선형 상태 관측기를 이용한 리튬이온 배터리의 SOC 추정 알고리즘

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SOC Estimation Algorithm for the Lithium-Ion Battery by Using a Linear State Observer

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ABSTRACT

Lithium-Ion batteries have become the best tradeoff between energy, power density and cost of the energy storage system in many portable high electric power applications. In order to manage the battery efficiently State of Charge (SOC) of the battery needs to be estimated accurately. In this paper a model-based approach to estimate the SOC of the Lithium-Ion battery based on the estimation of the battery impedance is proposed. The validity and feasibility of the proposed algorithm is verified by the experimental results.

1. Introduction

Currently, Lithium-ion batteries are considered as a highly prospective technology for automotive application such as Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) because of long life cycle, high energy density, low self-discharge rate characteristics and promising for cost reduction. SOC is a critical factor to guarantee the safety and reliable operation of the battery. Some approaches such as Fuzzy logic, artificial neural networks and the Kalman filter have been applied for online SOC estimation. However, the limitations caused by the complexity of those algorithms have prevented their commercial application. In addition, the battery impedance parameters are mainly required for SOC estimation based on electrical models. The parameters characteristics which are dependent significantly on current rate, SOC, temperature and aging effect can be investigated from experiments such as current pulse interruption and impedance spectroscopy techniques. Nevertheless, these methods are not only time consuming but also labor intensive and require test instruments. In this paper, the online estimation of battery parameters and a simple SOC estimation method which is suitable for low cost microcontroller applications are presented. The battery parameter can be estimated by the Auto Regressive with eXogenous input (ARX) method which considers exogenous input effect and additive noise and the battery SOC information can be explored by a linear state observer which can be simply and easily implemented. The validity and the feasibility of the algorithm will be proved by the experimental results.

2. Battery parameters identification

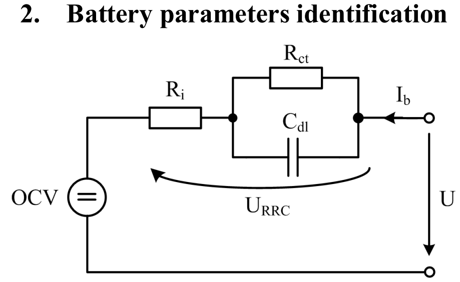

Fig. 1 The proposed equivalent circuit for Lithium-Ion battery

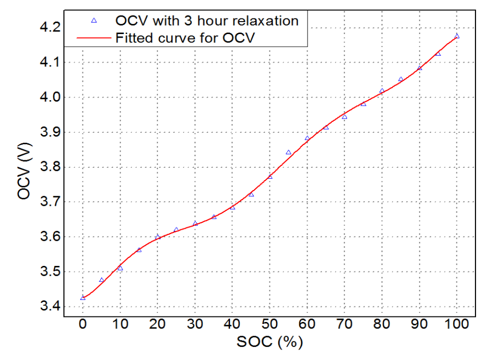

Fig. 2 OCV-SOC model of the Lithium-Ion cell

The proposed equivalent circuit of the battery contains an Open Circuit Voltage (OCV) connecting in serial with an internal resistance R_i and a RC parallel branch composed of a charge transfer resistance R_{tc} and a double layer capacitance C_{dl} as depicted in Fig .1 [1]. The electrical behavior of the battery equivalent circuit model can be expressed by (1) in the s-domain.

$$U(s) = OCV(s) + U_{RRC}(s) \tag{1}$$

The OCV-SOC relationship is modeled by seventh order polynomial function of SOC and expressed as (2) and shown in Fig .2.

$$\mathrm{OCV}(SOC) = \sum_{i=0}^{7} a_{i,k} SOC_k^i \tag{2}$$

The dynamic fraction of the battery voltage U_{HPF} and battery current I_{HPF} are extracted by high-pass filtering the measured voltage and current of the cell. The filter time constants for the voltage and current are equal. The dynamic voltage U_{HPF} which drops on the R_i and R_{ct}–C_{dl} network can be expressed in (3).

$$U_{HPF}(s) = I_{HPF}(s)R_i + I_{HPF}(s)\frac{R_{ct}}{(R_{ct}C_{dl})s+1} \tag{3}$$

