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RESEARCH ARTICLE

Enhanced Coulomb Counting Method for SoC and SoH Estimation Based on Coulombic Efficiency

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ABSTRACT The battery performance decreases as the charging/discharging cycles increase. Thus, a battery management system (BMS) is essential to properly estimating the battery states. In order to enhance the performance of the BMS, an accurate estimation method for lithium-ion batteries state is proposed. The main drawback of the coulomb counting method (CCM) for estimating a state of charge (SoC) is the error of initial value. To make-up this problem, the open circuit voltage (OCV) method which includes the internal resistance of the battery has been applied to update the initial value. In this paper, an enhanced coulomb counting (ECC) method is proposed to improve the accuracy of SoC estimation. Due to the battery aging by repeated charging/discharging cycles, the charging/discharging times become reduced and it can be formulated as a function of coulombic efficiency. Using the power equation to the battery, the state of health (SoH) can be estimated according to the change in the internal resistance. In the proposed flowchart, after the completion of charging/discharging in the k cycle, the internal resistance, coulombic efficiency, and capacities are calculated and those resultants will be utilized in $k + 1$ cycle. The proposed methods are verified by 3 kW energy storage system and the comparative experiment results are also presented to point out its effectiveness.

INDEX TERMS Battery management system (BMS), coulombic efficiency, state of charge (SoC), state of health (SoH).

NOMENCLATURE

V_b	Battery voltage
V_{ocv}	OCV Voltage
I_b	Charge or discharge current
R_s	Ohmic resistance
R_b	Internal resistance
$SoC_{0,k}$	SoC initial value of k cycle
$R_{b,k-1}$	Internal resistance of $k-1$ cycle
$SoC_{t,k}$	SoC at t of k cycle
$C_{b,k-1}$	Capacity of $k-1$ *cycle*
i_c	Charge current
$\eta_{b,k-1}$	Coulombic efficiency of $k-1$ cycle
i_d	Discharge current
$SoC_{tcc,k}$	SoC at CC-CV charging of k cycle
$SoC_{tcut-off,k}$	SoC at CC discharging of k cycle
$\eta_{b,k}$	Coulombic efficiency of k cycle
$C_{b,k}$	Capacity of k cycle
SoC_{tcc}	SoC at end of CC charging
t_{cc}	End time of CC charging
$SoC_{tcut-off}$	SoC at end of discharge
$t_{cut-off}$	When discharge, cut-off voltage arrival time
$SoH_{b,k}$	SoC at k cycle
R_{EoL}	Internal resistance limit value
R_{fresh}	Internal resistance initial value

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I. INTRODUCTION

In recent decades, lithium-ion batteries are widely used in many applications such as laptop, electric vehicle (EV), and energy storage system (ESS) due to their characteristics of high energy density, low weight, long life, and, great memory effect. However, there are over-charging and over-discharging risks in batteries with a large number of charging/discharging cycles, which also cause problems in the safety of the battery.

TABLE 1. Advantages and disadvantages of battery SoC estimation methods.

Category	Method	Advantages	Disadvantages
Direct measurement	OCV [10],[11]	1) High accuracy. 2) Simple and easily implementable.	1) Online estimation is unable. 2) Battery rest is required. 3) Measurable with the battery stable
	IR [12]	1) Simple and easily implementable. 2) Applications according to internal resistance are possible.	1) The accuracy of the SoC estimation is determined by the accuracy of the internal resistance. 2) Algorithm or circuit isolation for internal resistance measurement is required.
	IS [13], [14]	1) Simple and easily implementable. 2) No additional circuit configuration is required.	1) Charging/discharging current must be the same. 2) High dependence on current sensing.
Book-keeping	CCM [15], [16]	1) Simple and easily implementable.	1) Accuracy of SoC estimation decreases when the error of the initial SoC and sensing error is accumulated.
Model-based	KF [17]	1) High accuracy. 2) Strong against noise	1) Not suitable for non-linear systems. 2) Calculation time increases with increasing state variables.
	EKF [18]	1) High accuracy. 2) Strong to error reduction and noise in the model.	1) Calculation time increases with increasing state variables.
	UKF [19]	1) It has much higher accuracy than linearization of EKF. 2) Strong to error reduction and noise in the model.	1) Calculated more than EKF.
Data-driven	GA [20]	1) Increased state estimation accuracy in the battery ages.	1) Decreased estimated response by parameter settings.
	NN [21]	1) High accuracy 2) Not related to electrical and physical changes in the battery.	1) Repeated learning is required.
	CNN[22]	1) High accuracy 2) Enables analysis and recognition of specific parts of data.	1) The learning of visual data and target values of 3D data is required.
	DNN[23]	1) Fast learning performance for nonlinear systems.	1) Limits for continuous estimation operations.
Proposed	ECC	1) High accuracy. 2) Simple and easily implementable. 3) Parameter estimation without system separation.	1) Online estimation of internal resistance is not possible.

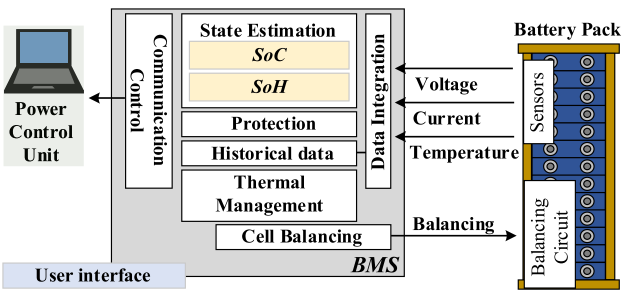

FIGURE 1. Main functions of BMS between power control unit and battery pack.

To solve this problem, lot of studies on a battery management system (BMS) have been conducted to encourage the efficient usage of battery but also improve its performance by accurately identifying the battery state [1], [2], [3], [4].

Fig. 1 shows the main functions of BMS. The roles of the BMS are 1) Protections of the battery from overvoltage, low voltage, over-current, and temperature. 2) Cell balancing. 3) Estimations for state of charge (SoC) and state of health (SoH). 4) Communication with the main controller [5].

A BMS not only maintains but also manages the optimum battery performance according to the battery states that mainly indicated by SoC and SoH [6], [7], [8]. The accurate estimation of the battery's SoC during charging/discharging can prevent over-charging and over-discharging of the battery and improve its safety [9].

