Improved SOC estimation of lithium-ion batteries with novel SOC-OCV curve estimation method using equivalent circuit model

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***Abstract*—The OCV-SOC curve is commonly used in SOC estimation and other battery management system (BMS) applications. Since the OCV indicates the magnitude of the charged battery voltage, the differs between estimated OCV-SOC curve and actual OCV-SOC curve are directly reflected in the accuracy of the SOC estimation and terminal voltage of model simulation. Thus, accurate OCVs are very needed but it is hard to obtain the suitable OCV-SOC curve for various current conditions. Furthermore, preliminary experiments for obtaining OCV-SOC curve spend lots of time due to repeats of the constant current discharge and taking enough rest time. In this paper, the new OCV-SOC curve estimation method is proposed to improve the accuracy of estimated SOCs and simulated terminal voltages of battery model without preliminary experiments. The proposed method uses equivalent circuit model (ECM) with parameter identification of recursive least square (RLS) algorithm, and is verified by experiments of various current conditions. Using the estimated OCV-SOC curve of proposed method, model accuracy is improved with lowered RMSE of simulated ECM terminal voltage and the SOCs were estimated less than 2% error.**

***Index Terms*—lithium-ion battery, open circuit voltage, equivalent circuit model, parameter estimation, state of charge**

I. Introduction

In these days, lithium-ion batteries are increasingly used in the electronics, the grid system and the electric vehicle industry due to their high energy density, low self-discharging and long lifespan [1] [2] [3]. As the use of lithium-ion batteries becomes wider, battery management system (BMS) is significantly important for maximizing battery performance and efficient power usage. For the BMS and its application, the accurate state of charge (SOC) estimation is a priority.

Many studies have been made on the models of lithium-ion batteries that reflect the characteristics of the battery [4], mainly lies in equivalent circuit models (ECM) [5] [6], electrochemical models [7] [8], and the impedance model [9]. In these models, the ECM reflects the electric properties of battery, and is commonly used in onboard state estimation cases and BMS due to the model simplicity and moderate model accuracy. The model accuracy of the ECM is determined by each of parameters, especially the OCV which indicates the charging voltages of battery has a great influence [10]. The OCV can be obtained through experimentation [11] [12] [13]. However experimental method has a disadvantage of time-consuming due to the repetition of having a constant current charge/discharge and a sufficient rest time, and hysteresis problems of the OCV-SOC curve [14] at the various current conditions. In this paper, the novel estimation method of the OCV-SOC curve is proposed to solve these disadvantages.

The main contributions of this paper is to improve accuracy of the estimates of SOCs and simulated terminal voltage of ECM. Furthermore, using the estimation method instead of the experiment to obtain the OCV, prelimanry experiment for the OCVs is not needed and the time required for constructing the model can be saved. Through the model simulation and the SOC estimation, the proposed algorithm is verified by improving the model accuracy and SOC estimation performance.

The remainder of this article is structured as follows. In the Section II, the equivalent circuit model with parameter estimation is described. The proposed method of open circuit voltage estimation is introduced in the Section III. The experiments are explained in the Section IV, followed by results of proposed method and discussions in the Section V. Finally, the VI concludes this paper.

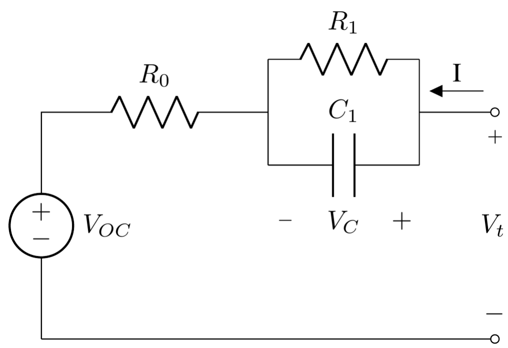

Fig. 1. Equivalent circuit model.

