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Research of the peak current in lithium-ion battery application with AI

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ABSTRACT

In this paper, the maximum charging or discharging current that the lithium-ion battery can withstand within safe voltage constraints, i.e., the peak current is researched. The equivalent circuit model is employed to describe battery dynamic. Three model parameter identifying methods are discussed to evaluate its influence on the peak current calculation. Results show that the parameter accuracy of both the offline and online methods is far lower than that of the optimization method. Moreover, the artificial intelligence is adopted to accelerate the prediction of peak current. The mean absolute percentage error of prediction results is only 0.373% and 1.447% for charging and discharging process, indicating its validity and practicability.

Keywords: lithium-ion battery, peak current, parameter identifying, artificial intelligence

NONMENCLATURE

Abbreviations	
AI	Artificial Intelligence
ECM	Equivalent circuit model
EV	Electric Vehicle
HPPC	Hybrid Pulse Power Characterization
IEA	International Energy Agency
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
RLS	Recursive Least Square
RW	Random Walk
RMSE	Root Mean Square Error
SOC	State of Charge
SOP	State of Power
SQP	Sequential Quadratic Programming

Symbols	
C_D	Polarization capacitance
i_L	Loading current
R_D	Polarization resistance
R_i	Resistor
U_t	Terminal voltage
U_{oc}	Open circuit voltage

1. INTRODUCTION

With the increasing awareness of environmental protection, carbon emission and neutrality have drawn many attentions in recent years, becoming a global focus [1]. The transport industry, e.g. vehicle is responsible for nearly a quarter of worldwide greenhouse gas emissions according to International Energy Agency (IEA) in 2018 [2]. Replacing the internal-combustion vehicles with electric vehicles (EVs) is forefront option, commented by IEA as one of the few technologies on track under the sustainable development scenario [3]. As one of the most important components in EV system, the effective monitoring and management of battery is of great concerns to manufacturers and customers, especially the peak current that battery can bear within a safe range. The peak current not only provide reference for maximum available power calculation and fast charging strategy formulation, but also instruct the safety operation of battery during charging and discharging process. Therefore, the accuracy assessing of peak current is of great importance to EV operation, which is also the basis of state of power (SOP) estimation [4][5].

1.1 Review of the peak current estimation

The commonly used peak current calculation method is hybrid pulse power characterization (HPPC) method, yielding low accuracy because of the adoption of Rint battery model [6]. [7] proposed peak current estimation based on SOC constraint. Although this method is capable of describing the charging and discharging process of the battery, the calculated peak current is often larger when the SOC span increases. Methods based on voltage constraint and multiple constraints are also reported in references [7][8] with details. However, these methods have not considered the influences of battery dynamic and model parameters. As a result, the estimation accuracy is not reliable enough. Therefore, in this paper, three parameter identifying methods, i.e., offline method, online method and optimization method are discussed to evaluate its influence on peak current calculation. Moreover, the artificial intelligence is employed to improve the calculation process, realizing the fast and accurate prediction of peak current.

1.2 Innovation

The key contributions of this paper are 1) exploring the effect of model parameters on the peak current calculation, 2) proposing the optimization method to improve calculation accuracy, 3) employing artificial intelligence algorithms to speed up the prediction of peak current.

1.3 Organization of the paper

Section 2 describes the data sources. Section 3 presents the influence of model parameter on estimation accuracy. The artificial intelligence algorithm used to improve calculation process is introduced in Section 4 while Section 5 gives conclusions and explores discussion.

2. DESCRIPTION OF DATA SOURCES

The data used in this paper was collected from the NASA Ames Prognostics Data Repository [9]. The test object is 18650 Li-ion batteries with upper and lower cut-off voltage of 4.2V and 3.2V. The battery was continuously cycled with randomly generated constant current (from -4.5A to 4.5A) referred as random walk (RW) step. Each RW step lasted for 5 minutes until the voltage reaches the limited upper and lower voltage, shown in Fig. 1.

