Real-time OCV and Capacity Estimation Algorithm for Reusable Lithium-ion Battery without Pre-experiment

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***Abstract*—This paper proposes real-time open circuit voltage (OCV) and capacity estimation algorithm without the initial state of the battery. The proposed algorithm estimates components of the equivalent circuit model (ECM) through the sum of square regression and obtains real-time OCV curve using the ECM voltage relationship and Coulomb counting method. The feasibility of the proposed algorithm has been demonstrated by simulation based on a lithium nickel manganese cobalt battery. Verification results show high accuracy of the OCV curve as the cycle repetition even though internal parameters of the battery are not provided.**

***Key words*—Lithium-ion battery, open circuit voltage, reusable battery, state of charge**

I. Introduction

With the increasing quantity of generated retired batteries from electrical vehicles, there is a growing need for a suitable end-of-life (EOL) battery recycling approach [1]. Chemical disassembly is one of the common methods for recycling batteries, but it is time-consuming and costly. [2]. Therefore, it is effective to reuse for relatively low power requirement without chemically recycling battery such as stationary energy storage system with battery management as shown in Fig. 1. [3]-[6].

From the viewpoint of lithium-ion battery management, it is important to obtain internal parameters such as open circuit voltage (OCV) and capacity for identifying the state of battery. Therefore, a pre-experiment is required to extract OCV and capacity with high accuracy. Especially, these parameters for reusable batteries are essential because the internal deviations are more prominent than fresh batteries depending on the operating environment, aging, and type. However, reusable batteries have parameter deviation, resulting in much time burden for extraction process, and ultimately it is impossible to test all those batteries in the garage.

For this purpose, conventional research proposed parameter extraction methods for lithium-ion batteries [7]-[8]. These methods make batteries fully charged and discharged to obtain highly accurate parameters. Since it is easy and exact with test equipment, the entire process is inefficient and time-consuming. Therefore, various

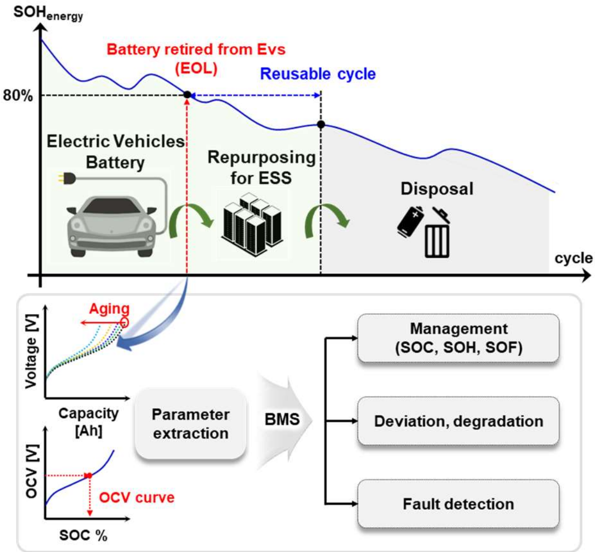

Fig. 1. Framework of repurposing EVs batteries.

research on estimating parameters in online without pre-experiment has been proposed [9]-[11]. In literature, [10] proposed a method for estimating the state of charge (SOC) without a current sensor based on RC model. However, since this method applied a simple model and fixed value, it is difficult to expect high accuracy for estimation results. To overcome this limitation, an ECM model-based Kalman filter and particle filter methods were proposed [12]-[13]. But these methods are still difficult to apply in reuse battery applications because the proposed method operates with advanced computing capability.

To address existing shortcomings, this paper proposes an algorithm for estimating OCV and capacity in real-time without pre-experiment for the battery. The proposed algorithm estimates the OCV curve with a 1st-order equivalent circuit model and the capacity is gradually updated when considering the upper and lower voltage based on the battery operation. Finally, the 27 [Ah] nickel manganese cobalt (NMC) type battery is used to verify the feasibility of the proposed algorithm, and the real-time OCV and capacity are estimated by applying the new European driving cycle (NEDC) at intervals of 5 hours.