In recent years, the variety of methods for estimating battery SoC have been intensively studied [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23] and Table 1 summarizes the advantages and disadvantages of the methods.

Reviewed SoC estimation methods are classified into 4-groups: direct measurement, book-keeping, model-based, and data-driven. First, an open circuit voltage (OCV) [10], [11], internal resistance (IR) [12], and impedance spectroscopy (IS) [13], [14] based estimation methods are investigated as a direct measurement category. Second, by measuring the current, a coulomb counting method (CCM) [15], [16] is categorized into book-keeping. Third, a Kalman filter (KF) [17] can be represented to model-based category which are dependent on the system. To overcome the drawback of KF, extended Kalman filter (EKF) [18] and unscented Kalman filter (UKF) [19] were studied. Last, based on the data analysis, the genetic algorithm (GA) [20] and neural networks (NN) [21] estimation methods were investigated as a data-driven category. In recent, a high accuracy and short-term charging data based convolutional neural network (CNN) [22] has been studied. In order to integrate an Ampere-hour counting method to deep neural network (DNN) based SoC estimation [23], there are state-of-the-arts studies that using Monte-Carlo dropout and KF.

Articles in [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], and [23] can estimate the SoC by high accuracy; however, those researches have intrinsic problems such as on-line estimation is unavailable and lots of computation and deep-learning data are required. Therefore, in this study, the cycle-based battery state estimation method that using internal resistance and capacity is proposed to achieve high accuracy and ease implementation.

Since the OCV method is only applicable when internal state of battery is stabilized, therefore it is not suitable for non-linear characteristic of battery system. The CCM estimates the SoC by accumulating currents, it may have an intrinsic drawback of accumulated error when a minor error is occurred in initial current. Thus, a method called enhanced coulomb counting (ECC) [24] was studied by applying both OCV and CCM.

In this study, the internal resistance and efficiency which can be simply formulated were employed therefore this proposed ECC method only requires less computational burden without training samples. In addition, SoH, which is an indicator to determine the remaining battery life, has a significant impact on the battery stability because it could predict not only a battery replacement time but also changes in internal parameters by aging. Thus, the proposed ECC method helps to reduce the SoC estimation error and increase its accuracy.

Some of the typical parameters that determine SoH are internal resistance [25], [26], capacity [27], [28], and power [29]. Practically, when the internal resistance doubled or the capacity decreased by 20%, it means complete aging [30]. Generally, capacity-based methods are frequently used to determine SoH.

In this paper, the characteristics of battery are fully considered. First of all, the charging constant current time and discharging cut-off time could be formulated based on the decreased battery capacity resulting from its aging. Then, this resultant is applied to the efficiency and internal resistance. Finally, the proposed SoH estimation can be obtained by improved internal resistance which has been considered decreased battery capacity. In addition, this battery capacity is reset every end of cycle to improve the initial value.

These derived equations are used to obtain the value of internal resistance in every k cycle to improve the accuracy of SoH estimation.

Furthermore, the internal resistance is closely related to information about performance and state such as the battery's efficiency, life, and capacity [31]. There are some related articles about measuring the internal impedance [32] and constructing an accurate model [33]. However, a direct current internal resistance (DC-IR) [34] and electrochemical impedance spectroscopy [32], [35], [36] measurement methods are considered only the initial battery internal resistance. Thus, they did not reflect the change in internal resistance in the actual situations such as EV and ESS.

In this study, the coulombic efficiency, capacity, and internal resistance are calculated based on the power equations of input and output to the battery for every charging/discharging cycle. According to the proposed flowchart, the SoC and SoH estimation could be conducted in the systematic way.

The structure of this paper is as follows: Section II describes the battery model's internal resistance and OCV to apply the proposed SoC and SoH estimation methods. In the Section III, a coulombic efficiency-based ECC method are proposed to estimate SoC and the internal resistance-based method is introduced for SoH considering the reduction of battery capacity. Experiment has been conducted in the 3 kW ESS system to verify the effectiveness of proposed estimation methods for SoC and SoH. Test results are present in Section IV compared to other conventional methods. Finally, Section V concludes the article.

II. BATTERY MODEL FOR IMPROVING SoC INITIAL VALUE

Fig. 2 shows the general equivalent circuit models (ECMs). In detail, the Rint model has only single R. On the other hand, still including single R, the Thevenin model has additional one of RC network, and the second-order ECM or dual polarization (DP) model have additional two of RC networks. The battery model is used for accurate SoC and SoH estimation of the battery.

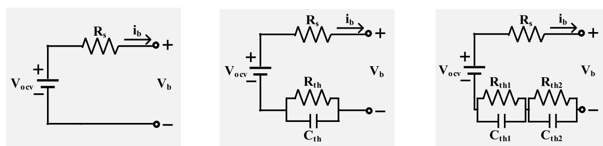

FIGURE 2. ECMs: (a) Rint. (b) Thevenin. (c) DP.

Fig. 3 shows detailed Thevenin model of the battery which indicating internal resistance R_b. It is composed of open circuit voltage V_{OCV} and battery terminal voltage V_b. Also, the internal resistance consists of an ohmic resistance R_s and a polarization resistance R_{th}. In detail, R_s represents the OCV state resistance and R_{th} is the faradaic resistance. Equivalent capacitance C_{th} is a capacitance representing the storage of energy. It is also the cause of excessive response due to charging/discharging. The electrical behavior of the Thevenin model can be expressed by (1) [37], [38], [39].

$$\begin{aligned} \dot{V}_{th} &= -\frac{V_{th}}{R_{th} \cdot C_{th}} + \frac{I_b}{C_{th}} \\ V_b &= V_{ocv} - V_{th} - I_b \cdot R_s \end{aligned} \tag{1}$$

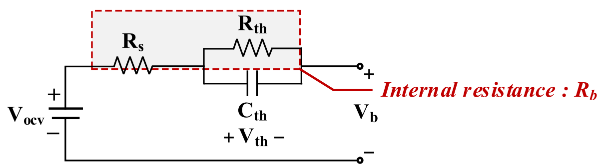

FIGURE 3. Schematic diagram for the Thevenin model.

