Online Detection of Soft Internal Short Circuit in Lithium-Ion Batteries at Various Standard Charging Ranges

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ABSTRACT Soft internal short circuit (ISCr) in lithium-ion batteries is a latent risk, and it is a primary reason for thermal runaway with blaze and explosion. Early detection of ISCr is necessary to ensure safe utilization of the batteries. Based on the applications of batteries, load currents are considerably diverse and occasionally do not satisfy the persistent excitation condition, resulting in inaccurate detection of soft ISCr with existing model-based methods. Using constant current for standard charging of the batteries, this study proposes a novel and accurate model-based algorithm to detect soft ISCr online irrespective of the specific type of load currents. An equivalent circuit model of the battery with ISCr is used to extract open circuit voltage of the battery. Enhanced relationship between open circuit voltage and state of charge is obtained to estimate ISCr resistance as a fault index. To improve estimation accuracy of the fault index, factors affecting the ISCr resistance are analyzed and considered. Experiments incorporating various charging ranges and soft ISCr conditions below 100 Ω are configured, and the proposed method is verified with experimental data. The results of the study indicate that the relative error of the estimated fault index does not exceed 6.4%; thereby, the battery management system is enabled to accurately detect an ISCr early.

INDEX TERMS Battery management system, early fault diagnosis, electric vehicles, short circuit resistance, safety problem.

NOMENCLATURE

Abbreviations

ISCr Internal short circuit
ESS Energy storage system
EV Electric vehicle
SOC State of charge
ESCr External short circuit
ECM Equivalent circuit model
MRE Maximum relative error
PE Persistent excitation
BMS Battery management system
OCV Open circuit voltage
DST Dynamic stress test
RLS Recursive least squares
PDF Probability density function
CC-CV Constant-current constant-voltage

Symbols

\( R_{ISCr} \) ISCr resistance, Ω
\( V_{OC} \) OCV, V
\( R_0 \) Ohmic resistance, Ω
\( I_L \) Load current, A
\( I_R \) Residual current, A
\( I_s \) Self-discharge current, A
\( k \) current iteration index
\( z \) RLS observation
\( \phi \) RLS parameter vector
\( T_0 \) PE time interval
\( \alpha_0, \alpha_1 \) PE positive coefficient
\( I_M \) PE identity matrix
\( \lambda_{max}, \lambda_{min} \) PE maximun and minimum eigenvalues
\( \beta \) Model error
\( C_{max} \) Maximum capacity, Ah
\( \eta \) Coulombic efficiency
\( T \) Sampling rate
I. INTRODUCTION

Demand for lithium-ion batteries in energy storage systems (ESS) and electric vehicles (EV) has significantly increased due to their high energy density, low self-discharging, and long cycle life [1], [2]. However, increasing attention has been paid to the safety of their usage due to many dangerous incidents caused by the thermal runaway of the batteries in aircraft, smart phones, and e-cigarettes across the world [3]–[5]. Specifically, internal short circuit (ISCr) is considered to be the main reason for the thermal runaway in the incidents [6]. An ISCr can occur from a variety of sources such as manufacturing defects (separator damage and contamination particles), changes in the chemical components of batteries (dissolution/deposition of electrode materials, lithium plating, and dendrite formation), or battery misuse by overcharging or overdischarging [6]–[9]. When an ISCr initially occurs in batteries, the level of the ISCr fault is weak and we call this weak fault as soft ISCr. However, the state of charge (SOC) that indicates remaining mileage of the EV cannot be estimated accurately if self-discharge current caused by the soft ISCr is not considered. Furthermore, continuous usage of the faulty batteries over time under normal or abusive conditions increases the severity of the soft ISCr and this severe fault is called as hard ISCr.

The ISCr is exhibited in a battery via ISCr resistance \( R_{\text{ISCr}} \), and the self-discharge current of the faulty batteries indicates levels of the ISCr. According to the industrial standard GB/T 31484-2015, the C-rate of leakage current in the batteries must not exceed C/4480 where C (C-rate) represents charging and discharging current of the battery. In case of the soft ISCr, maximum value of the self-discharge current (leakage current) is C/3.7 for the experiments [10]. When the self-discharge current reaches 274C, the temperature of the faulty batteries increases rapidly, and thermal runaway causing fire and explosion then occurs [11]. It is noted that detection of the soft ISCr is necessary for both user safety and accurate SOC. For this reason, the levels of ISCr can be categorized according to the value of self-discharge current in Fig. 1. The C-rate can be converted to the \( R_{\text{ISCr}} \) using the charge cut-off voltage (4.2 V) and the nominal capacity (2.850 Ah) of the lithium-ion battery used in the study.

Recently, many studies have been aimed at detecting external short circuit (ESCr) and ISCr in lithium-ion batteries. When the ESCR \( (R_{\text{ESCr}} < 5.4 \text{ m}\Omega) \) exists in the batteries, significant changes in measurements such as decrease in terminal voltage and increase in both current and temperature are monitored in short time [12]. ESCR detection methods are developed via using the aforementioned evident changes [13]–[18]. The ESCR is diagnosed after setting the thresholds obtained from the rapid changes in terminal voltages and temperatures [13]. The methods for detecting ESCR are explained via developing models for increment in terminal voltages [14], [15]. Temperature data is used to detect ESCR with leakage [16], [17]. The ESCR is predicted with criteria that are extracted from physical deformation of batteries [18]. However, it is not possible to use the aforementioned methods for ESCR for detecting soft ISCr where the significant changes in measurements are not caused by a big \( R_{\text{ISCr}} \).

