Article

Online Cell Screening Algorithm for Maximum Peak Current Estimation of a Lithium-Ion Battery Pack for Electric Vehicles

Tae-Won Noh ¹, Junghoon Ahn ² and Byoung Kuk Lee ^{1,*}

¹ Department of Electrical and Computer Engineering, Sungkyunkwan University, Suwon 16419, Korea; no6338@skku.edu

² Energy Convergence Research Center, Korea Electronics Technology Institute (KETI), Gwangju 61011, Korea; jhahn@keti.re.kr

* Correspondence: bkleskku@skku.edu; Tel.: +82-31-299-4581

Abstract: In this study, an online cell screening algorithm is proposed to estimate the maximum peak current considering the cell inconsistencies in battery packs for electric vehicles. Based on the equivalent circuit model, the maximum peak current is mathematically defined, and the inconsistency parameters affecting the maximum peak current are analyzed. The proposed algorithm compares the inconsistency parameters of each cell and subsequently selects a cell or a group of cells whose voltage can exceed the allowable voltage range. The maximum peak current is determined based on the selected cells, while ensuring that all the cells are charged and discharged within the allowable voltage range. The feasibility and superiority of the proposed algorithm are verified through an experiment conducted on a commercially manufactured battery pack for electric vehicles.

Keywords: battery management system; maximum peak current estimation; cell inconsistency

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1. Introduction

Lithium-ion batteries mounted in electric vehicles (EVs) operate under conditions more severe than those of other industrial applications. In particular, an instantaneous peak current is frequently generated because of the gradient climbing, rapid acceleration, and regenerative braking, causing the terminal voltage to exceed the allowable range. This problem leads to performance degradation and safety issues, such as the internal short and thermal runaway. Therefore, the battery management system (BMS) must estimate the maximum peak current of the battery pack in real time, and control a terminal current lower than the estimated value to manage the terminal voltage within the allowable range.

For this purpose, various studies have proposed online estimation algorithms for maximum peak current estimation [1–14]. In particular, Z. Wei et al. [15] compensated and attenuated the inevitable noise effect on the maximum peak current estimation. However, these studies cannot be directly applied in practical EVs because their battery packs typically consist of hundreds of cells in series with different maximum peak currents. Maximum peak currents vary due to cell inconsistencies, such as temperature, state-of-charge (SOC), state-of-health (SOH), terminal voltages, current capacities, and internal resistances because of the manufacturing process; these inconsistencies are aggravated during driving operations [16–19]. If the maximum peak current is determined without considering these cell inconsistencies, the terminal voltage of any cell can exceed its allowable voltage range.

To circumvent this problem, a direct method to estimate the cell parameter and the maximum peak current of each cell in real time was proposed [20]. However, this method is not desirable for implementation in EVs because of the computational burden involved with using a battery pack with hundreds of cells. The most common method to reduce the computational burden is to extract the maximum peak current experimentally under various SOC, SOH, and temperature conditions, and then compile the experimental

data into look-up tables. However, numerous experiments are required, and the cell inconsistencies generated during driving cannot be considered.

Therefore, effective online cell screening algorithms have been recently studied [21,22]. The main idea is to select the weakest cell or group of cells whose voltage can exceed the allowable voltage range because of the instantaneous peak current. Zhou et al. [21] selected two cells with the largest internal resistance and the highest voltage (or the lowest voltage), and Waag et al. [22] additionally selected the cells by comparing the inconsistencies in the open circuit voltage (OCV). However, it cannot be confirmed if the weakest cell has been included in the screening results of [21] or [22], because the maximum peak current is simultaneously affected by various parameters, such as internal resistance, terminal voltage, and current capacity. Moreover, these methods do not consider the inconsistency of the current capacity related to the maximum peak current, and the experimental verifications in [20–22] have been performed by connecting four to ten cells in series, which are insufficient to verify the feasibility of these methods in EVs.

Therefore, this study proposes an online cell screening algorithm that outperforms conventional algorithms in the following aspects: first, the cell parameters that affect the maximum peak current were mathematically and experimentally analyzed based on the equivalent circuit model; second, the proposed algorithm ensures the inclusion of the weakest cell in the screening results by simultaneously considering the inconsistency in the current capacity, internal resistance, and terminal voltage; third, an actual EV battery pack, with 110 cells in series, was used to verify the feasibility of the proposed algorithms, and the computational time was evaluated to validate the complexity reduction effect compared to that of the direct method for estimating the maximum peak current of all of the cells.