Considering the characteristics of the data itself, method based on voltage constraints (explained in Section 3) is adopted to calculate the peak current. The criteria for peak current calculation are shown in Fig.2. It includes three cases, i.e., 5-minute case (Fig.2(a) and (d)), non-intersecting case (Fig.2(b) and (e)) and intersecting case (Fig.2(c) and (f)). In 5-minute case, the result is considered reliable as long as the calculated peak current is larger than the loading current during the RW step time. In non-intersecting case, the result is considered reliable if the difference between the calculated peak current and loading current is less than 0.1 A at the last sampling point. In intersecting case, it requires 1) the intersection time is no earlier than 5 seconds before the end time of RW step; 2) the difference between the calculated peak current and loading current is less than 0.1 A at the last sampling point. It's clear that the criteria for the peak current calculation in the case 2 and case 3 are more stringent. Therefore, in the following section, 325 RW steps less than 5 minutes (including 124 charge RW steps and 201 discharge RW steps) are taken as the research object. The peak current calculation results of those RW steps satisfying case 2 or 3 are considered accurate.

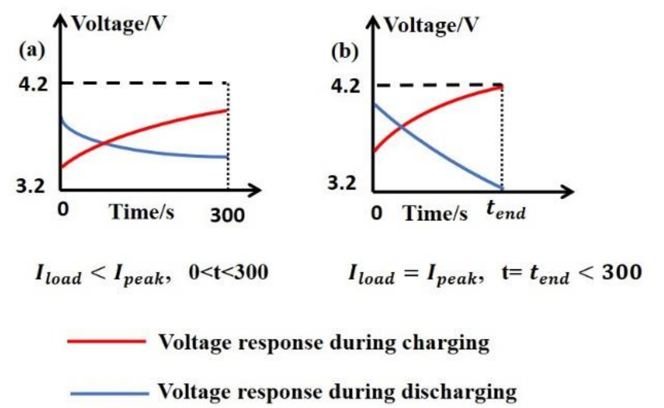

Fig. 1 The loading current and voltage response of battery during a RW step. (a) A complete RW step with 300s; (b) RW step with the cut-off voltage triggered in advance.

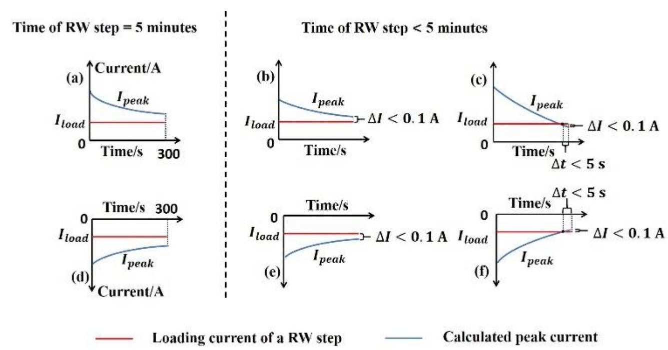

Fig. 2 The criteria for peak current calculation. (a-c) are the discharging RW steps; (d-f) are the charging RW steps.

3. RESEARCH OF THE PEAK CURRENT

Regarding the peak current calculation based on voltage constraints in a nonlinear battery system, method based on equivalent circuit model (ECM) is considered as the tradeoff between efficiency and complexity [10]. In this paper, a 1-RC equivalent circuit model is adapted to describe the battery dynamics shown in Fig. 3. The electrical behavior of the ECM can be expressed as follows:

$$\begin{cases} U_t = U_{oc} - U_D - R_i i_L \\ \dot{U}_D = \frac{i_L}{C_D} - \frac{U_D}{C_D R_D} \end{cases} \tag{1}$$

where R_i is the resistor describing the electrical ohmic resistance of ion movement, R_D is the polarization resistance and C_D is the polarization capacitance. RC combination branch can represent the transient response, i.e., polarization effect during charging and discharging. U_t is the terminal voltage and i_L is the loading current (positive for discharging and negative for charging). The U_{oc} represents the open circuit voltage of the battery, mainly determined by the SOC.