ISCr detection methods are implemented for a battery pack that consists of a faulty cell and multiple normal cells in series [19]–[24]. An ISCr is detected by estimating parameters in a mean difference model [19], [20]. The correlation coefficient is calculated with terminal voltages of normal and faulty batteries and used to detect the ISCr [21]. When a fully discharged battery pack is charged fully, an ISCr is predicted based on the charging time difference between normal and faulty batteries [22]. The excessive depletion of capacity and the abnormal heat generation are extracted from measured voltages and temperatures of the cells in the battery pack [23]. The methods are only applicable to the battery pack wherein terminal voltages of all cells in the pack are provided [19]–[23]. As a promising fault index, the \( R_{\text{ISCr}} \) that directly presents the level of fault is estimated using terminal voltage of the pack and equivalent circuit model (ECM) [24]. However, the accuracy of the estimated \( R_{\text{ISCr}} \) is low and their maximum relative error (MRE) is 31.2%.

To detect the ISCr in a single cell, several studies were conducted [10], [25]–[29]. The self-discharge current is used to detect the ISCr although a specific experimental equipment is required to measure the current [25]. Online ISCr detection is conducted using variations in estimated parameters in the ECM [26]. However, it is not possible to obtain the level of ISCr fault with the method. To enable early detection of an ISCr, a soft ISCr must be detected accurately and additionally various ISCr faults must be classified relative to each other. Thus, the \( R_{\text{ISCr}} \) is estimated to detect a soft ISCr in a battery after analyzing the self-discharge phenomenon, which is caused by an ISCr, in the estimated SOC [27], but low accuracy of estimation (MRE ≤ 26.1%) is the limitation of this method. By extracting the fault feature from the electrochemical-thermal model, the ISCr can be figured out and accuracy of estimates of the \( R_{\text{ISCr}} \) is high (MRE < 2%) [28]. However, it is difficult to obtain numerous parameter values of the electrochemical-thermal model when it is applied. The variation of variables in the P2D model of

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|---|
| \( p \) Fixed iteration, sample index |
| \( \Delta SOC \) Difference between SOC\((p)\) and SOC\((k)\) |
| \( \Delta SOC_{ini} \) Initial value of \( \Delta SOC \) |
| \( R_{fi} \) Final fault index, \( \Omega \) |
| \( R_{end} \) Estimated \( R_{\text{ISCr}} \) at last iteration, \( \Omega \) |
| \( h \) Number of \( R_{end} \)s |
| \( d \) Deviation of \( R_{end} \) |
| \( g \) Number of outliers |
ISCr is revealed and then used to diagnose the soft ISCr [10]. The problem with obtaining numerous parameters of the P2D model remains. A learning-based detection algorithm, for a soft ISCr, is introduced using the difference between normal and faulty batteries although it is necessary to obtain sufficient normal data for learning the features of a healthy battery [29].

The model-based methods [26]–[28] exhibit a common constraint, namely load currents must satisfy the persistent excitation (PE) condition to estimate parameters of the ECM accurately [30], [31]. Based on the applications of batteries, load currents are considerably diverse and occasionally do not satisfy the specific condition [32], [33]. This leads to inaccurate detection of an ISCr with existing model-based methods due to the incorrect estimated parameters. However, the battery management system (BMS) in applications, such as the EV and the ESS, must detect the ISCr irrespective of the type of load currents for user safety and accurate SOC. In order to conduct standard charging, most lithium-ion batteries are charged with constant current (CC) [34].

Therefore, in the study, a novel and accurate model-based detection algorithm for a soft ISCr is proposed using constant current to ensure the robustness of various load currents. In the absence of specific algorithms (for e.g., recursive least square and Kalman filter) to estimate parameters of the ECM, open circuit voltage (OCV) is calculated from the ECM using constant currents and terminal voltages of the cell. In order to accurately obtain SOC with the calculated OCV, the relationship between OCV and SOC is extracted from charging data of a normal cell and used instead of the relationship from prior experiments. As a promising fault index, the $R_{ISCr}$ is estimated with the obtained SOC, and the ECM of battery with ISCr is then updated using the estimated $R_{ISCr}$. Accuracy of estimates of the OCV and SOC increases after conducting the update process. Additionally, by considering factors that affect the estimation accuracy of the $R_{ISCr}$, the its accuracy is improved and a soft ISCr can be accurately detected with various charging ranges of the battery. The proposed algorithm is developed in MATLAB and verified via experimental data.