The transfer function G(s) of (13) can be written as (4).

$$G(s) = \frac{U_{HPF}(s)}{I_{HPF}(s)} = R_i + \frac{R_{ct}}{(R_{ct}C_{dl})s+1} = \frac{(R_iR_{ct}C_{dl})s + R_i + R_{ct}}{(R_{ct}C_{dl})s+1} \tag{4}$$

By using the forward transformation method shown in (5) the discrete transfer function of battery with sample time T can be obtained as (6).

$$s = \frac{z-1}{T} = \frac{1-z^{-1}}{Tz^{-1}} \tag{5}$$

Where, z is the discretization operation.

$$G(z^{-1}) = \frac{R_i + \dfrac{TR_{ct}}{R_{ct}C_{dl}+T} - \dfrac{R_iR_{ct}C_{dl}}{T+R_{ct}C_{dl}}z^{-1}}{1 - \dfrac{R_{ct}C_{dl}}{T+R_{ct}C_{dl}}z^{-1}} = \frac{b_0 + b_1z^{-1}}{1+a_1z^{-1}} \tag{6}$$

Where:

$$a_1 = -\frac{R_{ct}C_{dl}}{T + R_{ct}C_{dl}},\ b_0 = R_i + \frac{TR_{ct}}{R_{ct}C_{dl} + T},\ b_1 = -\frac{R_i R_{ct} C_{dl}}{T + R_{ct}C_{dl}} \quad (7)$$

The time domain relationship between different samples of input/output is as follows:

$$U_{HPF,k} = -a_1 U_{HPF,k-1} + b_0 I_{HPF,k} + b_1 I_{HPF,k-1} \quad (8)$$

The above function is the specific form of the ARX model [2] in (9) for the equivalent circuit shown in Fig .1.

$$y_k = -a_1 y_{k-1} + b_0 u_k + b_1 u_{k-1} \quad (9)$$

3. Online parameters estimation algorithm

The Recursive Least Square (RLS) algorithm is applied to estimate the coefficient factors [2].

$$L_k = \frac{P_{k-1}\varphi_k}{\lambda_k + \varphi^T{}_k P_{k-1}\varphi_{k-1}} \quad (10)$$

$$\hat{\theta}_k = \theta_{k-1} + L_k[U_{HPF,k} - \varphi_k^T \hat{\theta}_{k-1}] \quad (11)$$

$$P_k = \frac{1}{\lambda_k}\left[P_{k-1} - \frac{P_{k-1}\varphi_k\varphi_k^T P_{k-1}}{\lambda_k + \varphi_k^T P_{k-1}\varphi_k}\right] \quad (12)$$

Where: $\varphi(k) = \left[-U_{HPF,k-1}, I_{HPF,k}, I_{HPF,k}\right]^T$ (13)

$$\theta(k) = \left[a_{1,k}, b_{0,k}, b_{1,k}\right]^T \quad (14)$$

After identifying a_1, b_0, b_1, the parameters of the battery model at each time step can be determined by the inverse parameter transformation as (15).

$$R_i = \frac{b_1}{a_1},\ R_{ct} = \frac{(a_1 - 1)(b_1 - b_0 a_1)}{(a_1 + 1)a_1},\ C_{dl} = \frac{-Ta_1^2}{(a_1^2 - 1)(b_1 - b_0 a_1)} \quad (15)$$

4. SOC estimation using a linear state observer

The SOC estimation is conducted through two steps. Firstly, the priori estimation of SOC is forecasted through normalized current integration with (16).

$$SOC_k^- = SOC_{k-1}^+ + \frac{\eta I_{k-1}T}{C_n} \quad (16)$$

From the priori SOC the instantaneous OCV is calculated based on the nonlinear OCV-SOC function derived in (2). Furthermore, the battery impedance value calculated from previous section is used for reconstructing the dynamic voltage fraction U_{RRC}. The dynamic voltage fraction U_{RRC} is determined with (17) incorporating the battery current I_b.