Fig. 4 shows the difference in voltage estimation between the Rint and Thevenin model when a constant current is applied. Based on the assumption of adequate sampling speed in voltage sensing for battery [40], [41], the diffusion effect of C_{th} can be neglected so that the lithium-ion batteries can reach the steady-state condition quickly [42], [43]. Thus, the transient state can be ignored [42], [44] and the analysis could be simplified. Instead of (1), the battery voltage at the initial state can be simplified as (2). Here, negative sign means charging and positive sign means discharging. It can be noted that polarization resistance R_{th} and ohmic resistance R_s will be regarded as battery internal resistance R_b as (3) during this analysis.

$$V_b = V_{ocv} \pm I_b \cdot R_b \tag{2}$$

$$R_b = R_s + R_{th} \tag{3}$$

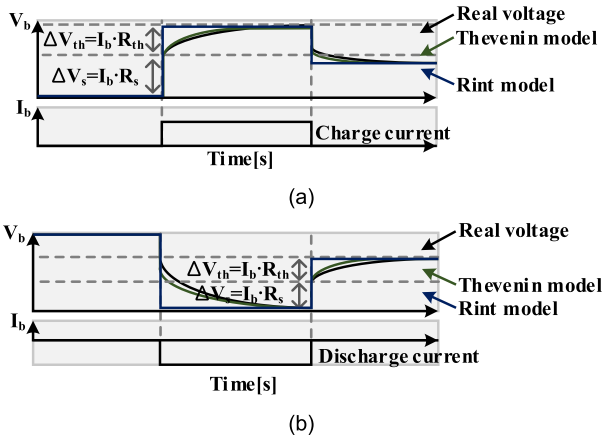

FIGURE 4. Difference in voltage estimation for Rint model (Blue trace) and Thevenin model (Green trace). (a) Charging period. (b) Discharging period.

The correlation between OCV and SoC changes in relation to the battery's performance degradation as shown in Fig. 5. The magnitudes of the battery's SoC and OCV are highly similar and they are reduced as much as the battery's $I_b \cdot R_b$ during charging/discharging. Thus, the current state of the battery can be determined if the internal resistance of the battery model can be accurately calculated.

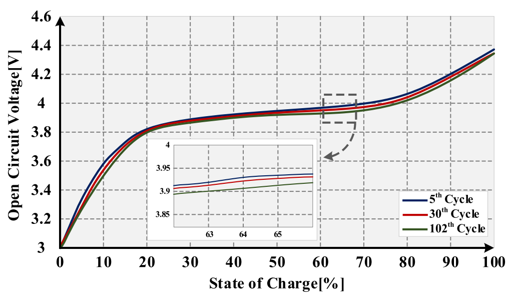

FIGURE 5. SOC-OCV curves under different battery aging statuses.

III. PROPOSED SoC AND SoH ESTIMATION METHODS

A. PROCEDURE OF PROPOSED SoC AND SoH ESTIMATION METHODS

Fig. 6 shows a flowchart of proposed SoC and SoH estimation methods. In the beginning of k cycle, the previous values of internal resistance, efficiency, and capacity which were calculated at k-1 cycle are read.

To compensate initial value problem in CCM, the initial value is updated using OCV in every k cycle. When the battery is in charging or discharging state, the SoC is estimated by proposed ECC method which is combined with OCV and CCM. Charging or discharging state is terminated when the current SoC value is lower than the minimum SoC value or higher than maximum SoC value.

The charging/discharging time are formulated after satisfying aforementioned requirements. Then, the coulombic efficiency and capacity of battery are calculated for next cycle in order to mitigate the initial value problem which was an issue in only-CCM. In addition, the internal resistance is calculated using the power equation considering input and output network at battery in order to estimate the SoH. Once SoH at the current state at k cycle is estimated, this flowchart is terminated and repeated from the beginning.

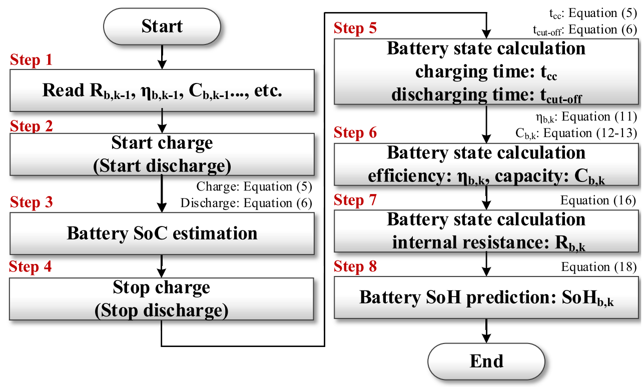

FIGURE 6. Flowchart of SoC and SoH state estimation in the *k* cycle.

Fig. 7 presents the time sequence during k cycle according to the Fig. 6. The SOC and SoH estimation method involves the following steps during k cycle:

Step 1: Once the charging/discharging signals are delivered from the main microcontroller, the internal resistance and efficiency are read which were collected in $k{-}1$ cycle.

Step 2: The charge or discharge process is started using the historical data which were collected in the previous cycle.

B. COULOMBIC EFFICIENCY-BASED ECC FOR SoC ESTIMATION

By cooperating the OCV and CCM, the estimation of SoC can be improved. As shown Fig. 8, the battery's initial value is first calculated during charging/discharging in *Step 3-1*. Then, the battery's SoC is estimated in *Step 3-2*.