The three main contributions of the proposed methodology are as follows; (1) When compared to the existing model-based methods (which can detect the ISCr with only specific load currents), the proposed algorithm can be broadly applied to applications of batteries because constant currents for standard charging are used to detect an ISCr as opposed to specific load currents. Furthermore, a novel method is examined to accurately estimate OCV and SOC with the constant currents; (2) The proposed method detects a soft ISCr with experimental data ($R_{ISCr} \leq 100 \, \Omega$); additionally, the accuracy of estimated $R_{ISCr}$ significantly improves ($MRE \leq 6.3837\%$) by considering the factors that affect the its estimation accuracy. Thereby, the BMS is enabled for early detection of the soft ISCr and accurate estimation of SOC; (3) Moreover, soft ISCr detection is reliable for various charging ranges including the diverse voltages to start and terminate charging the battery.

The rest of this paper is organized as follows: the proposed algorithm is presented in Section II. Subsequently, the experimental setup is discussed in Section III. Results and discussions are explained in Section IV. Finally, conclusions and future work of the study are summarized in Section V.

II. METHOD DESCRIPTION

The entire scheme of the proposed algorithm is shown in Fig. 2. For an online detection of soft ISCr, the $R_{ISCr}$ is estimated with the measured terminal voltage and constant current for the standard charging. To improve the estimation accuracy of the $R_{ISCr}$, and to obtain a reliable final fault index, various $R_{ISCr}$s are estimated with different estimation points. Mean value of this estimates is used as the final fault index after excluding the outliers with the largest deviation.

![FIGURE 2. Schematic of the proposed method.](image)

![FIGURE 3. Equivalent circuit models of (a) normal and (b) faulty batteries.](image)

A. EQUIVALENT CIRCUIT MODEL AND OCV ESTIMATION

The ECMs of normal and faulty (with ISCr) batteries are shown in Fig. 3. When the battery is charged with constant current having no change in its magnitude, both the Rint model and the Thevenin model show similar charging voltage curve [35]. Thus, the Rint model that has less model parameters is used as a normal model in the study. The normal battery model is represented with OCV $V_{OC}$ and ohmic resistance $R_0$, and the ISCr is described in the faulty battery model by connecting the $R_{ISCr}$ at the terminal of the normal model in parallel [36], [37]. Given the ISCr, the load current $I_L$ is divided into self-discharge current $I_2$ flowing through the $R_{ISCr}$ and residual current $I_1$. In (1) and (2), the terminal voltages $V_1$s in the normal model and the faulty model are...
induced by the Kirchhoff’s voltage law where \( k \) denotes a current iteration.

\[
\begin{align*}
V_i(k) &= V_{OC}(k) + R_0I_L(k), \\
V_i(k) &= V_{OC}(k) + R_0(I_L(k) - I_2(k)), \\
I_2(k) &= V_i(k)/R_{ISCr}.
\end{align*}
\]

For OCV and \( R_0 \) estimation in the faulty model, a parametric model in (4) is derived and the recursive least squares (RLS) algorithm is applied in the previous work [27], where \( z \) is the observation, \( \theta \) is the parameter vector, and \( \phi \) is the regressor [38]. The model parameters can be identified if the regressor \( \phi \) in (6) satisfies the PE condition [39]. The PE condition is satisfied if a time interval \( T_0 \) and positive numbers \( \alpha_1 \) and \( \alpha_0 \) exist such that (7), where \( I_M \) is the identity matrix with the same dimension as \( U(t) \).

\[
\begin{align*}
z &= \theta^T \phi, \\
\theta &= \left[ \frac{R_{ISCr}}{R_0 + R_{ISCr}}V_{OC}(k), \frac{R_0R_{ISCr}}{R_0 + R_{ISCr}}, \right], \\
\phi &= [1, I_L(k)], \\
\alpha_1I_M &\geq U(t) = \frac{1}{T_0} \int_{t-T_0}^{t} \phi(\tau)\phi^T(\tau)d\tau \geq \alpha_0I_M, \quad \forall t \geq 0.
\end{align*}
\]

However, if the load current \( I_L \) in (6) is constant current as opposed to dynamic current profile used in the EV, the \( \phi \) does not satisfy the PE condition any more and the model parameters also cannot be identified correctly. For \( 100 \leq t \leq 460 \), the \( U(t) \)s are calculated over the time interval \( T_0 = 360 \), because the dynamic current profile consists of repeated dynamic stress test (DST) cycles lasting for 360 s. To check the PE condition, eigenvalues \( \lambda \) of \( U(t) \) are calculated since \( U(t) \) is not a diagonal matrix. When the \( I_L \) is the DST current, positive \( \lambda_{max} \) and \( \lambda_{min} \) are obtained and shown in Fig. 4. Thus, the \( \alpha_1 \) and the \( \alpha_0 \) in (7) can be found as 2.2260 and 0.6634 respectively, which are maximum and minimum values from Fig. 4(b) and Fig. 4(c). Whereas, the \( \lambda_{min} \) is not positive and then the positive \( \alpha_0 \) cannot be chosen when the \( I_L \) is the constant current (1.375 A). It can be concluded that the PE condition is not satisfied if the battery is charged with the constant current. Therefore, the OCV should be calculated from the ECM with ISCr in (2) and (3) using the measured data. The two unknown parameters in the ECM with ISCr are the \( R_0 \) and the \( R_{ISCr} \). The \( R_0 \) is set as 0.01 \( \Omega \) by considering the data sheet of tested battery. The initial value of the \( R_{ISCr} \) is defined as a big value (500 \( \Omega \)); this means that by assuming the faulty battery is normal, the OCV is obtained. Although the criterion for normal operation is C/4480 (6602 \( \Omega \)) in Fig. 1, the self-discharge current of the battery with ISCr (500 \( \Omega \)) is C/339 and the value is highly small. Thus, the 500 \( \Omega \) is set as the initial value of the \( R_{ISCr} \) in the study. If the \( R_{ISCr} \) is estimated, the initial value of the \( R_{ISCr} \) is replaced with the estimated \( R_{ISCr} \), and the OCV is then calculated. The calculated OCV differs from true OCV which can be obtained from the particular resting test, and this is mainly because model error \( \beta \) is included in the calculated OCV in (8). The model error is positive and induced by incorrect pre-defined \( R_0 \). In addition, non-linearity of the battery (which represents the changed \( R_0 \) by SOC) is not considered in the ECM with ISCr, thereby resulting in the model error.