This study unifies and extends our previous research [23] by introducing the improved algorithm consisting of two processes that can preliminarily exclude the cells with a sufficient voltage margin compared to the upper or lower limit value. This study furthermore provides additional details and quantitative evaluations based on experimental results of the cell inconsistencies, cell screening performance, and comparisons with an existing method. The remainder of this paper is organized as follows. Section 2 provides a mathematical analysis to derive the maximum peak current and cell parameters that should be considered for cell screening. The detailed operating principles of the proposed cell screening algorithms are described in Section 3. In Section 4, the feasibility and superiority of the proposed algorithms are validated through experiments on a commercially available lithium-ion battery pack for EVs. Finally, Section 5 concludes the paper.

2. Analysis of Inconsistencies of Cell Parameters

As shown in Figure 1a,b, the maximum peak current is defined as a constant current for 10 s, making the terminal voltage (v_t) reach an upper or lower limit value (V_{upper} or V_{lower}) [23]. The time interval ($\Delta t = 10$ s) was determined considering that the instantaneous peak current generated during gradient climbing, rapid acceleration, and regenerative braking is generally shorter than 10 s [23,24].

Figure 1. Conceptual depiction of the maximum peak current: (a) I_{max}^{cha} ; (b) I_{max}^{dch} .

The maximum peak current is estimated based on an equivalent circuit model (ECM) consisting of an OCV and a diffusion resistance (R_s) based on the voltage drop for 1 s, as shown in Figure 2 [25]. In plenty of literature, n-th order resistor–capacitor (RC) model

was used to accurately simulate the polarization effects [10,24,26,27]. However, as the time scale of the polarization voltage is significantly longer than 10 s, RC networks can be neglected to estimate the maximum peak current. Based on the voltage equation of the ECM, v_t after applying the maximum peak current for charging ($I_{\max}^{\text{cha}}$) is derived as follows:

$$v_t(t + \Delta t) = V_{\text{upper}} = v_t(t) + \Delta \text{OCV}(t) + \Delta v_s(t), \quad (1)$$

where ΔOCV is the change in the OCV and Δv_s is the change in the voltage across R_s by $I_{\max}^{\text{cha}}$, respectively. ΔOCV can be calculated as follows:

$$\Delta \text{OCV}(t) = \frac{\partial \text{OCV}(\text{SOC}(t))}{\partial \text{SOC}} \times \left\{ -I_{\max}^{\text{cha}} \frac{\Delta t}{C_{\text{Ah}}} \times \frac{100\%}{3600\text{s/h}} \right\}, \quad (2)$$

where C_{Ah} is the current capacity, and $\partial \text{OCV}/\partial \text{SOC}$ is determined on the basis of an SOC-to-OCV look-up table, as shown in Figure 3a,b.

Figure 2. Equivalent circuit model for a lithium-ion battery.

Figure 3. Look-up tables for calculating (2): (a) SOC-to-OCV; (b) SOC-to- $\partial \text{OCV}/\partial \text{SOC}$.

The SOC-to-OCV curve can be divided into two sections based on the tendency of $\partial \text{OCV}/\partial \text{SOC}$, and the maximum value of $\partial \text{OCV}/\partial \text{SOC}$ in each section is used to calculate ΔOCV in Equation (2). Δv_s is calculated using Ohm's law, as follows:

$$\Delta v_s(t) = i_t(t)R_s(t) - I_{\max}^{\text{cha}}R_s(t + \Delta t) \approx i_t(t)R_s(t) - I_{\max}^{\text{cha}}R_s(t), \quad (3)$$

where i_t is the terminal current and the change in R_s is neglected because of short Δt . Rearranging Equation (1) using Equations (2) and (3), $I_{\max}^{\text{cha}}$ is obtained as follows:

$$I_{\max}^{\text{cha}}(t) = \frac{i_t(t)R_s(t) + v_t(t) - V_{\text{upper}}}{\frac{\partial \text{OCV}(\text{SOC}(t))}{\partial \text{SOC}} \cdot \frac{\Delta t}{C_{\text{Ah}}} \cdot \frac{100\%}{3600\text{s/h}} + R_s(t)}, \quad (4)$$

The maximum peak current for discharging ($I_{\max}^{\text{dch}}$) can be derived by substituting V_{upper} in Equation (4) by V_{lower} as follows:

$$I_{\max}^{\text{dch}}(t) = \frac{i_t(t)R_s(t) + v_t(t) - V_{\text{lower}}}{\frac{\partial \text{OCV}(\text{SOC}(t))}{\partial \text{SOC}} \cdot \frac{\Delta t}{C_{\text{Ah}}} \cdot \frac{100\%}{3600\text{s/h}} + R_s(t)}, \quad (5)$$