The discrete state-space equations of the equivalent circuit model can be further described as follows:

$$U_D(t+\Delta t) = e^{-\frac{\Delta t}{\tau}} U_D(t) + R_D(1 - e^{-\frac{\Delta t}{\tau}}) i_L(t) \tag{2}$$

Where t represents the sampling time, Δt is the sampling interval, $\tau = R_D C_D$.

Then, the calculation of peak current based on voltage constraint is expressed as follows:

$$\begin{cases} i_{max}^{dis} = \dfrac{U_{oc}[z(t)] - U_D(t) e^{-\frac{\Delta t}{\tau}} - U_{t,min}}{\frac{\eta \Delta t}{C_{max}} \frac{\partial U_{oc}(z)}{\partial z}\Big|_{z(t)} + R_D\left(1 - e^{-\frac{\Delta t}{\tau}}\right) + R_i} \\ i_{min}^{chg} = \dfrac{U_{oc}[z(t)] - U_D(t) e^{-\frac{\Delta t}{\tau}} - U_{t,max}}{\frac{\eta \Delta t}{C_{max}} \frac{\partial U_{oc}(z)}{\partial z}\Big|_{z(t)} + R_D\left(1 - e^{-\frac{\Delta t}{\tau}}\right) + R_i} \end{cases} \tag{3}$$

where i_{max}^{dis} and i_{min}^{chg} are the discharging and charging peak current at time t when cut-off voltage is triggered.

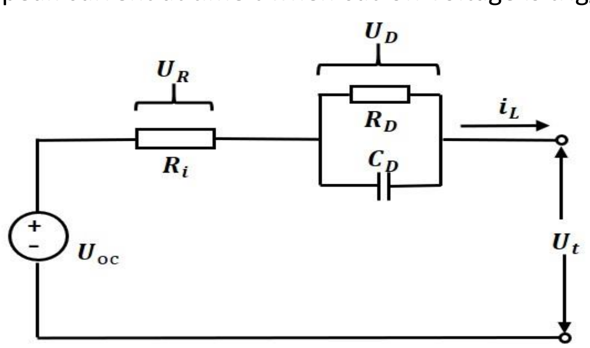

Fig.3 The 1-RC equivalent circuit model of lithium-ion battery

It's clear that the key element affecting the result of peak current calculation is the battery model parameter. In this paper, three different parameter identification methods, i.e., offline method, online method and optimization method are implemented to discuss its effect on peak current calculation result. As explained in section 2, the peak current calculation results of those RW steps satisfying case 2 or 3 are considered accurate. Count the number of accurate RW steps and divide by the total number 325 to get the overall accuracy, based on which the rationality and validity of these three parameter identification methods can be evaluated. If the overall accuracy of three methods are all lower than 90%, it indicates the key to invalidity is the approach of peak current calculation based on voltage constraint, not the model parameters. Otherwise, it's proven that the approach of peak current calculation based on voltage constraints is reasonable and the key to accuracy lies in model parameters. In this case, artificial intelligence algorithm can be further proposed to accelerate calculation and prediction rate. The research outline is shown in Fig. 4.