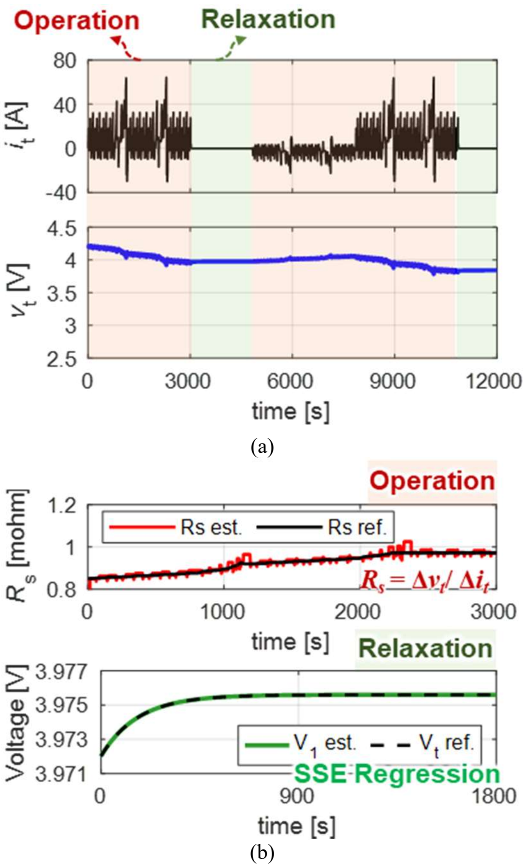

Fig. 2. ECM parameter estimation method: (a) Battery operation status acknowledgement (b) R_s for operation, RC ladder for Sum of square regression in rest period.

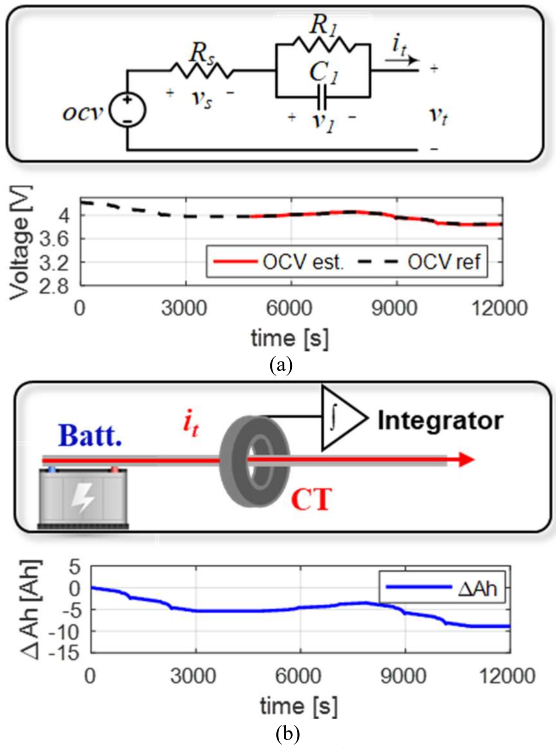

Fig. 3. Real-time OCV and capacity estimation method: (a) ECM parameter and voltage equation (b) Coulomb counting method.

The main advantages of the proposed algorithm are as follows:

1) Robustness to noise derived by empirical mode decomposition (EMD): When measuring the terminal voltage and current, the noise component affects the OCV curve estimation. The accuracy of the extracted curve is enhanced by using EMD to eliminate sensing noise.

2) Gradual capacity update based on ΔAh: Based on the Coulomb counting method, the capacity is estimated through the amount of real-time capacity during operation. The actual capacity is gradually estimated without the initial state.

