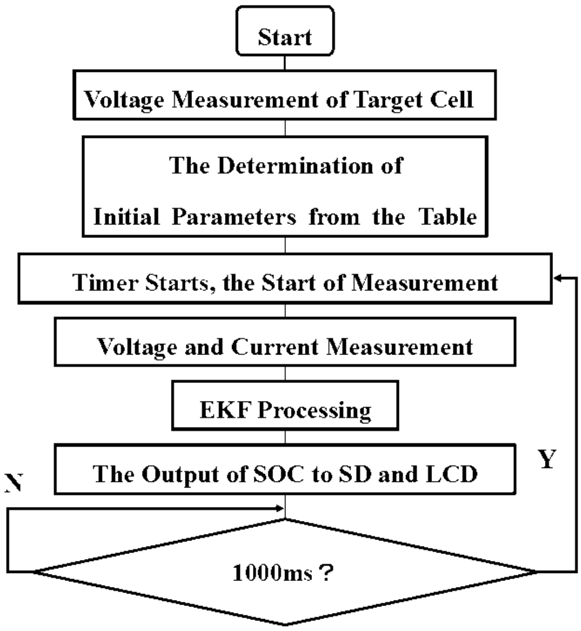


Fig. 11 SOC Estimation Flow

V. CONCLUSION

We proposed an accurate SOC estimation system of Lithium-ion battery. We verified the accuracy of SOC estimation system using evaluation experiment. The maximum error was less than 2%. It provides a noise tuning method using test discharge experiments. The experimental results shows that we have get a very accurate estimation. And build a practical SOC estimation application using mbed microcontroller.

In the future, to build an accurate and efficient SOC estimation, we research an adaptive optimization method of the process noise and observation noise.

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