Step 3-1: The initial value should be calculated to apply the CCM. The conventional CCM is strongly dependent on the initial SoC state. Therefore, once an error at the initial state occurs, the errors are accumulated causing failure in SoC estimation. The proposed internal resistance which is obtained from efficiency-relation has been applied into open-circuit to reduce the initial error on the battery. In the k cycle, the initial

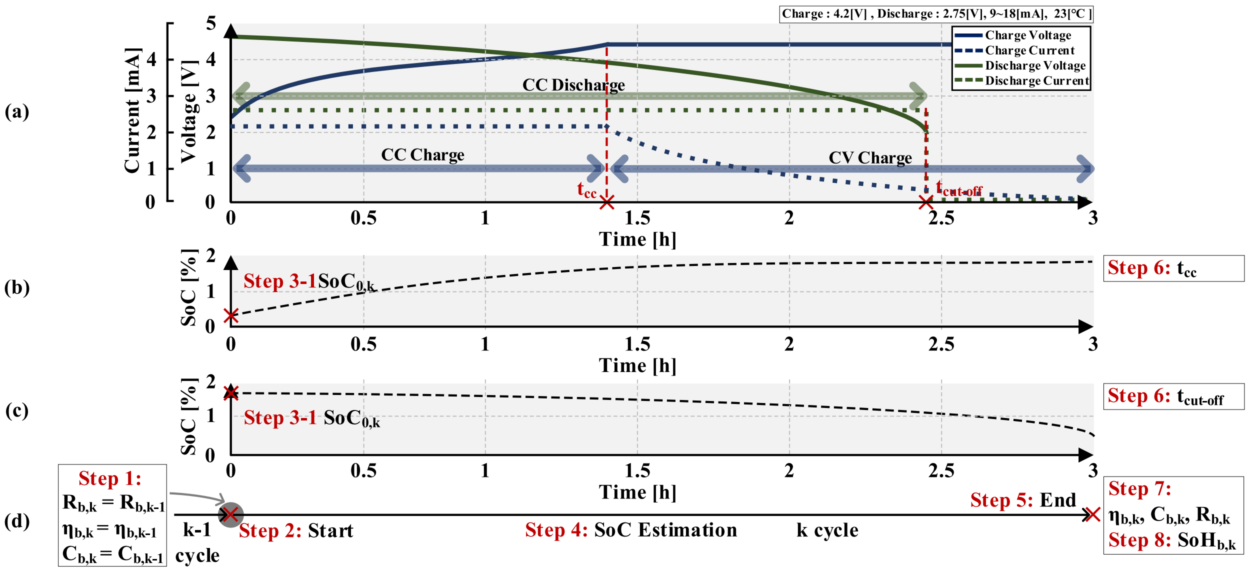

FIGURE 7. Time sequence of SoC/SoH estimation during *k* cycle. (a) Current and voltage curves of CC Charge, CV Charge, and CC Discharge. (b) SoC curve for charging condition. (c) SoC curve for discharging condition. (d) Detail description of each step.

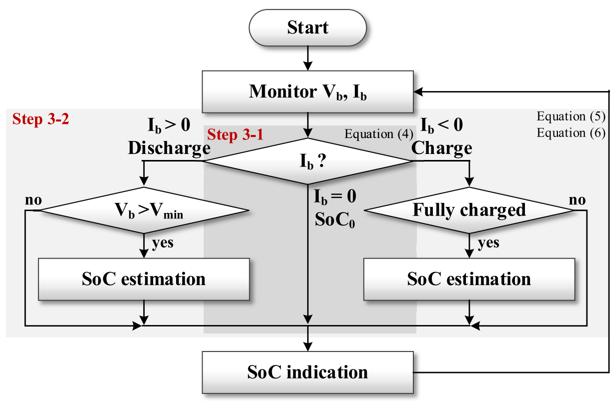

FIGURE 8. SoC estimation flowchart of step 3.

value of estimated SoC can be calculated using (4). In order to reduce the initial error caused by conventional CCM, the OCV in battery stack and voltage drop by internal resistance $R_{b,k-1}$ in the *k−1* cycle are considered.

$$SoC_{0,k} = V_{ocv} \pm (I_b \cdot R_{b,k-1}) \tag{4}$$

Step 3-2: After the initial SoC is indicated by the *step 3-1*, this step is conducted to estimate the SoC in *k* cycle at certain time as (5) and (6) during charging/discharging respectively. Proposed ECC method has been applied into these equations. First term is obtained by (4) to correct the initial value of SoC. The second term is calculated based on the integral form of efficiency and capacity which were collected in the previous cycle.

$$\begin{aligned} SoC_{t,k} &= SoC_{0,k} + \frac{1}{C_{b,k-1}} \int_0^t i_c \cdot \eta_{b,k-1} dt \\ &= V_{ocv} - (I_c \cdot R_{b,k-1}) + \frac{1}{C_{b,k-1}} \int_0^t i_c \cdot \eta_{b,k-1} dt \end{aligned} \tag{5}$$

$$\begin{aligned} SoC_{t,k} &= SoC_{0,k} - \frac{1}{C_{b,k-1}} \int_0^t i_d \cdot \eta_{b,k-1} dt \\ &= V_{ocv} + (I_d \cdot R_{b,k-1}) - \frac{1}{C_{b,k-1}} \int_0^t i_d \cdot \eta_{b,k-1} dt \end{aligned} \tag{6}$$

Step 4: The battery's charging/discharging are terminated when the battery's maximum and minimum values are reached during charging/discharging, respectively.

C. SoH ESTIMATION ACCORDING TO THE REDUCTION IN THE BATTERY CAPACITY

Step 5: The SoH estimation method is proposed according to the CC charging time and when discharging, cut-off voltage arrival time considering internal resistance and coulombic efficiency.

When the battery is charged in CC mode, the charging time of the battery decreases as the battery resistance increases. Since the CC charge is conducted with a fixed value of current, when the internal resistance increases or the capacity decreases due to deterioration, the CC charging time of the battery decreases. Thus, the change in the CC charging time is a significant factor for this study. Generally, when a battery is charged, it is charged with the same C-rate as that of the power conversion system (PCS).

The condition of the SoC estimation method in this study is as follows: Since battery charging/discharging are conducted with the same C-rate, I_b can be assumed as a constant current. By using (5), in the charging condition, the SoC can be expressed as (7) using CC charging time. Similarly, in the discharging condition, the SoC can be expressed using when discharging, cut-off voltage arrival time as (8) from the (6).

$$SoC_{tcc,k} = V_{ocv} - I_c \cdot R_{b,k-1} + \frac{1}{C_{b,k-1}} \cdot I_c \cdot \eta_{b,k-1} \cdot t_{cc} \tag{7}$$

$$SoC_{tcut-off,k} = V_{ocv} + I_d \cdot R_{b,k-1} - \frac{1}{C_{b,k-1}} \cdot I_d \cdot \eta_{b,k-1} \cdot t_{cut-off} \tag{8}$$

The definitions of CC charging time t_{cc} and when discharging, cut-off voltage arrival time $t_{cut-off}$ are required to apply for the proposed SoH estimation. Therefore, these definitions can be rearranged from (7) and (8) to (9) and (10).