As can be seen in Equations (4) and (5), as the maximum peak current is dependent on C_{Ah} , R_s , and v_t , the inconsistency of these parameters leads to the deviation in the maximum peak current. For further analysis, an experiment was performed to charge a battery pack consisting of 110 cells (B_1 – B_{110}) with a new European driving cycle (NEDC) profile, and the I_{max}^{cha} of each cell was calculated using Equation (4), as shown in Figure 4. The characteristics of the battery pack and the identification results of the cell parameters are detailed in Section 4. As can be seen in the experimental results, the cells have the different values of I_{max}^{cha} due to the inconsistencies, and the weakest cell with the minimum magnitude of I_{max}^{cha} varied unpredictably while the NEDC profile was applied.

Figure 4. Experiment results of i_t , v_t , and I_{max}^{cha} of all cells while the battery pack with cell inconsistency is charged with NEDC.

For example, as shown in Figure 5, B_{106} is the weakest cell at 521.0 s, even though it is not the cell with the highest v_t , the largest R_s , or the smallest C_{Ah} . The main reason for this behavior is that C_{Ah} , R_s , and v_t affect the maximum peak current simultaneously, and the dominant parameter is variable based on the tendency of the inconsistencies. Therefore, the screening methods to simply select a cell with the weakest C_{Ah} , R_s , and v_t may fail to accurately screen for the estimation of the maximum peak current. Thus, an online cell screening algorithm that can comprehensively consider these parameters is required.

Figure 5. Enlarged waveform of I_{max}^{cha} and the inconsistency of v_t , R_s , and C_{Ah} at a time point of 521.0 s.

3. Methodology of Proposed Online Cell Screening Algorithm

Figure 6 represents the scheme of the proposed online cell screening algorithm. The parameters required in the proposed algorithm are assumed to be provided as follows: i_t

and v_t are on-board measurement parameters, and R_s is calculated as the ohmic relation between the change in i_t and v_t [28–34]; C_{Ah} is obtained through the online SOH estimation algorithm as described in [35–38]. OCV is obtained by feeding the online SOC estimation results into the SOC-to-OCV look-up table [39–48]. In this section, the operating principle of the proposed algorithm is described based on I_{max}^{cha} , and the same principle can be applied to online cell screening for I_{max}^{dch} .

Figure 6. Scheme of the proposed online cell screening algorithm.

3.1. First Screening through Threshold Voltage

Typically, lithium-ion batteries have a rated peak current (I_{rated}^{cha}) for safe operation, and the magnitude of I_{max}^{cha} should be lower than I_{rated}^{cha} . Thus, $v_t(t + \Delta t)$ in (1) has a maximum value when I_{rated}^{cha} is applied, as follows:

$$\max\{v_t(t + \Delta t)\} = v_t(t) + \Delta OCV(t)|_{I_{rated}^{cha}} + \Delta v_s(t)|_{I_{rated}^{cha}}, \quad (6)$$

If $\max\{v_t(t + \Delta t)\}$ calculated by Equation (6) is lower than V_{upper} , as follows:

$$\max\{v_t(t + \Delta t)\} \leq V_{upper}, \quad (7)$$

then the cell can be excluded from the I_{max}^{cha} estimation, and I_{max}^{cha} is determined as I_{rated}^{cha} without additional screening. However, a large computational burden is inevitable because each cell in the battery pack must be checked based on whether it satisfies Equation (7).

Thus, a threshold voltage ($V_{threshold}$) is defined to determine the cells to be excluded by simply comparing v_t with $V_{threshold}$. Furthermore, $V_{threshold}$ can be calculated by rearranging Equation (6) as follows:

$$v_t(t) < V_{threshold} = V_{upper} - \max\{\Delta v_s(t)\} - \max\{\Delta OCV(t)\}, \quad (8)$$

where

$$\max\{\Delta v_s(t)\} = I_{rated}^{cha} \cdot \max\{R_s(t)\} - i_t(t) \cdot \min\{R_s(t)\}, \quad (9)$$

and

$$\max\{\Delta OCV(t)\} = -I_{rated}^{cha} \cdot \frac{\Delta t}{\min(C_{Ah})} \cdot \frac{\partial OCV(SOC(t))}{\partial SOC}, \quad (10)$$

where $\max\{R_s(t)\}$, $\min\{R_s(t)\}$, and $\min(C_{Ah})$ are the maximum or minimum values of each parameter among all cells in the battery pack. Considering that every cell has a different