$$U_{RRC,k} = -a_1 U_{RRC,k-1} + b_0 I_{b,k} + b_1 I_{b,k-1} \quad (17)$$

The estimated battery voltage is predicted by adding the battery voltage fraction U_{RRC} and the battery OCV as (18).

$$\hat{U}_k = OCV(SOC_k^-) + U_{RRC,k} \quad (18)$$

Secondly, a difference between the estimated voltage $\hat{U}_k$ and the measured voltage of the battery U_k causes an update of battery SOC shown in (18), where k_{SOC} is the constant voltage feedback gain.

$$SOC_k^+ = SOC_k^- + k_{SOC}(U_k - \hat{U}_k) \quad (19)$$

The linear state observer algorithm performed from (16) to (19) enables the online estimation of the battery SOC by evaluating the sequences of the battery voltage, current and considering the information of the battery impedance parameters derived from the dynamic fraction of the battery voltage.

5. Experimental Results

In order to validate the proposed algorithm, a dynamic charge/discharge current profile as shown in Fig. 3 is applied to the battery. The battery used for the test is a Lithium-Ion type 3.6V, INR18650-15L 1500mAh from Samsung SDI. The cell is connected to the bipolar DC power supply NF BP4610. A program created in Labview 11.0 automatically controls the output of the bipolar DC supply and records the voltage and current of the battery at every second through a NI PCI-6154 and a sensing circuit. The current profile exhibit dynamic characteristic with stiff change in the magnitude of the current and operates in the high and mid SOC range, which is typical in EVs applications.

The voltage estimation results in Fig. 3 show that the dynamic responses of the battery obtained from the simulation agree well with those obtained from the experiment. The voltage estimation error is less than 2% as illustrated in the bottom of the Fig. 3.

The upper graph of Fig. 4 depicts the comparison between the estimated SOCs by the proposed method and the coulomb counting method and the SOC estimation error is shown in the lower graph of Fig. 4. In this experiment, 50% of SOC was given as an initial value to verify if the proposed algorithm converges to the true SOC value. As shown in the Fig. 4 the estimated SOC tracks the true SOC value within 30 minutes and the estimation error is maintained less than 4% thereafter. This indicates that the proposed algorithm works successfully.

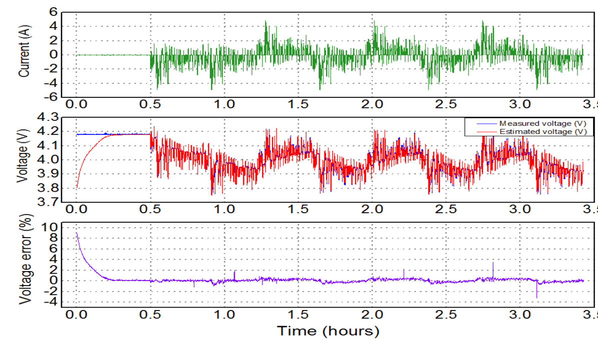

Fig. 3 Current profile, measurement voltage and estimated voltage

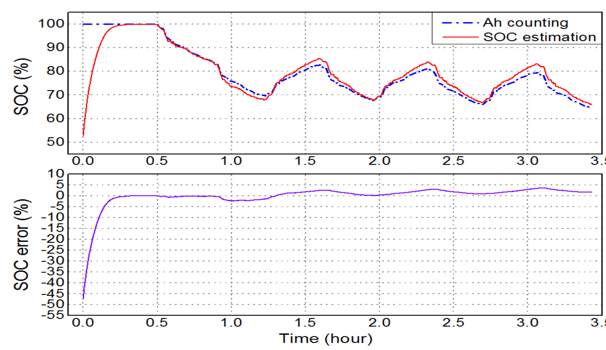

Fig. 4 SOC estimation result and SOC estimation error of the randomly current pulse test.

6. Conclusions

This paper presents the SOC estimation algorithm for Lithium-Ion battery by using a linear state observer based on the parameter identification. The parameter values estimated from the dynamic voltage fraction of the battery are applied for SOC estimation using model-based state estimation approach. The obtained results reveal that the proposed method works accurately and it can be used for the battery management systems for Lithium-Ion battery such as electric vehicle and energy storage applications.

References

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