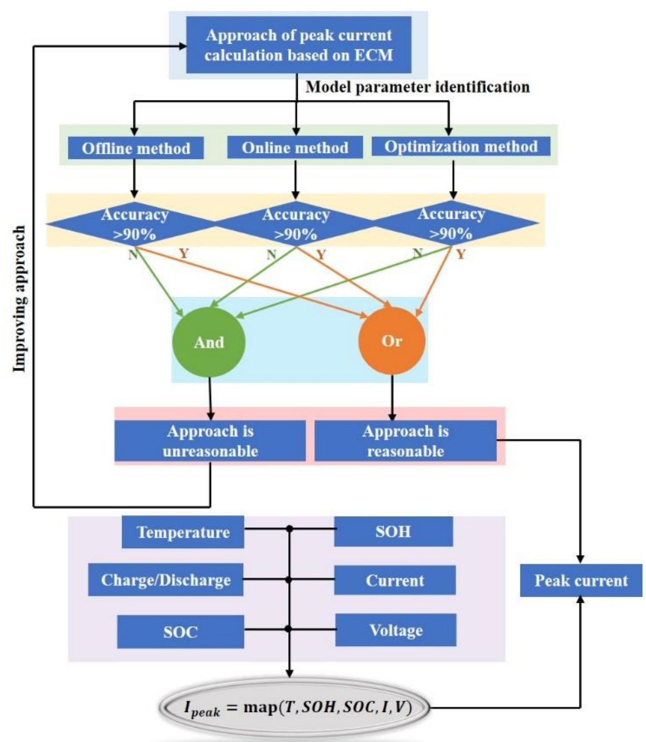

Fig. 4 The research outline of peak current calculation

3.1 Offline method

The U_{oc} is an important parameter in ECM, primarily determined by SOC. The relationship between U_{oc}-SOC can be calculated referred to [11], expressed as

Eq. (4). The remaining parameters, i.e., R_D, C_D and R_i are offline identified based on HPPC test, with more details described in [12].

Fig.5 (a) shows the voltage difference of RW steps with offline method. Each point represents the average of the difference between the calculated terminal voltage and the measured terminal voltage at all samplings in a single RW step. The voltage difference remains approximately 0.061V throughout 325 RW steps, indicating that the 1-RC equivalent circuit model can reflect the voltage dynamic of the battery. The calculated peak current of 325 RW steps satisfied case 2 or 3 is only 26 (including 10 charging RW steps and 16 discharging RW steps), with an overall accuracy of 8%. This result proves that the parameter identified through offline method is inaccuracy regarding the peak current calculation.

$$U_{oc} = a_0 + a_1 Z^1 + a_2 Z^2 + a_3 Z^3 + a_4 Z^4 + a_5 Z^5 + a_6 Z^6 + a_7 Z^7 \tag{4}$$

where $a_i, i = 1,2 \ldots \ldots 7$ are the fitting coefficients listed in Table 1 and Z represents the SOC.

Table 1. The fitting coefficients of the polynomial fitting of the $U_{oc} - SOC$.

Coefficient	Fitting Value	Coefficient	Fitting Value
a_0	3.339	a_4	-2.335×10^{-6}
a_1	0.061	a_5	2.461×10^{-8}
a_2	-0.004	a_6	-1.389×10^{-10}
a_3	1.268×10^{-4}	a_7	3.269×10^{-13}

3.2 Online method

Here, the recursive least squares (RLS) method is adopted to implement online parameter identification with algorithm details described in [13].

Fig.5 (b) shows that the voltage difference of 325 RW steps with online method approximately remain 0.060 V. The percentage of voltage different defined as Eq. (5). Comparing to offline method, the fluctuation of voltage difference has been improved but with larger minimum, resulting in no RW step satisfied case 2 or 3.

$$\text{Percentage of voltage difference} = \frac{|\alpha - \beta|}{\beta} \tag{5}$$

where α and β are the calculated terminal voltage and the measured terminal voltage respectively.

3.3 Optimization method

In this part, Sequential Quadratic Programming (SQP) is employed for optimizing model parameter. The objective function is formed as the voltage difference between measured terminal voltage and calculated terminal voltage, expressed as Eq. (6). The optimization is realized by adjusting parameters to minimize the objective function. The algorithm steps and more details can be found in [14].

$$\text{Minimize: } f(X) = \sum_{t=1}^{n} (V_{mea}^t - V_{cal}^t)^2 \tag{6}$$

where $X = [R_i, R_D, C_D]$, V_{mea}^t and V_{cal}^t are the measured and calculated terminal voltage at sampling time t.

From Fig. 5(c) and Table 2, it's clear that the voltage difference of 325 RW steps are greatly reduced. The number of RW steps satisfying case 2 or 3 is as high as 302 (including 124 charging RW steps and 178 discharging RW steps), and the overall accuracy reaches 92.9%.