SOC because of the inconsistency in C_{Ah} , the $\partial OCV/\partial SOC$ in Equation (10) is determined as shown in Figure 3b, which can be expressed as follows:

$$\frac{\partial OCV(SOC(t))}{\partial SOC} = \begin{cases} \left. \frac{\partial OCV}{\partial SOC} \right|_{\max}^{\text{section1}}, & SOC_{\min} \leq SOC_{\max} < 20\% \\ \left. \frac{\partial OCV}{\partial SOC} \right|_{\max}^{\text{section1}}, & SOC_{\min} \leq 20\% < SOC_{\max} \\ \left. \frac{\partial OCV}{\partial SOC} \right|_{\max}^{\text{section2}}, & 20\% \leq SOC_{\max} < SOC_{\min} \end{cases}, \quad (11)$$

where $SOC_{\min}$ and $SOC_{\max}$ are the minimum and maximum SOC values among the cells, respectively.

Figure 7a shows the calculation results of $V_{\text{threshold}}$ based on the experimental results in Figure 4. The screening results through $V_{\text{threshold}}$ can be divided into two sections. During t_1 , all the cells are excluded, as shown in Figure 7b, because all the cells satisfy the condition in Equation (8). Therefore, $I_{\max}^{\text{cha}}$ of the battery pack was determined as $I_{\text{rated}}^{\text{cha}}$ without the second screening process. In contrast, the voltage of some or all cells started to exceed $V_{\text{threshold}}$ during t_2 , as shown in Figure 7c,d. Therefore, these cells were screened through the second screening process, as described in the following sections.

Figure 7. First screening results through $V_{\text{threshold}}$: (a) calculation results of $V_{\text{threshold}}$ and comparison with terminal voltages of the cells; (b) screening results at 150.0 s; (c) screening results at 361.5 s; (d) screening results at 521.0 s.

3.2. Second Screening and Determination of the Maximum Peak Current

To simply describe the operating principle of the second screening process, eight cells (B_A – B_H) were arbitrarily selected from Figure 7d, and the cell parameters are listed in Table 1.

Table 1. Cell parameters of B_A – B_H .

	B_A	B_B	B_C	B_D	B_E	B_F	B_G	B_H
Cell number [–]	3	26	58	72	88	96	105	106
C_{Ah} [Ah]	80.61	80.54	80.43	79.08	79.44	80.00	79.40	79.63
R_s [mΩ]	0.559	0.591	0.555	0.559	0.568	0.629	0.600	0.609
v_t [V]	4.098	4.103	4.097	4.109	4.104	4.105	4.111	4.110
$I_{\max}^{\text{cha}}$ [A]	−264.71	−198.48	−237.95	−214.45	−225.52	−189.86	−197.18	−180.94

The screening result should include B_H , which has a minimum magnitude of $I_{\max}^{\text{cha}}$. The second screening selects a cell or group of cells through the following steps, as visually illustrated in Figure 8.

- step. 1: The cells are arranged in ascending order of C_{Ah} and descending order of R_s and v_t . These orders indicate that battery cells arranged on the left side have a higher probability of exceeding V_{upper} according to the correlation of C_{Ah} , R_s , and v_t with $I_{\max}^{\text{cha}}$ in Equation (4).
- step. 2: Select the cell with the smallest C_{Ah} (B_D).
- step. 3: Find the cells with smaller R_s or lower v_t values than those of the cells selected in Step 2.
- step. 4: Exclude the cells commonly found in Step 3 from the $I_{\max}^{\text{cha}}$ estimation.
- step. 5: Select the largest R_s cell and the highest v_t cell (B_F and B_G) and repeat the same process in Step 3 and Step 4, respectively.
- step. 6: Select the remaining cells after Step 2–Step 5 as $I_{\max}^{\text{cha}}$ calculation targets.

Figure 8. Operating principle of the second screening process according to Steps 1–6.

The $I_{\max}^{\text{cha}}$ of the cells selected in Step 6 are calculated, and the final $I_{\max}^{\text{cha}}$ of the battery pack is determined as the minimum magnitude (B_H). Thus, the proposed algorithm can manage all the cells, such that V_{upper} is not exceeded without an additional output restriction, and it can reduce the complexity because $I_{\max}^{\text{cha}}$ is calculated only for the selected cells.