II. Modeling of lithium-ion batteries

The ECM represents the electrical characteristics of Lithium-ion batteries using the Thevenin model with RC networks. The ECM consists of open circuit voltage expressed by voltage source, internal ohmic resistance R_0, and parallelly connected polarization resistance R and capacitance C networks representing the transient response during a charge or discharge process (Fig. 1). As the number of RC networks increases, the order of the model increases and calculation is more complicated. Therefore, first-order ECM and second-order ECM are widely used in applications due to the advantages of simple calculation and proper model accuracy, and the first-order ECM is used in this paper. Using ECM, the expression of terminal voltage V_t is shown in (1)

$$V_t = OCV + R_0 I + V_C + \omega \tag{1}$$

Where V_{OC} is open circuit voltage, V_C is voltage of RC network, and ω is battery dynamics not included in ECM because of the nonlinearity of batteries.

$$\begin{aligned}
&x(k+1) = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{T}{R_1 C_1}} \end{bmatrix} x(k) + \begin{bmatrix} \frac{T}{Cmax} \\ R_1(1-e^{-\frac{T}{R_1 C_1}}) \end{bmatrix} u(k), \\
&V_t(k) = \begin{bmatrix} 0 & 1 \end{bmatrix} x(k) + R_0 u(k) + V_{OC}(k), \\
&x(k) = \begin{bmatrix} soc(k) \\ Vc(k) \end{bmatrix}, u(k) = I(k), V_{OC}(k) = OCV(soc(k))
\end{aligned} \tag{2}$$

The expression (2) represents the discrete-time state equation of first-order ECM for simulating in MATLAB except ω which cannot be measured.

Where C_{max} is maximum capacity of battery, T is sampling time and I is load current flowing in ECM.

The unmeasurable parameters R_0, R_1 and C_1 of ECM are obtained by estimation using RLS algorithm [15] [16]. The estimates of parameters are expressed about functions of SOC which is calculated by coulomb counting.

III. Estimation of open circuit voltage

Using RLS algorithm, the OCVs of ECM can be estimated simultaneously with other parameters using RLS algorithm.

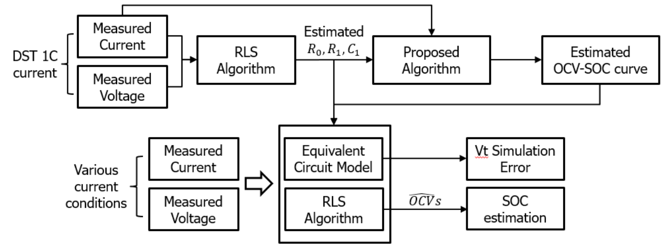

Fig. 2. Overall process of experiments.

These OCVs are used as OCV values representing current battery status, not as a OCV-SOC curve because RLS algorithm is not performed well in low SOC region. On the contrary, there is experimental method to obtain open circuit voltage. By the method of applying constant current discharge and giving enough rest time at constant SOC intervals to batteries, OCVs can be obtained by measuring the terminal voltage. The measured OCVs are used as a OCV-SOC curve and adjusted as a V_{OC}(soc), function of SOC.

However, obtaining the OCV-SOC curve by preliminary experiments spend many hours because of rest times. Furthermore, the OCV curves obtained by experiments based on charge, discharge and various C-rates are measured differently. This characteristic causes model inaccuracy when input current profile different from that of OCV test are applied to the ECM. Various studies have been conducted to find a suitable OCV curve, but the experiment-based OCV-SOC curve has a limitation of current profile dependency, which results in model errors.

Therefore, estimation method is proposed to obtain more accurate OCV-SOC curve for estimates of SOC and simulated model terminal voltages. In Fig. 2, overall process of proposed method is shown. From measured data, parameters $\hat{R}_0$, $\hat{R}_1$ and $\hat{C}_1$ are estimated by RLS algorithm. Using these parameters, expression of terminal voltage changes from (1) to (3).

$$V_t = OCV + \hat{R}_0 I + \hat{V}_C + \omega \tag{3}$$

Then estimate $\hat{V}_{OC}$ can be represented in (4).

