Online Estimation of SOC and Parameters of Battery Using Augmented Sigma-Point Kalman Filter and RLS

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Abstract

In this paper, an estimation scheme based on an augmented sigma-point Kalman filter to estimate the state of charge (SOC) of the battery is presented, where the battery parameters of the series resistance (R_o), diffusion capacitance (C_1) and resistance (R_1) are also estimated through the recursive least squares (RLS) for better accuracy of the SOC. The effectiveness of the proposed method is verified by simulation results.

1. Introduction

Estimation of the SOC and SOH (state of health) of batteries is important in the view of optimal performance, availability, and reliability of the battery. Direct measurement of the SOC and SOH is difficult due to the complicated chemical operation inside the battery [1]. There are many research results which have been proposed for the SOC and SOH estimation such as Coulomb counting, OCV (open-circuit voltage)-based method, Kalman filter, artificial neural network (ANN), etc.

Coulomb counting is the simplest method, based on the integration of the battery current. However, this method demands the accurate initial SOC and calibration. If not accurate, the accumulation of error will lead to the inaccurate SOC value. Although the SOC estimation based on the OCV is the accurate and simple algorithm, the online measurement of the OCV is almost impossible [1]. Recently, some intelligent methods, which use the ANN or the fuzzy logic, have been introduced for the battery management system (BMS). Even though these methods can provide the accurate value of the SOC, due to the heavy burden of computation, it is challenging for a real-time implementation. Another SOC estimation algorithm using an adaptive state observer such as extended Kalman filter, sigma-point Kalman filter, etc. have drawn a lot of attention since they give a precise result with an simple implementation. Nevertheless, the drawback of these methods is that an accurate model of the battery is required. The variation of the battery parameters with aging, temperature, humidity, etc. may lead to inaccurate estimation.

This paper proposes an algorithm to estimate the SOC of the battery with associated parameter calibration to quantify the battery parameter uncertainties for more precise SOC estimation. The simulation results show that the estimation error of the SOC is about 3.6% in the case of 50% error of the parameter.

2. Battery Modeling

The equivalent circuit of a lithium-ion battery is shown in Fig. 1, where the voltage source, V_{oc}, is modeled for the OCV of the battery. The OCV varies with the variation of the SOC and is affected by hysteresis effects [2]. For simplicity, the hysteresis effect is not considered in this work. R_0 is the internal resistance, which represents the equivalent series resistance of the battery, and the diffusion effect is represented by the parallel circuit of R_1 and C_1. The initial values of these parameters at the beginning state of cycling are obtained by experiment which has been introduced in [3].

From Fig. 1, the discrete state equation for the battery modeling is expressed as [4].

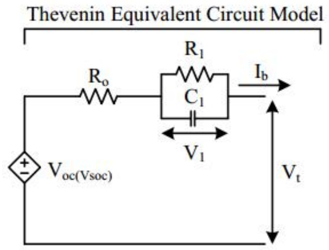

Fig. 1. Battery model.

$$x_k = \begin{bmatrix} SOC_k \\ V_{1,k} \end{bmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1-\dfrac{\Delta t}{R_1 C_1} \end{pmatrix} \begin{bmatrix} SOC_{k-1} \\ V_{1,k-1} \end{bmatrix} + \begin{bmatrix} \dfrac{\Delta t}{C_n} \\ \dfrac{\Delta t}{C_1} \end{bmatrix} I_{b,k} \quad (1)$$

$$V_{t,k} = \mathrm{OCV}\left(SOC_k\right) - V_1 - R_{o,k} i_k \quad (2)$$

where x_k is a state vector, V_1 is the voltage across the diffusion circuit, C_n is the capacity of the battery, Δt is the sampling time, $I_{b,k}$ is the battery discharging current, k is the k^{th}-sampling instant, and V_t is the terminal voltage. In this modeling, the SOC and V_1 are chosen as the state variables, and $I_{b,k}$ and V_t are the input and output variables, respectively.