II. Real-Time OCV Curve Estimation

A. ECM parameter extraction

The schematic of the proposed algorithm that extracts the ECM components is shown in Fig. 2(a). The proposed method consists of ECM parameter extraction for OCV curve estimation. There are two parameters to be extracted based on ECM. One is R_s which represents an ohmic voltage drop component of battery ECM and is extracted in an operating state based on a terminal voltage and current differential. Second, RC parameter is extracted from the time constant τ for the terminal voltage curve in the relaxation state using regression based on SSE as shown in Fig. 2(b). R_1 is obtained through the assumption that the RC voltage is saturated during the idle time, and C_1 is calculated through the relational equation. The principle of SSE regression for deriving the time constant parameter is as follows:

$$v_{RC}(t) = v_{RC,0} \cdot e^{-t/\tau} \tag{1}$$

where τ is the parameter of RC time constant and by taking the natural logarithm for both sides, (1) can be simplified as follows:

$$\ln(v_{RC}(t)) = -\frac{t}{\tau} + \ln(v_{RC,0}) \tag{2}$$

$v_{RC}(t)$ and $v_{RC,0}$ in (1) shows the initial and final values of the rest voltage data respectively, and (1) is modified to apply an exponential function-based regression model as shown in (2). The right side of (2) corresponds to linear function can be expressed as follows:

$$y_i = ax_i + b \tag{3}$$

Through SSE regression, the polarization voltage curve is estimated with the minimum sum of the rest data and the square error, and through this, the time constant ($\tau = R_1 \cdot C_1$) is estimated.

$$SSE = \sum_i^n (\hat{y}_i - y_i)^2 \tag{4}$$

$$a = \frac{\sum_i^n (x_i - \bar{x}_i)(y_i - \bar{y}_i)}{\sum_i^n (\hat{y}_i - y_i)^2}, b = \bar{y} - a_0\bar{x} \tag{5}$$

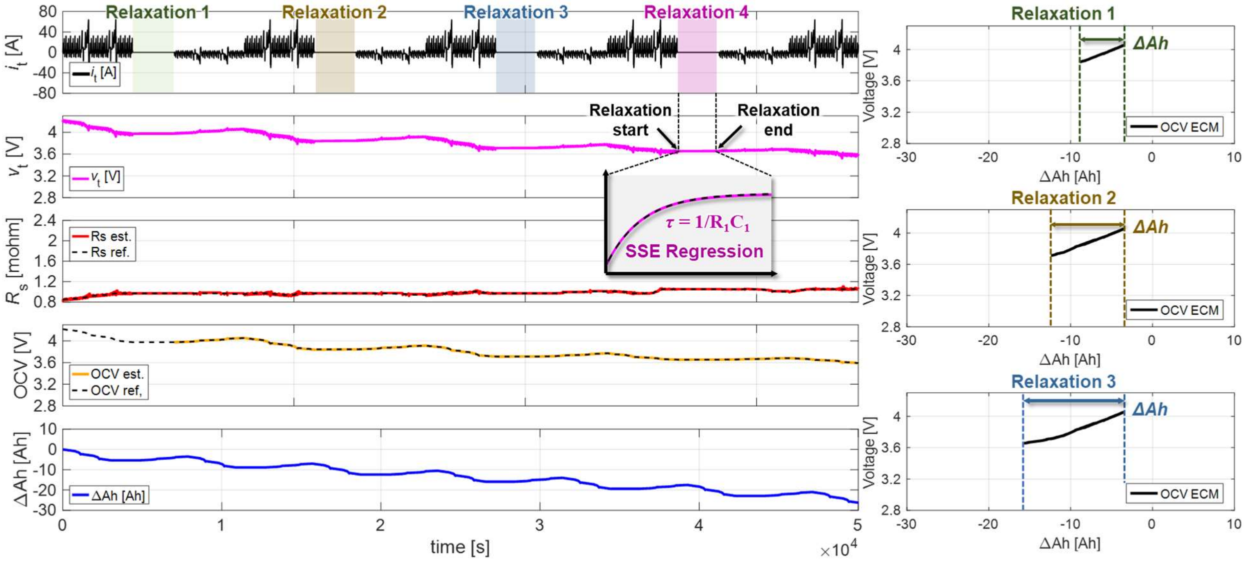

Fig. 4. Real-time OCV estimation and Coulomb counting results through ECM parameter estimation.