$$t_{cc} = C_{b,k-1} \cdot \left(\frac{SoC_{t_{cc}} - V_{ocv} + I_c \cdot R_{b,k-1}}{I_c \cdot \eta_{b,k-1}} \right) \tag{9}$$

$$t_{cut-off} = C_{b,k-1} \cdot \left(\frac{V_{ocv} - SoC_{t_{cut-off}} + I_d \cdot R_{b,k-1}}{I_d \cdot \eta_{b,k-1}} \right) \tag{10}$$

D. COULOMBIC EFFICIENCY FOR SoC AND SoH ESTIMATION OF k+1 CYCLE

Step 6: The coulombic efficiency for the *k+1* cycle is calculated. As the cycle increases, the battery's charging/discharging capacity decreases. Thus, the coulombic efficiency $\eta_{b,k}$ can be expressed with (11) as the ratio of charging/discharging capacities [45].

$$\eta_{b,k} = \frac{Q_d}{Q_c} = \frac{\left| I_d \cdot t_{cut-off} \right|}{I_c \cdot t_{cc}} \tag{11}$$

To estimate the remaining battery capacity, the battery capacities $C_{b,k}$ at the k cycle are calculated from (7) and (8) as (12) for charging and (13) for discharging. Those results will be recalled in the beginning of the *k+1* cycle.

$$C_{b,k} = \frac{Q_c}{SoC_{tcc,k}} \tag{12}$$

$$C_{b,k} = \frac{Q_d}{SoC_{tcut-off,k}} \tag{13}$$

Step 7: To calculate the battery's internal resistance, the input and output of battery network is considered in terms of power as (14) [46]. To simplify the analysis, the charging current I_c and discharging current I_d are expressed as battery current I_b in (14). P_S refers to the supplied power in the battery.

$$I_b \cdot V_{ocv} - I_b^2 \cdot R_{b,k} - \eta_{b,k} \cdot P_S = 0 \tag{14}$$

$$P_S = I_b \cdot V_{ocv} \tag{15}$$

By arranging (14) and (15), the internal resistance at the k cycle is calculated with (16). In this study, the internal resistance is calculated through the battery voltage, current, and capacity without additional circuits and parameter measurement, resistance separation, and complex operation.

$$R_{b,k} = V_{ocv} \cdot \left(\frac{1 - \eta_{b,k}}{I_b} \right) \tag{16}$$

Step 8: In this study, since the battery's SoC and SoH can be predicted using the internal resistance which has been applied the charging/discharging time, the battery's SoH at the k cycle of the battery can be estimated through (17). Limit value of resistance, R_{EoL} means the end point (End of Life) at which the internal resistance of the battery is doubled. Initial value of resistance, R_{fresh} is the initial internal resistance of the battery. In conclusion, SoH can be estimated in an off-line state, but it can be estimated without separation of resistance.

$$SoH_{b,k} = \frac{R_{EoL} - R_{b,k}}{R_{EoL} - R_{fresh}} \tag{17}$$

IV. EXPERIMENTAL RESULTS

To verify the proposed SoC and SoH estimation method, a 3 kW ESS was used. Fig. 9 shows the hardware configuration for test bench. The PCS configuration was composed of the 2-level inverter, full-bridge converter, and main controller. The output terminal was composed of lithium-ion battery using three modules. One module has 90 cell and cell voltage is 3.7 V. Each BMS (TMS320F28035S) is placed by each module to estimate SoC and SoH. A controller area network (CAN) bus was used to deliver the battery's status to the main controller (TMS320F28377D). The verification was conducted through the charging/discharging operations by delivering the battery's status to the PCS controller (TMS320F28377S) through RS-232. In the experiment, an oscilloscope and notebook computer were also used to check the real-time operation.

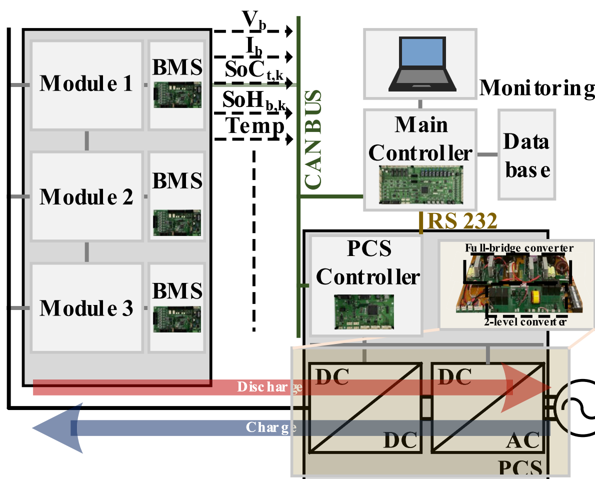

FIGURE 9. Schematic of the battery test bench.

The measured information of voltage, current, and the obtained data through the proposed SoC and SoH estimation methods were transmitted to the PCS and main controllers. The main controller determines the energy management in the ESS. While, the PCS controller determines the converter's operation using the information received from the main controller. Table 2 presents the specification of battery data for the ESS which has been used for the experimental verification.

TABLE 2. Battery data in the ESS.

Controller	Battery data	Purpose
BMS	V_b, I_b, $Temp$ $SoC_{t,k}$ $SoH_{b,k}$ $C_{b,k}$	1) Data collection for estimation 2) Identify battery charging/discharging status with battery voltage and current
Main	V_b, I_b $SoC_{t,k}$ $SoH_{b,k}$	1) ESS energy management 2) Check the battery status 3) Applying charging/discharging signal of power controller
PCS	V_b, I_b $SoC_{t,k}$	1) During charging/discharging, determine battery condition 2) Data collection for CC-CV charge and CC discharge

To evaluate the performances regarding SoC estimation, the conventional methods such as CCM [10], OCV [15], EKF [18] are implemented and compared with proposed ECC method and real SoC. Table 3 presents the datasheet of Samsung SDICR18650-26F that used in verification for the SoC and SoH estimation methods.

TABLE 3. Lithium-ion battery data sheet of Samsung ICR18650-26F.