From (1), the SOC is calculated by Coulomb counting method, where the accumulation of error may be included. Then, with Kalman filter algorithm, the SOC estimation process is calibrated [4].

3. Principle of Proposed Estimation

i) Augmented sigma-point Kalman filter (ASKF)

A sigma-point Kalman filter is a combined algorithm of unscented transform (UT) and Kalman filter (KF). In this work, the ASKF is applied for the battery state estimation.

ii) Recursive least squares with multiple forgetting factors:

There are two main advantages of the RLS algorithm for parameter estimation. First, the RLS with forgetting factor is simple and easy to implement. Second, it is appropriate to apply to the system which drifts very slowly such as the battery parameters.

Moreover, the conventional RLS has the covariance "wind-up" problem and the algorithm has no way of knowing if there are some errors due to one or more parameters. The RLSMF algorithm shown in the table 1 can overcome these problems of the standard RLS [5].

iii) Implementation for lithium-ion battery

a. OCV versus SOC

Fig. 2 shows the trajectory of OCV versus SOC. By using curve fitting, the relationship between OCV and SOC can be expressed as

$$\mathrm{OCV} = 1.18\times\mathrm{SOC}^3 - 2.105\times\mathrm{SOC}^2 + 1.299\times\mathrm{SOC} + 3.658. \quad (3)$$

From Fig. 1 and (1), the terminal battery voltage can be rewritten as

$$V_{t,k} = y_k = OCV + I_{b,k} R_{0,k} - (A_k V_{1,k-1} + B_k I_{b,k-1}) \quad (4)$$

where

$$A_k = \exp\left(\frac{-\Delta t}{R_{1,k} C_{1,k}}\right) \quad (5)$$

Table 1. RLS algorithm with forgetting factor.

$$
\begin{aligned}
& for\ k = 1:N \\
& \lambda = [\lambda_1\ \dots\ \lambda_n]^T \\
& input:\ \hat{\theta}_{k-1},\ P_{k-1},\ \Psi_k,\ y_k,\ \lambda \\
& K_k = \frac{P_{k-1}\Psi_k\lambda^{-1}}{1+\sum_{j=1}^{n}(P_{k-1}\Psi_k^2/\lambda_j)} \\
& \hat{\theta}_k = \hat{\theta}_{k-1} + K_k\left(y_k - \hat{y}_k\right) \\
& P_k = diag\left(diag((I - K_k\Psi_k^T)P_{k-1})/\lambda\right) \\
& ouput: \hat{\theta}_k, P_k
\end{aligned}
$$

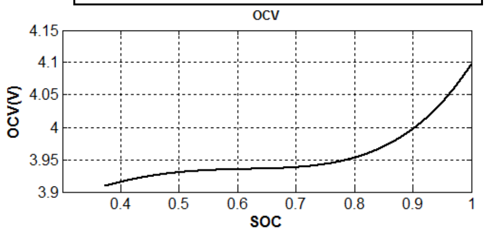

Fig. 2. OCV versus SOC.

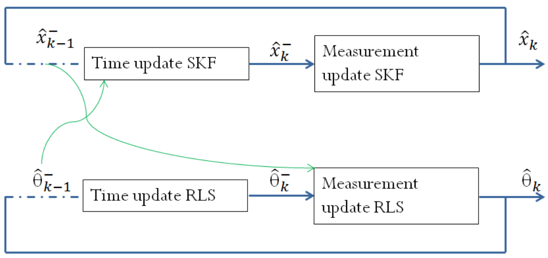

Fig. 3. Flow diagram of dual algorithm of ASKF & RLS.