\[
V_{OC}(k) + \beta = V_i(k) - R_0(I_L(k) - V_i(k)/R_{ISCr}).
\]

**B. SOC ESTIMATION**

To obtain SOCs that are in agreement with the calculated OCVs, an OCV-SOC curve, which describes the relationship between OCV and SOC and can be obtained from the prior
experiment [40], is required. However, the accuracy of the SOC's obtained via the experimental OCV-SOC curve is low because the calculated OCVs have the model error $\beta$. Therefore, a novel OCV-SOC curve, which is appropriate for the calculated OCVs, is necessary to obtain accurate SOCs.

The novel OCV-SOC curve can be obtained with the pre-defined $R_0$ and normal data, which are terminal voltages and constant currents for fully charging a fresh battery [41]. An initial value of normal SOC is defined as 0, and normal SOCs are then calculated using the Coulomb counting method. It is important to use both (1) and the pre-defined $R_0$ when obtaining normal OCVs, because the model error must be included in the obtained normal OCVs; This process means that the model error caused by the incorrect $R_0$ and the non-linearity of the battery is compensated in the novel OCV-SOC curve. Using the normal SOCs and OCVs, the novel OCV-SOC curve is estimated.

![OCV-SOC curve comparison](image1.png)

**FIGURE 5.** Comparison results: (a) OCV-SOC curves from experiment and estimation; (b) reference SOC and estimated SOCs from experimental and estimated curves.

The OCV-SOC curves, which are extracted from the prior experiment and estimated with the normal data respectively, are as shown in Fig. 5a. With respect to all SOC ranges, OCV values of the estimated curve exceed those of the experimental curve. By assuming the current SOC is 0.4 in Fig. 5a, the SOC can be estimated accurately, if the $V_{OC}$ is estimated with the RLS algorithm and the experimental curve is used. However, when the $V_{OC} + \beta$ is obtained from (8), accurate SOC can be estimated with the estimated curve as opposed to the experimental curve. Thus, it is concluded that the novel estimated OCV-SOC curve is suitable in terms of the calculated OCVs having the model error. We use calculated OCVs from the normal charging data, and SOCs obtained with the two OCV-SOC curves are shown in Fig. 5b. As reference SOCs, true SOCs were calculated with the Coulomb counting method. The true SOCs and estimated SOCs from the experimental curve are significantly different, but the estimated SOCs from the novel curve are extremely close to the true values. Although estimation errors of SOC for the estimated curve are observed in a low SOC range having severe non-linear properties of the battery, the errors are generally low when compared with those for the experimental curve. Therefore, it is noted that the novel estimated OCV-SOC curve is appropriate for the calculated OCVs in the proposed algorithm. In the estimated OCV-SOC curve, the range from 0% SOC to 80% SOC is reliable, and it is used to develop the proposed algorithm in the study because a maximum value of estimated normal SOCs is approximately 0.8.

**C. ISCr RESISTANCE ESTIMATION**

When an ISCr occurs in a battery, the battery is continuously discharged with the self-discharge current $I_2$. Thus, in case of standard charging, the faulty battery is charged with the residual current $I_1$ as opposed to the charging current $I_L$. The phenomenon is represented with (9) induced from the Coulomb counting method where $C_{\max}$ denotes the maximum capacity, $\eta$ denotes the coulombic efficiency, and $T$ denotes the sampling rate. In the study, $\eta$ and $T$ are set as 1 and 0.1, respectively. Equation (10) is derived from both (3) and (9), and used to estimate the $R_{ISCr}$. The $C_{\max}$ is set as a experimental value after conducting the capacity test with tested batteries. If the battery is degraded or used under various ambient temperatures, the $C_{\max}$ can be changed and the $R_{ISCr}$ is then estimated inaccurately because of errors of the $C_{\max}$. However, in the study, the factors such as battery aging and temperatures that could change the $C_{\max}$ are not considered, and the detailed discussion about practicability of the proposed method under battery aging and temperatures is covered in Section IV-D.