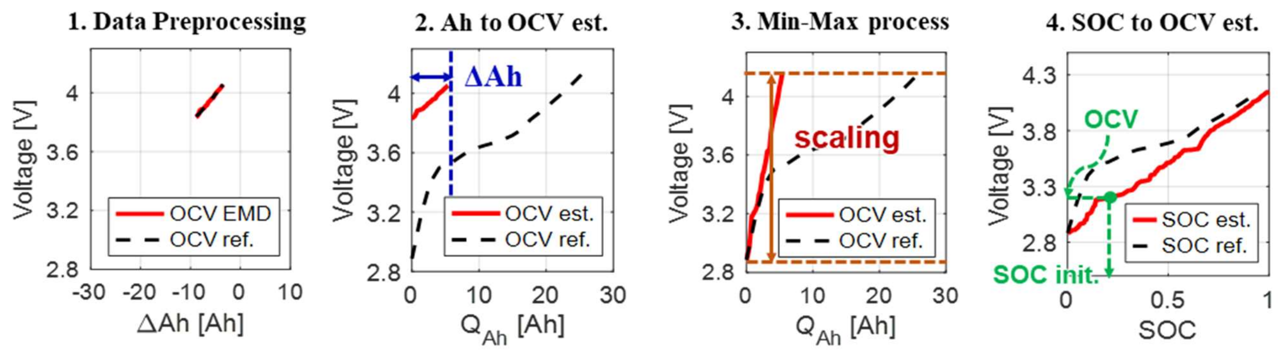

Fig. 5. Data preprocessing methods for Ah to OCV curve estimation.

Where a and b are the parameter of (5) represent minimized SSE and $\bar{x}$, $\bar{y}$ are the average of training data. The regression makes it possible to derive optimized parameters R_1, and C_1 using rest time as shown in Fig. 2.

B. Real-time OCV and ΔAh estimation

The process of estimating real-time OCV based on ECM parameters is shown in Fig. 3(a). The principle of estimating OCV based on the ECM voltage equation is as follows:

$$OCV(t) = v_t(t) + v_s(t) + v_{RC}(t) \tag{6}$$

Where $v_t(t)$, $v_s(t)$ and $v_{RC}(t)$ is terminal voltage, ohmic voltage drop, and RC ladder voltage respectively. ΔAh is also estimated based on the Coulomb counting method during operation as shown in Fig. 3(b). Therefore, real-time OCV and ΔAh are estimated based on the terminal voltage and current, as shown in Fig. 4. Since parameters cannot be obtained through the SSE regression in the initial operating section, the real-time OCV is estimated after the first relaxation. For gradual capacity estimation, the sum of battery relaxation data is as follows:

$$\Delta Ah = \frac{sampling\ time}{3600}\int i(t)dt \tag{7}$$

Then, the relationship between ΔAh to OCV curve could be derived from the results of (6), (7).

C. OCV to Ah curve estimation

The process of estimating the OCV curve for the real-time capacity of the battery is carried out through 4 steps as shown in Fig. 5. First, data preprocessing of the voltage curve is performed through empirical mode decomposition [14]. When estimating OCV based on the terminal voltage, sensing noise makes it difficult to estimate the real-time OCV curve. Thus, it is necessary to preprocess noise for obtaining precise OCV data. However, an OCV curve organized through EMD is estimated only based on the current integration method, so it is difficult to reflect the overall curve of the actual battery. Therefore, min-max is performed for partial SOC-OCV curves. Thus, the proposed algorithm creates an SOC-OCV curve by scaling the upper and lower voltages of the reused battery supposing that the change in current capacity extracted for each operation section is the current capacity, and this process can be expressed as follows:

$$Scaling\ factor = \frac{V_{t\_max} - V_{t\_min}}{OCV(t)_{max} - OCV(t)_{min}} \tag{8}$$