$$\hat{V}_{OC} = OCV + \omega = V_t - \hat{R}_0 I - \hat{V}_C \tag{4}$$

The estimate $\hat{V}_{OC}$ physically includes OCVs and nonlinear dynamics ω of batteries. The dynamics ω which is not included in ECM have a tendency of being largely dependent on current profile I. To reduce the tendency affected by current, the input current for estimating OCVs should have low magnitude of momentary changes such as DST current with low c rate or constant current, and moving average filter is adjusted to $\hat{V}_{OC}$ for preventing estimates from over fitting by the input current. The OCV-SOC curve is created by sorting the filtered $\hat{V}_{OC}$ according to the SOC which is calculated by coulomb counting. The estimated OCV-SOC curve and parameters are used in ECM to simulate terminal

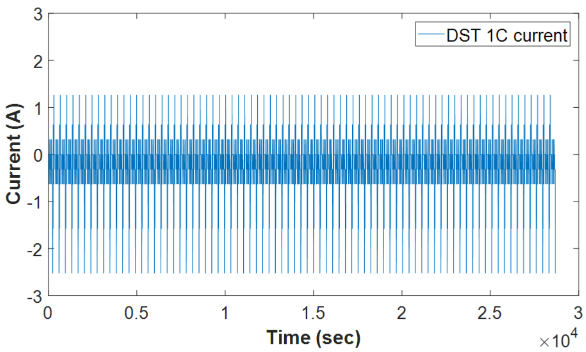

Fig. 3. DST 1C current profile used in parameter and OCVs estimation.

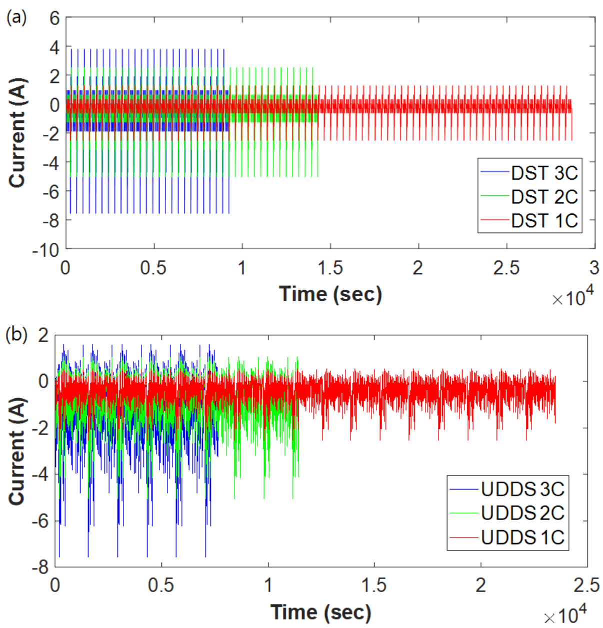

Fig. 4. Currents for validation (a) DST 1C, 2C, and 3C (b) (a) UDDS 1C, 2C and 3C.

voltage and to estimate SOC at various current conditions.

IV. Experiments

The batteries used in experiments are SAMSUNG INR18650 25R NMC batteries, of which nominal capacity is 2500 mAh. The experiment was carried out in a constant temperature chamber set at 25 °C, and the applied current and terminal voltage were measured and used as data for model construction. The applied current is DST 1C profile (Fig. 3), due to satisfying persistent excitation for RLS algorithm and minimizing the effect of current in OCVs estimation. The model was verified by comparing the measured terminal voltage with the simulated terminal voltage using the proposed OCV-SOC curve and by comparing the estimates of SOC from the measured OCV-SOC curve and the estimated OCV-SOC curve. The current used for verification are DST 1C, 2C and 3C, and UDDS 1C, 2C and 3C (Fig. 4).

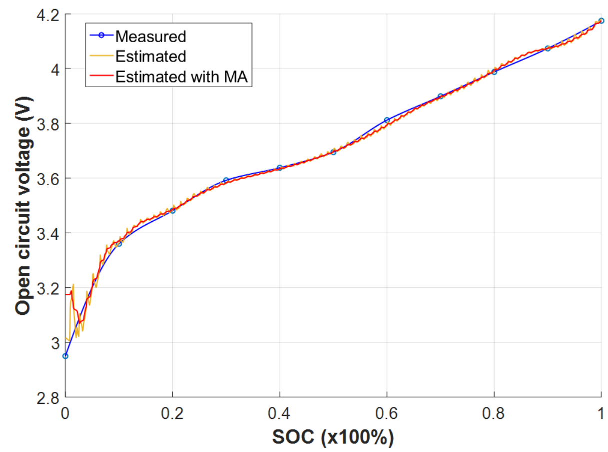

Fig. 5. Comparison of OCV-SOC curves from different methods.