When the estimated SOC reaches a specific value, the current iteration $k$ is regarded as a fixed iteration $p$, and $SOC(p)$ denotes SOC at the $p$. After obtaining the estimated $R_{ISCr}$ at $k$th, the $k + 1$th OCV is calculated with the $k$th estimated $R_{ISCr}$ as opposed to the initial value, i.e. the ECM of the battery with ISCr in (2) and (3) is updated by using the estimates of the $R_{ISCr}$. This model-update increases the accuracy of estimated OCVs and SOCs in the subsequent iterations. The model-update process is continuously repeated until the end of the measured data.

\[
SOC(k) = SOC(k - 1) + \frac{\eta T}{C_{\max}}(I_L(k) - I_2(k)), \quad (9)
\]

\[
R_{ISCr}(k) = \frac{T}{C_{\max}} \sum_{n=p+1}^{k} V_I(n) \frac{1}{SOC(p) - SOC(k)} + \frac{T}{C_{\max}} \sum_{n=p+1}^{k} I_1(n). \quad (10)
\]
The two important factors affecting accuracy of the estimated $R_{ISC}$ are a position of the $SOC(p)$ and the difference between SOCs in (10). For the first factor, if the $SOC(p)$ is determined as the SOC estimated initially, the $SOC(p)$ is different in every battery charging cases because the batteries can have different initial SOCs before they are charged. Depending on initial SOC of the battery, the $SOC(p)$ can have either small or large estimation error. When errors of obtained SOCs with the initial value of the $R_{ISC}$ (500 Ω) under various ISCr faults are depicted in Fig. 6, it shows that the SOC errors are not constant and changed according to time. It is noted that the similarity between two errors of the $SOC(p)$ and the current SOC $SOC(k)$ significantly affects estimation accuracy of the $R_{ISC}$ rather than error magnitude of the $SOC(p)$ where the similarity means both sign and magnitude of the two SOC errors are identical. It is because the difference between two estimates of the $SOC(p)$ and the $SOC(k)$ is calculated and used in (10). The $SOC(p)$ with the high similarity can lead to accurate $R_{ISC}$, whereas the $SOC(p)$ with the low similarity cannot lead to it. For the case of ISCr 20 Ω, the $SOC(p)$s are set as 10% and 20%, respectively in Fig. 7a, and the $R_{ISC}$s are estimated with the two different $SOC(p)$s in Fig. 7b. When an average value of SOC error is 0.9389% in Fig. 7a, the first point ($SOC(p) = 10\%$) is closer to the average value than the second point ($SOC(p) = 20\%$), and the first point has the high similarity. Thus, the enlarged view in Fig. 7b shows estimates of the $R_{ISC}$ with the first point are more accurate than those of the second point. At the begining of the estimation of $R_{ISC}$s, the difference between the similarities of the two points causes large differences in the estimates. Although the difference between the two estimates obtained from the two points gradually decreases over time, the estimated $R_{ISC}$s with the first point are closer to the true value than those of the second point continuously. However, an optimal $SOC(p)$ which has the high similarity cannot be chosen with only measured data and estimates of SOC online because true SOC corresponds to unknown values. In order to consider uncertainty of the $SOC(p)$, the $SOC(p)$ is determined as different points ($SOC(p) = 0, 2, 4, \ldots, 70\%$) and diverse $R_{ISC}$s are then obtained in the study. The range of $SOC(p)$ can be changed because the battery can have different initial and final SOCs depending on various charging ranges.

As the second factor affecting accuracy of the estimated $R_{ISC}$, $\Delta SOC$ denotes the difference between the $SOC(p)$ and the $SOC(k)$ in (10). $\Delta SOC_{ini}$ denotes the initial $\Delta SOC$ and
represents a point to start estimating the $R_{ISCr}$. When the $SOC(p)$ and the $\Delta SOC_{ini}$ are set as 10% and 1%, respectively, the $R_{ISCr}$ can be estimated if the $SOC(k)$ is $\geq 11%$. The small $\Delta SOC$ indicates small decrease in the charging amount due to the ISCr or small amount of self-discharge. The errors of estimated SOCs in the small $\Delta SOC$ can largely affect the estimation accuracy of the $R_{ISCr}$ relatively when compared to the errors in the large $\Delta SOC$. In order to overcome this problem, it is important to estimate the $R_{ISCr}$ when the $\Delta SOC$ is large enough. For the case of ISCr 30 $\Omega$, the $\Delta SOC_{ini}$s (1, 2, 3, …, 7%) are set and marked in Fig. 7c. The same $SOC(p)$ is used to estimate the $R_{ISCr}$s with different $\Delta SOC_{ini}$s and leads to similar estimates of the $R_{ISCr}$ after 1500 s in Fig. 7d. The estimates of $R_{ISCr}$s exhibit big fluctuations before 1100 s when the $\Delta SOC_{ini}$ are 1% and 2% in the enlarged view in Fig. 7d. This fluctuations are caused by estimation errors of SOC in the small $\Delta SOC$ and decrease steadily because the $\Delta SOC$ increases over time. For other ISCr cases ($\geq 50$ $\Omega$), the big fluctuations in estimates of the $R_{ISCr}$ can occur easily due to the small amount of self-discharge in the small $\Delta SOC$ if the $\Delta SOC_{ini}$ is determined as a small value. Hence, the estimation of the $R_{ISCr}$ commences when the $\Delta SOC$ is $\geq 5$% ($\Delta SOC_{ini} = 5\%)$ in the study.