$OCV(t)_{max}$, $OCV(t)_{min}$, V_{t_max}, and V_{t_min} of (8)

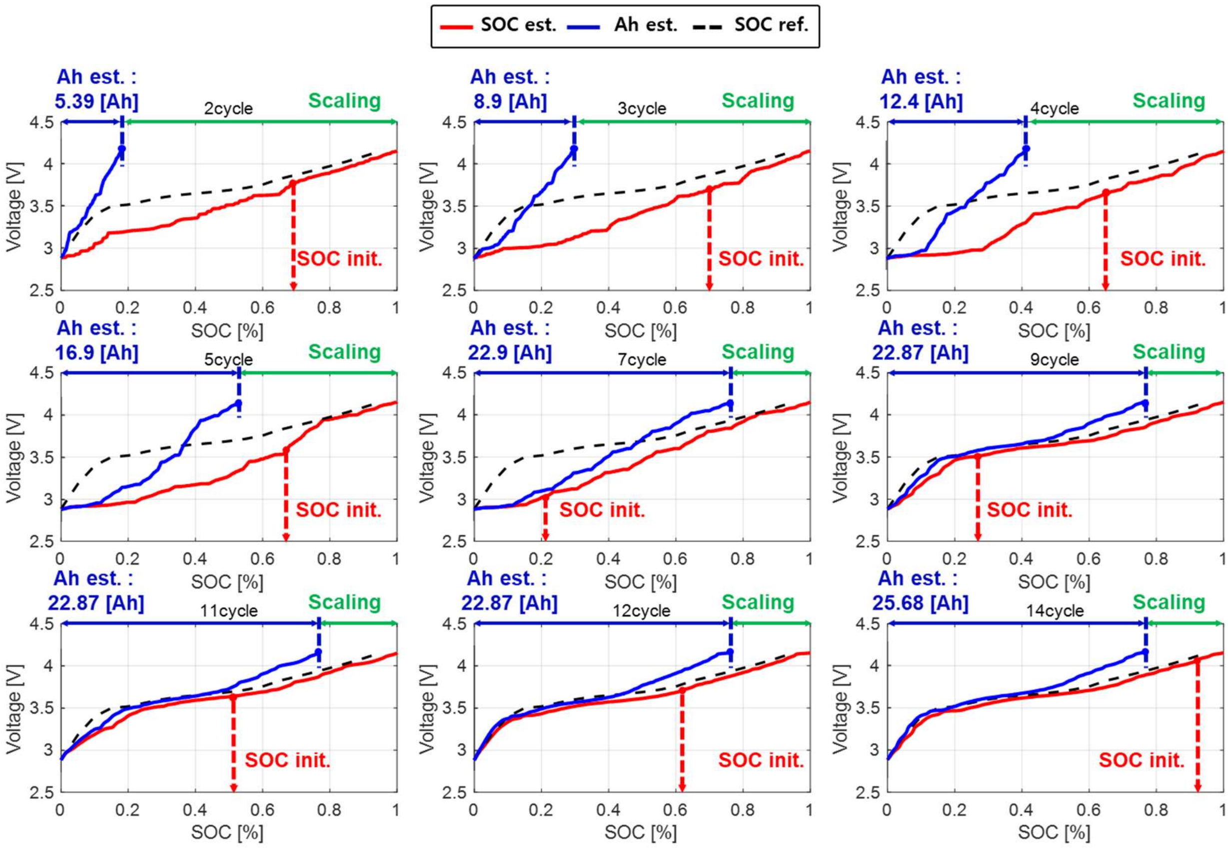

Fig. 6. SOC-OCV curve estimation for the real-time capacity in each operation cycle.

represent the estimated OCV maximum and minimum values, and the battery upper and lower limit voltage, respectively. The scaling range of the curve is limited to the sizes of the limit voltages of the reused battery and is calculated through the ratio of the maximum and minimum values of the estimated OCV curve. Therefore, as the depth-of-discharge increases during operation, the scaling range decreases. As the operation data of the battery accumulates, the SOC-OCV curve of the actual battery is accurately simulated.