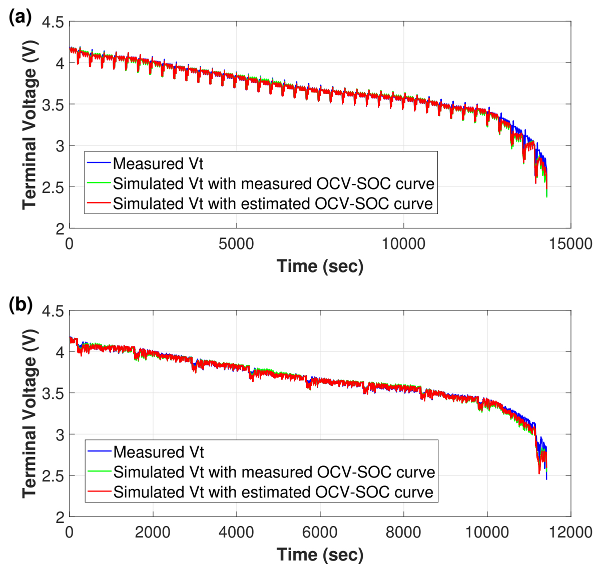

Fig. 6. Comparison of Terminal voltages (a) at DST current (b) at UDDS current.

V. Results and Discussions

The estimated OCV-SOC curve from measured currents and terminal voltages is shown in Fig. 5 comparing with the curves from experiment and estimates with no filter. Overall trajectories are similar except low SOC region which has strong nonlinearity, but there are differences in some SOC points, where the estimated OCV-SOC curve from proposed method improves accuracy of simulated ECM terminal voltage and estimates of SOC.

A. Model simulation

In order to provide a comparison between real batteries and equivalent circuit model, estimated R_0, R_1, C_1 and OCV-SOC curves are used. With estimated parameters and OCV-SOC curve, ECM is simulated in MATLAB using the expressions of ECM state equation (2). Fig. 6 shows three terminal voltages when DST and UDDS profiles are applied as load currents

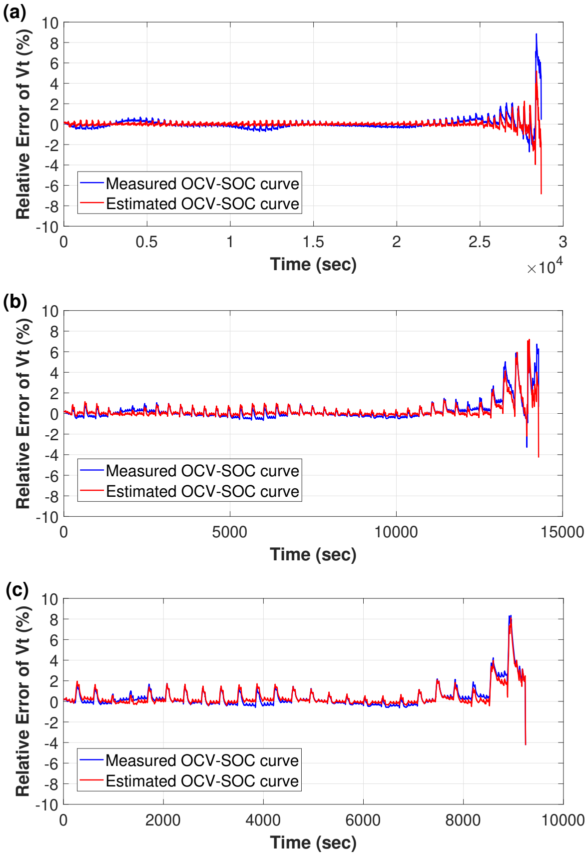

Fig. 7. Relative errors between measured terminal voltage and simulated terminal voltages (a) at DST 1C (b) at DST 2C (c) at DST 3C.