### D. FINAL FAULT INDEX CALCULATION

After estimating the $R_{ISCr}$s with the various $SOC(p)$s and the fixed $\Delta SOC_{ini}$ online, a representative value among the estimates of $R_{ISCr}$ should be determined as a final fault index $R_{fi}$ to detect the soft ISCr. The mean value $\overline{R_{ISCr}}$ of diverse $R_{end}$s is calculated in (11) where $R_{end}$ denotes the $R_{ISCr}$ estimated at the last iteration with a $SOC(p)$ and $h$ is the number of $R_{end}$s. In (12), $d$ denotes deviation of the $R_{end}$ and is then calculated. The $R_{end}$ which has the largest $d$ is considered as an outlier. Therefore, the $R_{fi}$ is obtained with (13) after the $R_{end}$s, which have the $1^{st}$, $2^{nd}$, $3^{rd}$, …, $g^{th}$ largest $d$s, are excluded where $g$ denotes the number of excluded outliers ($g < h$). In the study, the $g$ is set as 2.

$$\overline{R_{ISCr}} = \frac{\sum_{n=1}^{h} R_{end}(n)}{h}, \quad (11)$$

$$d = |R_{end} - \overline{R_{ISCr}}|, \quad (12)$$

$$R_{fi} = \frac{\sum_{n=1}^{h-g} R_{end}(n)}{h-g}, \quad (13)$$

For the cases of ISCr 50 $\Omega$ and ISCr 30 $\Omega$, the $R_{end}$s are obtained with the various $SOC(p)$s. The histograms show distribution of the $R_{end}$s and their probability density functions (PDF) are depicted in Fig. 8. For the case of ISCr 50 $\Omega$, the $R_{fi}$ is calculated after eliminating the $R_{end}$s having the $1^{st}$ and $2^{nd}$ largest $d$s, such as 37.5936 $\Omega$ and 53.6842 $\Omega$, respectively. Then, the $R_{fi}$ is 47.4032 $\Omega$ and relative error is 5.0226%, whereas the $R_{ISCr}$ is 47.3052 $\Omega$ (5.2190%). For the case of ISCr 30 $\Omega$, the $R_{fi}$ is 28.4592 $\Omega$ (5.0727%). Thus, it is concluded that the $R_{fi}$ is suitable as the final fault index because the $R_{fi}$ is more accurate than the $\overline{R_{ISCr}}$.

### III. EXPERIMENTAL SETUP

In the study, experiments for a soft ISCr were carried out to verify the proposed method. Two identical batteries (SAMSUNG INR 18650-29E), A and B, were used to obtain the experimental data, and the nominal capacity of the cells is 2.850 Ah. The charge and discharge cut-off voltages corresponded to 4.2 V and 2.5 V, respectively, and the nominal voltage corresponded to 3.65 V (Table 1). Prior tests were conducted to obtain the capacities and the OCV-SOC curve. According to the capacity test, the cells were charged with the constant-current constant-voltage (CC-CV) protocol and then discharged with 0.2C (0.57 A) as CC discharging. The discharge capacities were defined as true capacities and the values corresponded to 2.8374 Ah and 2.8340 Ah for cells A and B, respectively. With respect to the OCV-SOC curve test, the fully charged battery cell was rested for 4 hours to measure the OCV, which is equal to the terminal voltage at 100% SOC. Subsequently, the discharging current with 0.5C was applied to the cell for 720 s to set 90% SOC, and the cell was then rested for 4 hours to obtain the OCV. The process was repeated until it reached 0% SOC, and the experimental OCV-SOC curve was obtained.

Fig. 9 describes the configuration of the battery test bench. The battery cells were tested in the thermal chamber
where the ambient temperature of the cells was maintained at 25±1 °C. A battery test device (Regenerative Battery Pack Test System 17020, Chroma) was utilized to conduct experiments with the battery cells, and the sample period was 0.1 s. The experimental data including the charging current and terminal voltage signals were measured via the data logger and saved in computer. In order to represent the various soft ISCr faults, resistances with ±5% tolerance were connected with the battery in parallel, and their measured true values corresponded to 99.83, 49.91, 29.98, and 20.00. When the resistance is 99.83, the self-discharge current of the battery is C/67 and the value represents 3% of a standard charging current (1.375 A and C/2). In the study, the resistance range was set as 20.00 to 99.83 because the 99.83 is a big value enough to describe the weak fault. The validation of the proposed method with experimental data having the wide resistance range (R<sub>ISCr</sub> > 100) remains as future work. Relative errors of the R<sub>ISCr</sub> were calculated with the true resistance values. The soft ISCr faults were triggered with a switch when the standard charging current was applied to the cell which had various initial SOCs. The cell A was applied to the soft ISCr faults with 49.91, 29.98, and 20.00, and the cell B was applied with 99.83.

**IV. RESULTS AND DISCUSSIONS**

**A. TERMINAL VOLTAGES OF THE BATTERY CELL**

The terminal voltages based on the various R<sub>ISCr</sub> values in the experiments are shown in Fig. 10. In the initial charging time, a significant difference is not observed between the normal voltage and those of various ISCr faults because the self-discharge current is low. However, when the battery is charged continuously until the terminal voltage reaches the charge cut-off voltage, increase in the terminal voltage leads to high self-discharge current in (3). Additionally, the difference is evident because amount of leakage current caused by the self-discharge current gradually increases in accordance with the charging time. Thus, the level of ISCr affects the slope of terminal voltages and total time for charging the battery. The hard ISCr causes the gradual slope and increases the charging time.