Finally, the SOC-OCV curve for the real-time capacity in each operation cycle is estimated as shown in Fig. 6. Since it is difficult to estimate the actual capacity accurately in the initial operation section, the accuracy of the curve is very low. However, the accuracy of the SOC-OCV curve gradually increases as the estimated current capacity increased and the OCV-SOC curve gradually becomes similar to the actual curve as shown in Fig. 6.

D. Dataset for simulation and simulation results

To verify this algorithm, the OCV curve is extracted through a new European driving cycle (NEDC) charging/ discharging profile. Fig. 7 shows the results of real-time OCV, and SOC extracted by applying the NEDC profile based on NMC type battery with 27.144 Ah capacity. Real-time OCV shows high accuracy based on ECM parameter extraction through SSE regression. The time series noise component is included according to the current profile as a result of the real-time OCV estimation in Fig. 7. Therefore, the proposed curve estimation algorithm extracts time series noise with the EMD technique to satisfy the one-to-one correspondence of the SOC-OCV curve and expands the partial OCV curve for the operating section through the min-max scaling process. The proposed algorithm verified the expansion of the OCV curve scaled to the upper and lower voltage ranges as Ah-OCV curve is updated 14 times according to the NEDC profile and rest periods. Thus, as the DOD increases by the number of profiles, estimated current capacity data is updated gradually in the operation range and the estimated current capacity approaches the actual current capacity. Therefore, the entire profile is divided into two areas to compare the accuracy of the OCV curve according to the current capacity update.

As a result of applying the NEDC driving profile with proposed algorithm, the error of the real-time OCV was estimated to be within 0.3%. In the case of SOC estimation results, it is divided into area 1 and area 2 through the tendency of SOC estimation error. The large SOC estimation error in area1 compared to area 2 is due to the lack of estimation value compared to the actual value of the capacity during initial operation. Thus, the estimation accuracy of the Ah-OCV curve is degraded. For this reason, there is a large error when the initial SOC value corresponds to the OCV in area 1. However, as the real-time capacity is gradually updated, the estimation accuracy of the Ah-OCV curve increases. Therefore, the accuracy of the initial SOC and the real-time SOC also increases. Table I shows the results of applying the NEDC charge/discharge profile to the NMC battery, an estimated