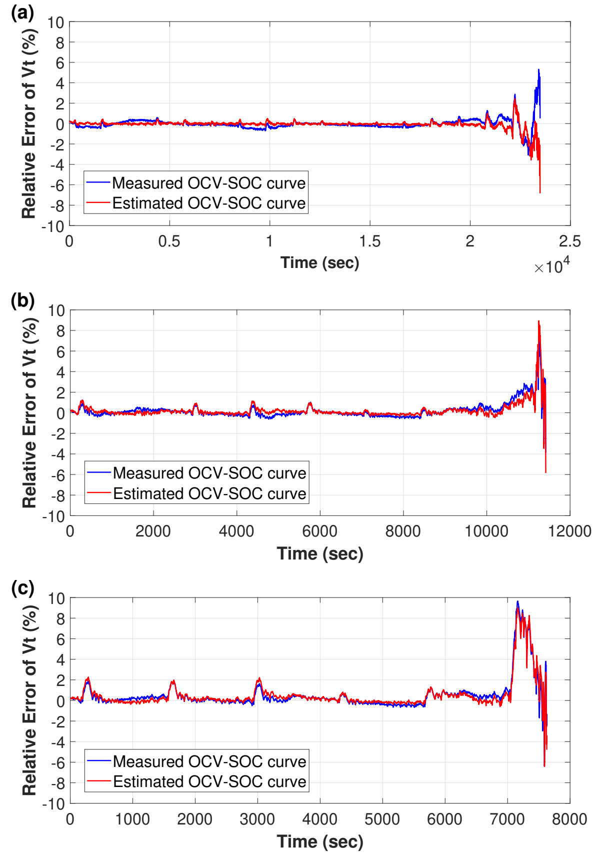

Fig. 8. Relative errors between measured terminal voltage and simulated terminal voltages (a) at UDDS 1C (b) at UDDS 2C (c) at UDDS 3C.

respectively. Compared to the measured terminal voltage, simulated voltages using measured OCV-SOC curve and estimated OCV-SOC curve show no significant difference except the low SOC region. The relative errors between the measured terminal voltage and the simulated terminal voltages of two different OCV-SOC curves are compared at various current C rates of DST profile (Fig. 7) and UDDS profile (Fig. 8). From the results, the overall wave-shaped errors are flattened comparing with the experimentally obtained OCV-SOC curve. Table I shows the maximum relative errors (MRE) and root mean square error (RMSE) for those comparisons. The MRE does not show any noticeable improvement when comparing the results of two OCV curves, because the spike-shaped errors which are caused by dynamic current changes are shifted as the waveform error is flattened. However, from the RMSE point of view, the accuracy of the model is improved when the estimated OCV-SOC curve is used.

B. Estimation of state of charge

The estimation of the battery SOC is essential for BMS applications. The SOC is estimated on-line by obtaining current battery OCVs using RLS algorithm and putting the OCVs to the pre-acquired SOC-OCV curve [11]. The SOC-OCV curve is calculated by inversion of OCV-axis and SOC-axis from OCV-SOC curve.

TABLE I

MRE (%) AND RMSE (%) OF SIMULATED TERMINAL VOLTAGES AT VARIOUS CURRENT CONDITIONS. OCV_M AND OCV_E MEAN THE MEASURED OCVS AND THE ESTIMATED OCVS RESPECTIVELY.

	MRE (%)		**RMSE (%)**	
	OCV_M	OCV_E	OCV_M	OCV_E
DST 1C	1.06	1.10	0.0230	0.0110
DST 2C	1.47	1.33	0.0320	0.0263
DST 3C	2.18	2.09	0.0379	0.0347
UDDS 1C	0.72	0.50	0.0179	0.0126
UDDS 2C	1.03	1.23	0.0254	0.0245
UDDS 3C	1.88	2.27	0.0501	0.0490