**B. SOFT ISCr DETECTION RESULTS**

Experimental data of normal and faulty batteries were used to verify the proposed algorithm. For the normal case, estimated SOC is shown in Fig. 11a where the various SOC(p)s (0, 2, 4, · · · , 70%) are marked with squares and the different points to start estimating the R<sub>ISCr</sub> are marked with crosses. The first square (SOC(p) = 0%) is paired up with the first cross (SOC(k) = 5%) because the SOC<sub>ini</sub> is set as 5%. In accordance with this rule, the remainder of the squares matches with the rest of the crosses in order. In Fig. 11b, the marked squares are paired up with the marked crosses according to the established rules in Fig. 11a. The R<sub>ISCr</sub>s were not immediately estimated during the initial estimation period, and they were maintained at the initial value (500 Ω). When the ΔSOCs are ≥5% for all various SOC(p)s, the estimation of R<sub>ISCr</sub>s commenced. The R<sub>ISCr</sub>s estimated for the first time are found by the marked crosses in Fig. 11b. When the battery is normal, the self-discharge current is zero value and then the value of R<sub>ISCr</sub> has to be infinite value in (2) and (3). Thus, the estimated R<sub>ISCr</sub>s exhibit big fluctuations and values above 1000 Ω although the y-axis in Fig. 11b is limited to 1000 Ω. The estimates of R<sub>end</sub> did not converge on a specific value over time, and the variance of R<sub>end</sub>s was large.

For all ISCr cases, estimated R<sub>ISCr</sub>s are depicted in Fig. 12, and the estimates of R<sub>ISCr</sub> changed according to time are observed clearly when compared with the normal case.
FIGURE 11. For normal battery, (a) various SOC ($p$)s (square) and different estimation points (cross) for $R_{ISCr}$s; (b) diverse estimated $R_{ISCr}$s from the pairs of squares and crosses.

The soft ISCr faults have more big fluctuations at the initial estimation period because the $\Delta SOC$ is not large enough to reflect the self-discharge phenomenon; this is related with the second factor in Section II-C. In small $\Delta SOC$, the reduction in charging amount, which is caused by the self-discharge, is small because the difference is not significant between the normal voltage and those of soft faults. Thus, errors of estimated SOCs considerably affect the estimates of $R_{ISCr}$ with respect to the small $\Delta SOC$. However, this sensitive effect of SOC estimation errors decreases steadily because the $\Delta SOC$ increases over time and the reduction in charging amount becomes also large. The initial estimates of $R_{ISCr}$ by various SOC($p$)s are different because the SOC($p$)s have different estimation errors; this is related with the first factor in Section II-C. The enlarged views in Fig. 12 show the detailed variations of estimated $R_{ISCr}$s, and the estimated $R_{end}$s gradually approach true resistances for each fault cases because effect of estimation errors of SOC($p$)s decreases steadily due to the increasing $\Delta SOC$. The $R_{end}$s which have small variance are then obtained.

With respect to numerical analysis of $R_{ISCr}$ estimation, as the final fault index, the $R_{f}$s for various ISCr faults were obtained. Subsequently, relative errors were calculated with the $R_{f}$s and measured true values of resistances (Table 2).

The maximum value of the relative errors corresponded to 6.3837%. Hence, the estimates were sufficiently accurate to classify the level of various ISCr faults and enable early detection of ISCr online.

### TABLE 2. Relative errors of $R_{f}$.

| True ISCr resistance ($\Omega$) | Estimate ($\Omega$) | Relative error (%) |
|-------------------------------|--------------------|-------------------|
| Normal                        | 3250               | -                 |
| 99.83                         | 93.4572            | 6.3837            |
| 49.91                         | 47.4032            | 5.0226            |
| 29.98                         | 28.6919            | 4.2966            |
| 20.00                         | 18.7969            | 6.0155            |

C. SOFT ISCr DETECTION UNDER VARIOUS CHARGING RANGES

Commonly, the batteries in the ESS and the EV start to be charged with diverse initial SOCs as opposed to 0% SOC. Furthermore, when the charging is finished, the batteries can have different final SOCs because the user does not always charge the batteries until 100% SOC. To verify the proposed algorithm in a typical charging condition, experimental data of various charging ranges were used. The estimation result of $R_{f}$ in Table 2 was obtained from the data (3.45 V to 4.20 V) for fully charging the battery which had 0% SOC initially. The charging data consisting of various initial or final terminal voltages of the batteries were used to detect the soft ISCr, and the $R_{f}$s and their relative errors are summarized in Table 3. The different charging range changes the number of both the selected SOC($p$)s and the estimated $R_{end}$s to calculate the $R_{f}$. Thus, the estimation results of $R_{f}$ varied depending on the various charging ranges because the SOC($p$) with either high or low similarity can be included or excluded in accordance with the charging ranges. In addition, when the final terminal voltage is 3.909 V, the relative errors of $R_{f}$s increased largely because the $\Delta SOC$ was not large enough to decrease the effect of errors of the SOC($p$)s; this means that the enough time required for the estimated $R_{ISCr}$s to approach the true resistances was not given in case of the SOC($p$) with low similarity. However, the relative errors of $R_{f}$s do not exceed 14.7350%, and it is noted that by using the $R_{f}$ as the final fault index, the soft ISCr faults can be classified relative to each other and reliably detected under the various charging ranges.