Nominal capacity	2600 mAh
Nominal voltage	3.7 V
Charge method	constant current-constant voltage (CC-CV)
Discharge method	constant current constantconstnat
Charge voltage	4.2 V
Max. charge current	1 C
Max. discharge voltage	2.75 V
Max. discharge current	2 C
initial internal resistance	9~18 mΩ

Fig. 10 shows a BMS block diagram to validate the proposed method. The signal block and SoC estimation block always communicate the SoC data. First, the k-1 cycle data of efficiency, resistance, and capacity are received. Each cell voltage V_{b_1}~V_{b_90} is summed up to V_b, while each open circuit voltage V_{ocv_1}~V_{ocv_90} is summed up to V_{ocv}. Through V_{ocv}, V_b, and I_b, the initial value of SoC (4) can be calculated and then SoC can be estimated by (5) or (6). By using CC charging time (9) and cut-off time (10), the battery efficiency is updated (11). Finally, SoH can be estimated by power relations (14) and internal resistance (16). During this process, the BMS is conducting a protection, thermal management, and communication by microcontroller. $T_{b\_1} \sim T_{b\_90}$ mean the temperature of each cell.

In this paper, the performance index of mean absolute error (MAE) was used to compare the SoC and SoH.

To validate the improvement of initial value in proposed method, the experiment is conducted comparing other conventional methods during CC-CV charging. Fig. 11 shows the SoC waveforms of the five SoC estimation methods for one battery cell and zoomed-in waveforms are also presented for initial state. Due to the ECC based proposed method, SoC error in the initial state is only 0.39% which is the least value compared to other methods.

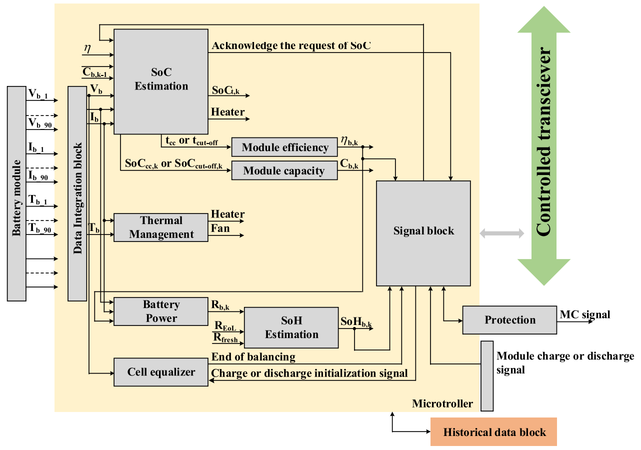

FIGURE 10. BMS block diagram for estimating SoC and SoH by proposed method.

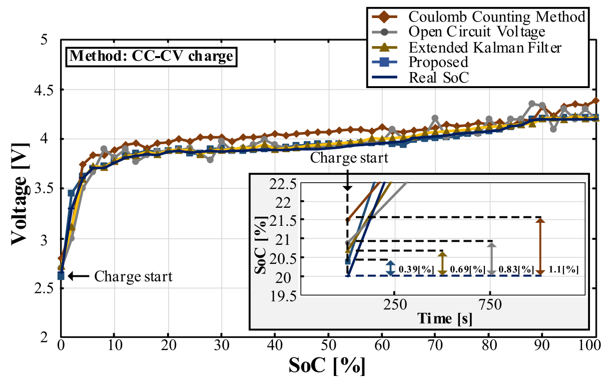

FIGURE 11. Comparison of initial values of SoC estimation methods during charging.

In Fig. 12(a)-(d), the experimental results of SoC values that using proposed method, CCM, OCV, and EKF are compared to real SoC. Based on the data, the MAE (SoC deviation with real SoC) can be obtained as 0.019%, 0.237%, 0.113%, and 0.037% respectively. Proposed SoC estimation method could achieve the least MAE referred to the real SoC among the conventional methods. Table 4 summarized the comparison experiment results between proposed, CCM, OCV, and EKF methods and Real SoC during charging state. Proposed SoC estimation method has the highest accuracy to other existing methods.

TABLE 4. Comparisons between proposed, CCM, OCV, and EKF methods and Real SoC during charging.

	Proposed	CCM	OCV	EKF
MAE	0.019%	0.237%	0.113%	0.037%
SoC initial error	0.39%	1.1%	0.83%	0.69%

Since, the battery is often to implemented as module in its application, the proposed SoC estimation method needs to be validated in battery modules. Fig. 13 shows the SoC

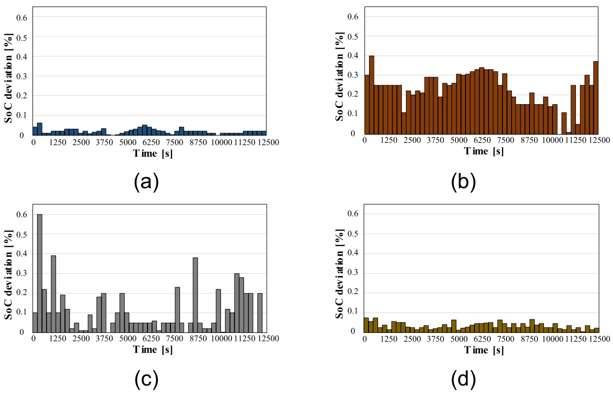

FIGURE 12. (a) MAE between the real SoC and the proposed method. (b) MAE between the real SoC and CCM. (c) MAE between the real SoC and OCV. (d) MAE between the real SoC and EKF.

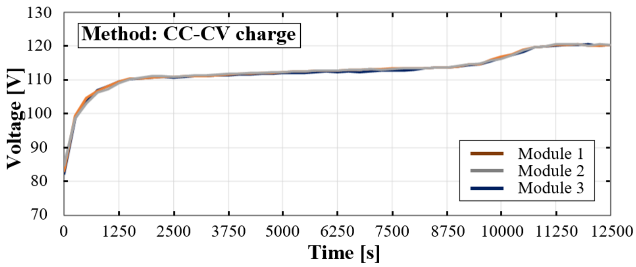

FIGURE 13. The proposed SoC estimation method during charging period through the module configuration.

estimation results when charging three battery modules. The voltage curves are almost identical for three modules which means those modules are well-balanced during the test. Based on the voltage results on Fig. 13, the estimated SoC can be easily obtained as Fig. 11.