4. Experiment Discussion and Verification Results

4.1. Tested Battery Pack and Experiment Setup

The experimental verification was performed using a nickel manganese cobalt oxide (NMC)-type battery pack commercially used for EVs. The battery pack consisted of 110 cells in series, and the basic characteristics of the cell are listed in Table 2.

Table 2. Specifications of the battery cell in the tested pack.

Contents	Value
Type [–]	NMC
Nominal voltage [V]	3.7
Voltage range [V]	2.7–4.2
Current capacity at begin of life [Ah]	90.5
Rated peak current for charging ($I_{\text{rated}}^{\text{cha}}$) [A]	–200
Rated peak current for discharging ($I_{\text{rated}}^{\text{dch}}$) [A]	400

This battery pack was used as the main energy source for EVs until the SOH reached 89% (the end of life was 80%). OCV and $\partial\text{OCV}/\partial\text{SOC}$ are shown in Figure 3a,b, and the identification results of C_{Ah} and R_s are presented in Figure 9a,b. C_{Ah} was measured through a fully charging and discharging experiment at 0.3 C, and OCV and R_s were extracted by repeating a discharge at 0.3 C to reduce the SOC by 5% and relaxation for 4 h to reach equilibrium [24]. C_{Ah} and R_s have inconsistencies that make $I_{\text{max}}^{\text{cha}}$ and $I_{\text{max}}^{\text{dch}}$ of every cell different from each other.

Figure 9. Identification results of the cell parameters: (a) C_{Ah} and (b) R_s .

Figure 10 presents the experimental setup for the verification of the proposed algorithm. The proposed algorithm was implemented using MATLAB Simulink and loaded into MicroAutoBox. MicroAutoBox measures the i_t and v_t of each cell in real time and uses these measured data for online screening and maximum peak current estimation. The cell parameters required in the proposed algorithm are obtained as follows: R_s is calculated in real-time using the relation between the change in i_t and v_t ; the method in [46] was implemented to estimate the SOC of each cell. The output current of the battery cyler is controlled such that the maximum peak current estimated form the MicroAutoBox was not exceeded.

Figure 10. Experimental setup.

4.2. Experimental Results of the Proposed Algorithm

The feasibility of the proposed algorithm was verified based on $I_{\max}^{\text{cha}}$, and the battery pack was charged from an initial SOC of 25% by repeatedly applying the NEDC profiles at room temperature (25 °C). The experiment was stopped if the battery pack was charged to an SOC of 95% or if the voltage of one of the 110 cells reached V_{upper} (4.2 V). To further verify the proposed algorithms, an experiment for a counterpart that used the average values of C_{Ah} , R_s , and v_t without considering the cell inconsistencies was performed, as shown in Figure 11a. The experiment was stopped when the battery pack was charged to an SOC of 85.3%, because one of the v_t in the battery cells reached V_{upper} , as shown in Figure 11b.

Figure 11. Experimental results for the counterpart (neglecting cell inconsistencies): (a) i_t , v_t , and SOC; (b) the enlarged v_t of the cells during 1070.0–1150.0 s.

This result indicates that all cells have different $I_{\max}^{\text{cha}}$ because of cell inconsistencies, and these inconsistencies should be considered to manage v_t within the allowable range.

In contrast, as shown in Figure 12a,b, the proposed algorithm can manage all the cells such that they are charged in the allowable voltage range, and the battery pack was charged to an SOC of 95%. For the first screening, $V_{\text{threshold}}$ was calculated in real time and the calculation results are plotted in Figure 12a using a red line. As shown in Figure 13a, the first screening excluded all the cells from 0–537.8 s, because $V_{\text{threshold}}$ was larger than v_t of all the cells. Therefore, $I_{\text{max}}^{\text{cha}}$ of the battery pack was determined to be $I_{\text{rated}}^{\text{cha}}$ (−200 A) without the second screening. After 537.8 s, some or all cells had v_t greater than $V_{\text{threshold}}$, and the second screening was performed on these cells. Consequently, the proposed algorithm selected a few cells, as shown in Figure 13b, where the maximum and average numbers of cells were 10 and 2.18 cells, respectively.

Figure 12. Experimental results for the counterpart (neglecting cell inconsistencies): (a) i_t , v_t , and SOC; (b) the enlarged v_t of the cells during 1070.0–1150.0 s.