In Fig. 9, comparison of the three SOCs using the coulomb counting method, the estimated SOCs of the measured SOC-OCV curve and the estimated SOC-OCV curve of proposed algorithm are shown. In the low SOC region, a large error occurred due to the strong nonlinearity. However, all the three SOCs showed similar values in the remaining regions. Especially, the SOC values from the SOC-OCV curve of proposed algorithm was found to be more similar to the SOC obtained by the coulomb counting used as the ground truth. A numerical comparison of the three SOC graphs is shown in Fig. 10. The SOC error is calculated by subtraction the SOCs of the measured SOC-OCV curve and the estimated SOC-

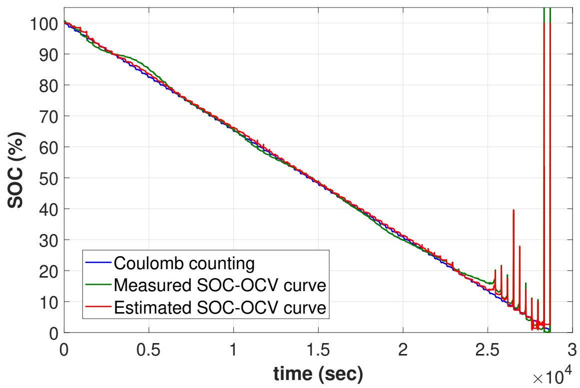

Fig. 9. The estimated SOC by using coulomb counting, measured SOC-OCV curve and estimated SOC-OCV curve.

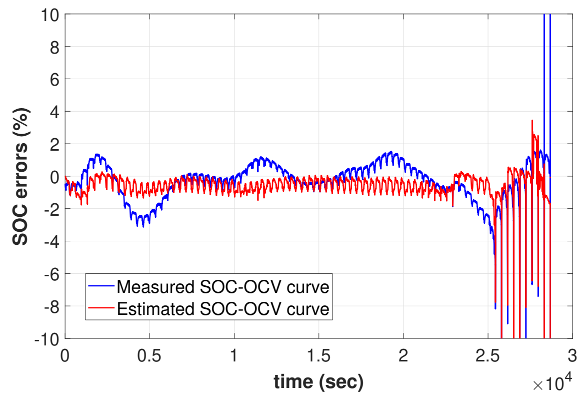

Fig. 10. The SOC errors obtained by subtracting the SOCs of the measured SOC-OCV curve and the SOCs of the estimated SOC-OCV curve from the SOCs of the coulomb counting method respectively.

TABLE II
MAXIMUM ERROR (ME)(%) AND RMSE (%) OF THE SOC ERRORS IN FIG. 10.

	Maximum error	**RMSE**
The measured SOC-OCV curve	3.13	0.010
The estimated SOC-OCV curve	1.84	0.006

OCV curve from the OCVs obtained by coulomb counting method respectively. In Table II, maximum error and RMSE is calculated except the region of low SOC. Because of the lower maximum error and RMSE, it is more effective to use the estimated SOC-OCV curve of the proposed algorithm than the measured SOC-OCV curve.

VI. CONCLUSION

In this paper, a model-based OCV-SOC curve estimation algorithm is introduced to enhance the model accuracy of equivalent circuit model of lithium-ion batteries. Obtaining OCV-SOC curve from experiments spend lots of time due to repeating of constant current discharge and taking enough rest time. In addition, model inaccuracy of the simulated ECM terminal voltage and the estimates of SOCs has occurred by the characteristic of the OCV-SOC curve which changes at different current conditions. Thus, new algorithm of obtaining OCV-SOC curve is developed using estimated ECM parameters R_0, R_1 and C_1 from dynamic current profiles. As using this method, no preliminary experiments of measuring OCVs is needed so that time can be saved, and more accurate OCV-SOC curve can be obtained simultaneously when estimating the remaining parameters of ECM. After simulation, the maximum relative errors (MRE) and RMSE is used as a index of model accuracy. In terms of MRE, there was no significant improvement due to the dynamics from DST current profile, but it was confirmed that the model was improved in terms of RMSE. Furthermore, the SOC estimation showed better results of low maximum error and RMSE from the estimated SOC-OCV curve. Thus, the ECM with the proposed OCV-SOC curve estimation can improve the accuracy of SOC estimation and model terminal voltage which uses ECM of lithium-ion batteries.

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