D. PRACTICABILITY OF THE PROPOSED METHOD FOR BATTERY AGING AND TEMPERATURE

When the battery is degraded by calender and cycle aging, main aging phenomena, such as an increase in the $R_{0}$ and a change in the OCV-SOC curve, are observed [42], [43]. Additionally, the batteries in the EV and the portable IT devices are used under various ambient temperatures, and the model parameters of the battery are changed by the temperatures [44]. Thus, to estimate accurate SOC and detect the
ISCr for aged batteries and various temperatures, the novel OCV-SOC curve, which is appropriate for both aging and temperature conditions, must be updated. After conducting battery aging test and experiments under various temperatures, the novel curves can be obtained with normal charging data and capacity data which are changed by the two factors. Then, the proposed method can be applied to aged batteries and different temperature conditions. The researches related about aging and temperature remain as future work.
the soft ISCr, the proposed algorithm can be broadly applied to the BMS. The ECM of the battery with ISCr is used to cal-
ticate the OCV with constant currents and terminal voltages. Subsequently, the SOC is obtained using the novel estimated
OCV-SOC curve, which is extracted from normal data of the battery, as opposed to the experimental curve, thereby leading
to increase in the estimation accuracy of the SOC. To detect
battery, as opposed to the experimental curve, thereby leading
to increase in the estimation accuracy of the SOC. To detect
the soft ISCr, the $R_{ISCr}$ is estimated with the obtained SOCs as a promising fault index indicating the level of ISCr fault.
The ECM is updated with the estimated $R_{ISCr}$ to increase the estimation accuracy of OCV and SOC. To improve estimation accuracy of the $R_{ISCr}$ and obtain the reliable final fault index, the two factors affecting the $R_{ISCr}$ are considered after analyzing the cause of the error in the estimated $R_{ISCr}$. With respect to various soft ISCr conditions ($R_{ISCr} \leq 100$ Ω) in the experiment, the proposed method is verified and detects the soft ISCr with a significantly high accuracy of the final fault index ($\geq 93.6\%$); the detection results were obtained with the experimental data (3.45 V to 4.20 V) for fully charging the battery which had 0% SOC initially. Additionally, for the various charging ranges (3.575 V to 4.20 V, 3.709 V to 4.20 V, 3.839 V to 4.20 V, 3.45 V to 4.038 V, 3.45 V to 3.909 V, and 3.592 V to 4.012 V), the soft ISCr is detected reliably ($\geq 85.2\%$); this means that the constraint of requiring the fully charging data was overcome. Thus, early detection of an ISCr with the proposed algorithm prevents thermal runaway with fire and explosion in the batteries. Furthermore, a user can obtain sufficient time to safely cope with the hard ISCr. A future study will focus on extending the availability of the proposed method to batteries under diverse aging and temperatures and to experimental conditions such as wide fault range and fast battery charging.

### V. CONCLUSION

In the study, a model-based method to detect a soft ISCr in lithium-ion batteries is introduced. Detection of the soft ISCr is difficult when load currents satisfying the persistent excitation are not applied to the existing model-based methods. It is not always possible to discharge the batteries in applications with the particular load currents. However, most batteries are charged with constant currents for standard charging. Therefore, by using the constant current to detect the soft ISCr, the proposed algorithm can be broadly applied to the BMS. The ECM of the battery with ISCr is used to calculate the OCV with constant currents and terminal voltages. Subsequently, the SOC is obtained using the novel estimated OCV-SOC curve, which is extracted from normal data of the battery, as opposed to the experimental curve, thereby leading to increase in the estimation accuracy of the SOC. To detect the soft ISCr, the $R_{ISCr}$ is estimated with the obtained SOCs

### E. EFFECT OF CHARGING CURRENT C-RATE ON THE PROPOSED METHOD

Although the tested batteries were charged with the standard charging current (C/2) based on the data sheet, the batteries can be charged with various charging currents. According to magnitude of the charging current, ratio of the self-discharge current to the charging current is changed, for e.g. if the $R_{ISCr}$ is 49.91 Ω (the self-discharge current is C/34), the ratio is 6% for the standard charging current, whereas the ratios correspond to 12% and 3% for a slow charging current (C/4) and a fast charging current (1C), respectively. Therefore, increase in the ratio can increase the accuracy of $R_f$, whereas decrease in the ratio can decrease the accuracy of $R_f$. An additional experiment with a new battery (2.8450 Ah) and the $R_{ISCr}$ (49.91 Ω) was conducted using the fast charging current. The obtained $R_f$ and the relative error corresponded to 42.9653 Ω and 13.9144%, respectively; this means that the estimation result can be slightly changed by magnitude of the charging current. The research to improve accuracy of the $R_f$ under the fast charging condition will continue as future work.
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