Figure 13. Total number of cells selected by the proposed algorithm: (a) at first screening and (b) at second screening.

The accuracy of the proposed algorithm was verified by comparing the values of $I_{\text{max}}^{\text{cha}}$ estimated in this study to those of the weakest cell. As shown in Figure 14a,b, the estimation results of $I_{\text{max}}^{\text{cha}}$ was accurately equal to the minimum magnitude among the cells. Thus, the screening results of the proposed algorithm ensure that the weakest cell is included.

Figure 14. Comparison results of $I_{\max}^{\text{cha}}$ between each cell and the proposed algorithm: (a) at the time interval from 0–1500.0 s and (b) the enlarged waveform from 1100.0–1300.0 s.

4.3. Comparison of Screening Results with an Existing Method

The screening performance of the proposed algorithm was compared to the existing method in [21], which selects two cells with the largest R_s and the highest v_t (or the lowest v_t for $I_{\max}^{\text{dch}}$). As shown in Figure 15a, the existing method cannot ensure to include the weakest cell in the screening results. The main reason for this problem is that $I_{\max}^{\text{cha}}$ is affected by R_s , v_t , and C_{Ah} , simultaneously, but the existing method simply considers only R_s and v_t separately. In contrast, the proposed algorithm always includes the weakest cell, as shown in Figure 15b, and it is significantly superior to manage all the cells within the allowable voltage range.

Figure 15. The cell number selected by the screening algorithm in the time interval of 1100.0–1300.0 s: (a) based on the existing method in [21] and (b) based on the proposed algorithm.

As seen in the results, the magnitude of $I_{\max}^{\text{cha}}$ estimated by the existing method is larger than that of the proposed algorithm, as shown in Figure 16a,b, where the numerical difference between two methods ($\Delta I_{\max}^{\text{cha}}$) is calculated as follows:

$$\Delta I_{\max}^{\text{cha}}(t) = I_{\max}^{\text{cha}} \Big|_{\text{by proposed}} - I_{\max}^{\text{cha}} \Big|_{\text{by existing}}, \quad (12)$$

To verify the complexity reduction effect, the computational times of the existing method and the proposed algorithm were evaluated using MicoAutobox II-1401 with IBM PPC 750GL, as shown in Table 3. The computational time was compared with that of the direct method, which estimated $I_{\max}^{\text{cha}}$ of each cell and selected the minimum magnitude value. These results include the online screening process and $I_{\max}^{\text{cha}}$ calculation. Although the existing method has a lower complexity than the proposed algorithm, it cannot ensure that the weakest cell is always included in the two selected cells. When compared to the direct method, the proposed algorithm reduces the complexity by 56.95–63.31% while screening the weakest cell accurately.

Figure 16. Comparison results of $I_{\max}^{\text{cha}}$ between the proposed algorithm and the existing method in [21]: (a) the estimation results of $I_{\max}^{\text{cha}}$; (b) the numerical difference of $I_{\max}^{\text{cha}}$ between the proposed algorithm and existing method in the time interval of 1100.0–1300.0 s.

Table 3. Evaluation results of the computational times.

Contents	Direct Method	Existing Method	Proposed Method
Number of selected cells [ea]	110	2	5–10 (variable)
Computational time [us]	248.60 (100%)	81.02 (32.59%)	141.58–157.40 (56.95–63.31%)

5. Conclusions

This study proposed an online cell screening algorithm to estimate the maximum peak current of a battery pack, considering cell inconsistencies as a critical factor. The proposed algorithm screens a small number of battery cells by comprehensively comparing the parameters affecting the maximum peak current. The screening results must include a cell with the minimum value of the maximum peak current. The feasibility and robustness of the algorithm were experimentally verified using a battery pack consisting of 110 cells. The experimental results demonstrated that the proposed algorithms managed all cells within the allowable voltage range until the cell was charged to an SOC of 95%. Furthermore, the proposed algorithm screened 5–10 cells in the battery pack, which corresponded to 4.5–9.1% of the total number of cells. The maximum peak current was calculated only for the screened cells, significantly reducing the complexity by 56.95% compared to that of the direct method of estimating the maximum peak current of each cell. The proposed algorithm can effectively screen the weakest cell in the battery pack with a high accuracy and robustness, and is suitable for estimating the maximum peak current in practical EVs. In our future works, the online identification methods for cell parameters will be investigated and combined with the proposed algorithm to reflect the influence of the temperature variation. Moreover, to the proposed algorithm will be extended for online cell screening in the parallel-connected battery packs.

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