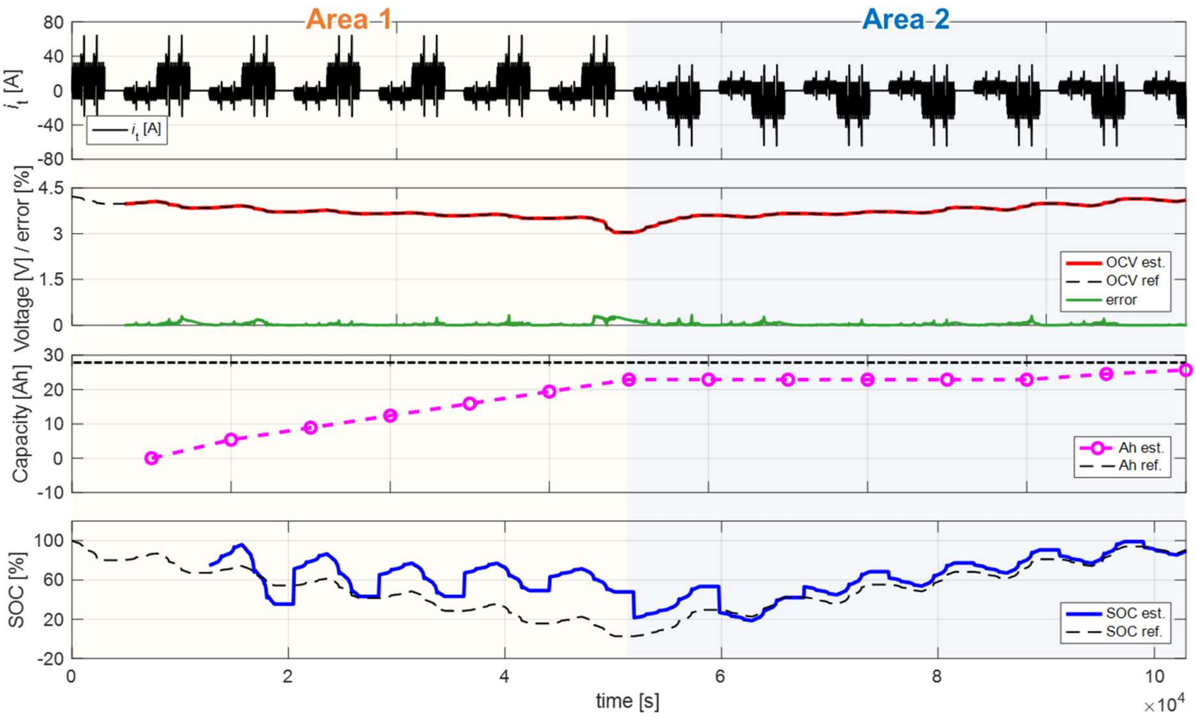

Fig. 7. NEDC simulation results for real-time OCV, capacity and SOC and error.

TABLE I
BATTERY PARAMETER ESTIMATION ERROR OF AREA 1

Num. of cycles	2	3	4	5	6	7
Area	1					
Capacity [Ah]	**27.144**					
Capacity est. [Ah]	5.39	8.9	12.4	16.9	19.4	22.9
Capacity estimation error	80.1	67.2	54.3	37.73	28.5	15.63
SOC to OCV curve error [%]	23.3	22.1	27.5	20.8	19.5	18.3

TABLE II
BATTERY PARAMETER ESTIMATION ERROR OF AREA 2

Num. of cycles	8	9	10	11	12	14
Area	2					
Capacity [Ah]	**27.144**					
Capacity est. [Ah]	22.8	22.9	22.9	22.8	22.8	25.7
Capacity estimation error	16	15.63	15.63	16	16	5.3
SOC to OCV curve error [%]	14.5	6.6	1.9	1.3	0.3	0.2

error of capacity, and an error of the Ah-OCV curve according to the 2 – 7 cycles. A capacity estimated by 4 cycles compared to the actual capacity was estimated to be 15.9 Ah. However, the result of updating the real-time capacity for 14 cycles, Table II shows the high accuracy of the estimated real-time capacity of 25.7 Ah and the error of 5.3% was confirmed. The estimation error of the SOC-OCV curve represents up to 18.3% in area 1, and based on the real-time capacity update, high estimation accuracy of at least 0.2% was achieved. Therefore, it is confirmed that estimate the OCV curve in real-time sufficient to apply stationary energy storage system.

III. CONCLUSIONS

In this paper, real-time OCV curve and capacity estimation algorithm is proposed without the initial state of the battery. The proposed algorithm extracts ECM parameters and estimates the OCV curve by applying the 1st-order ECM voltage equation and update battery capacity with Coulomb counting method. The parameters are estimated gradually without requiring additional experiments. Through the estimated parameters, it is possible to gradually estimate OCV curves in the upper and lower voltage ranges through time series operation data with EMD method, and curve scaling process for upper and lower cut-off values of the batteries. Simulation results show the error of the real-time OCV within 0.3%, and the minimum error for the current capacity according to the sequential current capacity update was 5.3% when the cycle was repeated through the NEDC profile. The SOC-OCV curve error verified the validity of the proposed algorithm by confirmed up to 23.3% and 0.2% with high accuracy for cycle repetition.

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