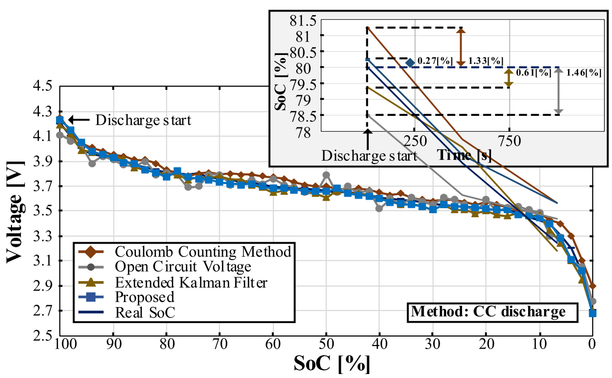

FIGURE 14. Comparison of initial values of SoC estimation methods during discharging.

Fig. 14 shows the voltage values of CCM, OCV, EKF, proposed method, and real SoC in one battery cell according to SoC. Experiment results of discharging period are identical with charging period. The least value of SoC error in the initial state is confirmed as 0.27% during discharging period.

TABLE 5. Comparisons between proposed, CCM, OCV, and EKF methods and Real SoC during discharging.

	Proposed	CCM	OCV	EKF
MAE	0.024%	0.078%	0.062%	0.031%
SoC initial error	0.27%	1.33%	1.46%	0.61%

Fig. 15(a)–(d) show the MAE of SoC for above methods when those are compared to real SoC as an actual referred value. The MAE between the proposed method and the real SoC was 0.039%, which verified the proposed method had the minimum MAE compared to other conventional methods. Table 5 summarized the comparison experiment results between proposed, CCM, OCV, and EKF methods and Real SoC during discharging state. Proposed SoC estimation method has the highest accuracy to other existing methods.

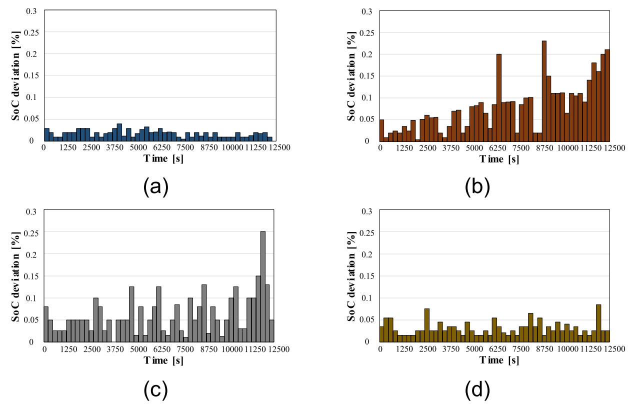

FIGURE 15. (a) MAE between the real SoC and the proposed method. (b) MAE between the real SoC and CCM. (c) MAE between the real SoC and OCV. (d) MAE between the real SoC and EKF.

Fig. 16 shows the SoC voltage estimation result when discharging three battery modules. It can be proved that each of module voltage identically decreases by the time.

In this article, the coulombic efficiency has been considered to obtain the SoC and SoH in a simple way. As formulated in (11), this efficiency is the function of charging/discharging time. It is obvious that this time is changed when the battery is aging. Therefore, the coulombic efficiency is required to be investigated by hardware setup when the charging/discharging cycle are repeated (Increased cycle number means the aging).

Fig. 17(a) shows the change in the coulombic efficiency according to the increase in the charging/discharging cycle in one battery cell. Fig. 17(b) shows the change in the coulombic efficiency in three battery modules. As shown the experimental results in Fig. 17, it can be noted that coulombic efficiency is reduced by increased number of cycles and the effectiveness of (11) is validated. The trends are identified as dot lines in the Fig. 17 to figure out the profiles of coulombic efficiencies.

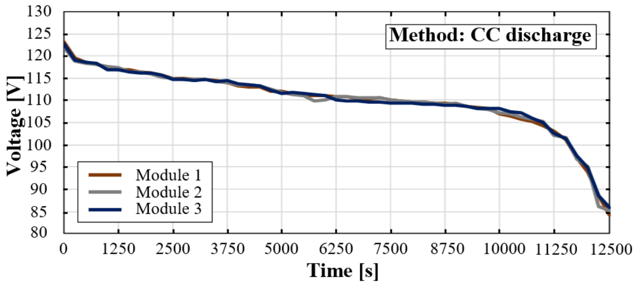

FIGURE 16. The proposed SoC estimation during discharging period through the module configuration.

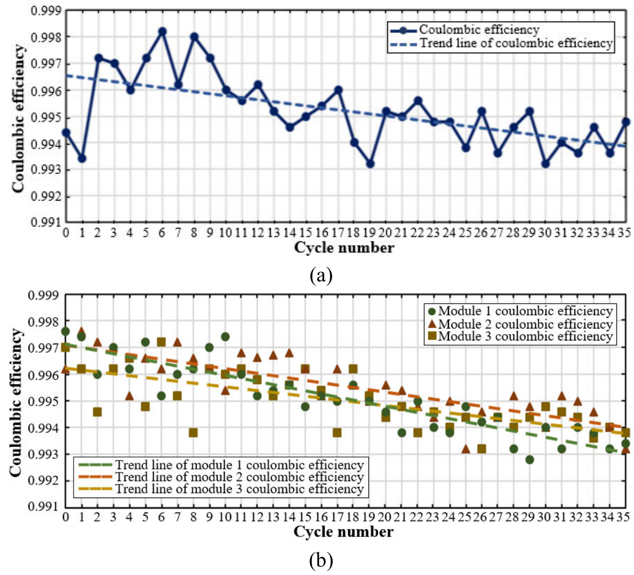

FIGURE 17. Coulombic efficiency by increased charging-discharging cycles. (a) One battery cell. (b) 3-battery modules.

As following the flowchart in Fig. 6 and relations between (11) and (16), the proposed calculation method of internal resistance is strongly correlated with coulombic efficiency. To validate the effectiveness of the (16), the value of internal resistance is estimated by repeated cycle test. The experimental results are in Fig. 18(a) with one battery cell and in Fig. 18(b) with three battery modules.