$$B_k = R_{1,k}\left(1-\exp\left(\frac{-\Delta t}{R_{1,k}C_{1,k}}\right)\right) = R_{1,k}(1-A_k) \quad (6)$$

$$V_{1,k} = A_k V_{1,k-1} + B_k I_{b,k-1}. \quad (7)$$

b. Calculation flow

At first, the ASKF is applied to estimate the *SOC* and the diffusion voltage V_1. For better performance, this step is operated for several calculation loops before proceeding to the next step. Then, RLS is employed to estimate the battery parameters. From (3) to (7), the battery terminal voltage can be expressed as

$$V_{t,k} = y_k = OCV(SOC) + \theta_k \psi_k^T \quad (8)$$

where,

$$\theta_k = \left[R_{0,k},\ A_k,\ B_k\right]^T \quad (9)$$

$$\psi_k = \left[-I_{b,k},\ V_{1,k-1}, -I_{b,k}\right]^T. \quad (10)$$

Before advancing to the second step, it is noted that the values of current, SOC and V_1 should be known. Substituting (8), (9) and (10) into the equations in Table 1, the estimated battery parameters can be obtained. The "^" indicates the estimated value. Herein, $\hat{y}_k$ and y_k are the estimated and measured voltages, respectively. Fig. 3 shows the flow chart of the proposed method.

4. Simulation Results

Simulation tests have been carried out for a lithium-ion battery, which is modeled as shown in Fig. 1. Fig. 4 shows the input current profile and the battery terminal voltage. The voltage curve is obtained by discharging a Li-ion battery cell 0.85-Ah with a pulse current 0.32A.

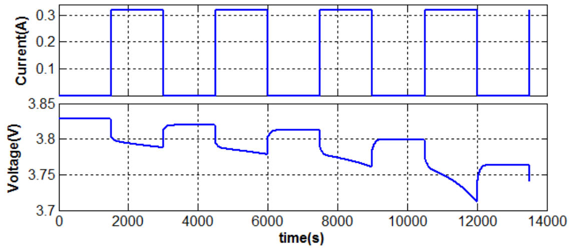

Fig. 4. Terminal voltage with the pulsed current discharge.

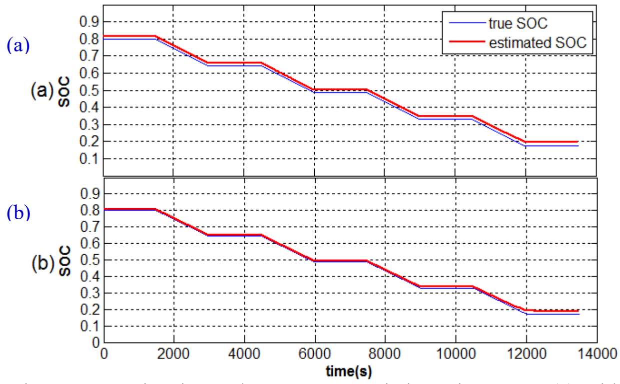

Fig. 5. SOC estimation under parameter variation using ASKF. (a) Without RLS. (b) With RLS (proposed method).

The relationships of the parameters are derived from the pulsed current and voltage waveforms as [3]

$$R_0 = 17440e^{-143.7SOC} + 0.15e^{-0.01644SOC} \quad (11)$$

$$R_1 = 1.391e^{-6.35SOC} + 0.1289. \quad (12)$$

$$
\begin{aligned}
C_1 = & \left(-6.819\times10^6\right)SOC^3 + \left(9.009\times10^6\right)SOC^2 \\
& -(2.342\times10^6)SOC + 1.644\times10^5.
\end{aligned} \quad (13)
$$

Fig. 5 shows the estimated SOC values by the ASKF with and without the adaptation of the battery parameters by the RLS algorithm under the condition of the battery parameter variation. The reference SOC is obtained by an accurate Coulomb counting progress. From the figure, the estimation error of the method without the adaptation is about 3.6% whereas that of the proposed method as shown in Fig. 5(b) is 1.57%.

5. Conclusions

In this research, a novel estimation scheme to estimate the SOC of the battery has been presented, where the ASKF algorithm is employed. The estimation accuracy has been improved by using the battery parameters updated by the RLS in the ASKF algorithm. The proposed scheme has been verified by the simulation results.

References

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