Proposed SoH estimation method which has been applied the internal resistance has following sequences. 1) Conduct the charging/discharging, 2) Obtain the data regarding charging/discharging, 3) Apply the (9), (10) which are function of charging/discharging time, and 4) Extracting data. Finally, the estimated SoH can be obtained by (17). To validate the proposed SoH estimation method, the charging/discharging times which are the dominant factor to discern the SoH are measured in the different SoH cases.

According to each of SoH case, the reduced charge and discharging times are identified in Fig. 19 which is the experimental result using battery module 1. Final SoH value is determined by the average of SoH values in each cell. Fig. 19(a) verifies the reduction in the battery's CC

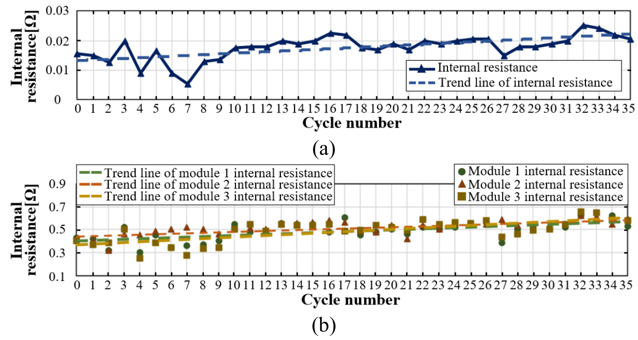

FIGURE 18. Coulombic efficiency by increased charging-discharging cycles. (a) One battery cell, (b) 3-battery modules.

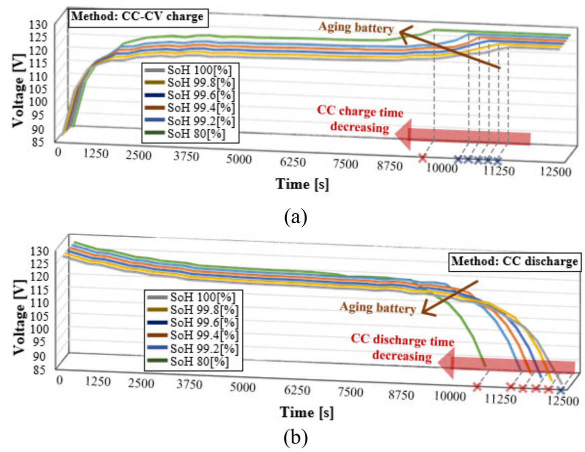

FIGURE 19. (a) Comparison of CC charging times by SoH. (b) Comparison of cut-off voltage arrival time by SoH.

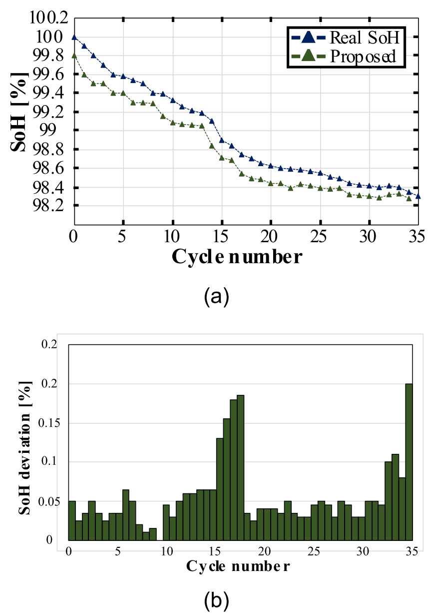

FIGURE 20. (a) Comparison between the real SoH and the proposed SoH. (b) SoH error.

charging profile according to battery aging during battery charging. Fig. 19(b) verifies the reduction in the cut-off voltage arrival time according to battery aging during battery discharging.

During this experiment, the Real SoH has been obtained as following criteria [47]. 1) Identical charging-discharging condition. 2) Using the battery which has the error of SoC lower than 0.1%. 3) Using result values of actual capacity through offline test. To validate the SoH estimation method, the new battery of SoH 100% is utilized and charging-discharging cycles are repeated by identifying the battery aging.

Fig. 20 shows the comparison of the proposed SoH estimation method with actual values to verify the proposed method. Enough number of charging/discharging cycles are conducted in the experiment to estimate the SoH. It verifies that the MAE of the proposed method was 0.056%. This value is acceptable for BMS to determine the state of battery. The failure can also be diagnosed by obtained SoH.

V. CONCLUSION

In this study, the accurate and simple methods for estimating the SoC and SoH were proposed to improve the performance in BMS for battery application. In respect to the improvement of SoC estimation, the least values of initial value error can be achieved by 0.39% and 0.27% charging and discharging periods respectively compared to the other methods. During charging and discharging, the minimum values of MAE in proposed SoC method are confirmed as 0.019% and 0.039% respectively compared to the real SoC. The smallest MAE could be obtained with proposed ECC method compared to the reviewed articles for SoC estimation. The formulated charging/discharging times were verified through the experiment proving the analyzed battery characteristics that the capacity is decreased by repeated cycles of charging/discharging. Furthermore, the internal resistance values were calculated using the power relations of input and output for the battery after the process of charging either discharging is finished. The trend of increasing the internal resistance is demonstrated during the 35-cycle test using battery modules. Calculated data set (charging/discharging time, efficiency, capacity, and internal resistance) are obtained at the end of current cycle k and then those are applied in the beginning of the cycle $k+1$. Therefore, the SoH can be estimated more accurately only indicating the MAE value of 0.056% which is a predominant test result compared to the existing methods that even complicated as well as requiring excessive computation.

In this paper, offline estimation-based method is proposed and proved its great accuracy. However, it has a limitation that an online estimation for SoH is unavailable. Even though the proposed method achieved a significant advantage, there is a research potential regarding online estimation method. For example, as one kind of machine learning method, NN-based method can be applied to internal resistance for estimating SoH by online. Along with the battery aging, the battery capacity and internal resistance will be varied. These variations can be used the deep-learning data in offline. Based on the trained model of NN-based method, the SoH estimation can be conducted in online. In the future work, the estimation accuracy will be compared between offline and online methods.

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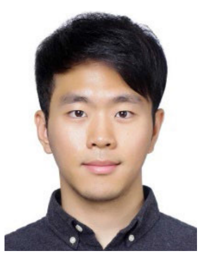

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