Table 2. The voltage difference and overall accuracy comparison of three methods

	Minimum / V	Maximum / V	Mean / V	Overall accuracy
Offline	0.005	0.179	0.061	8%
Online	0.015	0.107	0.060	0%
Optimization	1.66×10^{-4}	0.096	1.6×10^{-3}	92.9%

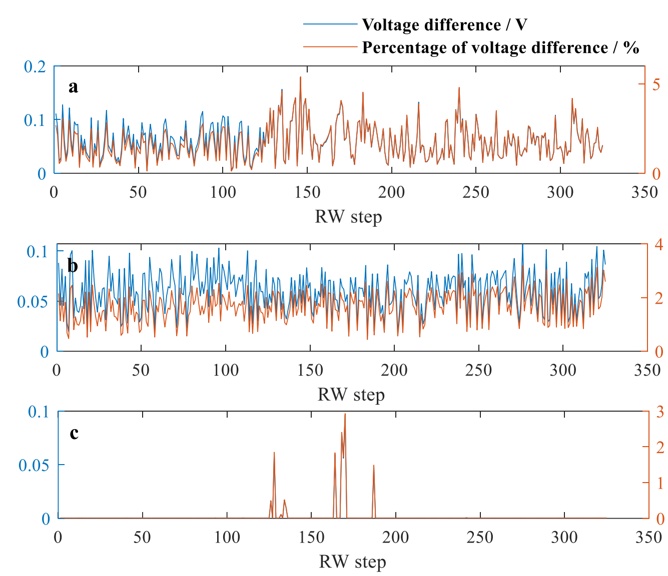

Fig.5 The average of the difference between calculated terminal voltage and measured terminal voltage. (a) Offline method; (b) Online method; (c) Optimization method

Comparing the overall accuracy based on three different parameter identification methods, the following conclusions could be inferred: 1) the approach based on voltage constraints can undoubtedly calculate the peak current as long as the battery model parameters are accurately identified. 2) the parameters identified through optimization method are more accurate than those calculated by the offline and online methods. 3) given the minimum value of voltage difference based on offline and online methods, as well as their overall accuracy, the model parameters should keep the voltage difference on the order of 0.001 to make it possible to calculate the peak current accurately.

4. PREDICTING PEAK CURRENT USING AI

Matlab 2019b was used in the optimization method running on Intel(R) Core (TM)i7-9700 CPU @ 3.00GHz with RAM 16.0GB. The average consuming time for each RW step in optimization is about one minute, greatly limiting the practical application of this method. In this section, artificial intelligence, i.e., LightGBM is chosen to establish the peak current prediction model so as to calculate the peak current quickly by feeding variables, e.g., voltage, current and SOC. LightGBM is an open-source implementation of a gradient boosting framework that uses a sequence of trees to solve classification or regression models [15].

The 124 charging RW steps and 178 discharging RW steps were divided into training set, verification set and test set, with the proportions of 60%, 20% and 20% respectively. The AI model employed here is trained based on LightGBM Python-package [16]. The consuming time for training, validation and prediction are less than one minute for 124 charging RW steps and 178 discharging RW steps. The information feed into LightGBM contains SOC, voltage, temperature, capacity and current. The output is the peak current of each sampling point. Fig. 6 shows the prediction result of the test set. The calculated peak current based on optimization method is considered as true value and the predicted peak current is the output of LightGBM model. The mean absolute error (MAE), root-mean-square error (RMSE) and mean absolute percentage error (MAPE) of peak current are listed in Table 3. As we can see, the predicted peak current of both charging and discharging test set can accurately track the true value. Moreover, the MAE, RMSE and MAPE of charging RW test set are all less than that of discharging RW test set, indicating the better training result of charging process in LightGBM model. The MAE of predicted peak current in charging and discharging test set are 0.056 A and 0.125 A, accounting for only 0.373% and 1.447% of true value respectively, which proves the potential utility of AI algorithm in future cloud computing application.

Table 3. The prediction error of test set in LightGBM

	MAE	RMSE	MAPE
Test set of charging RW steps	**0.056**	**0.095**	**0.373%**
Test set of discharging RW steps	**0.125**	**0.247**	**1.447%**

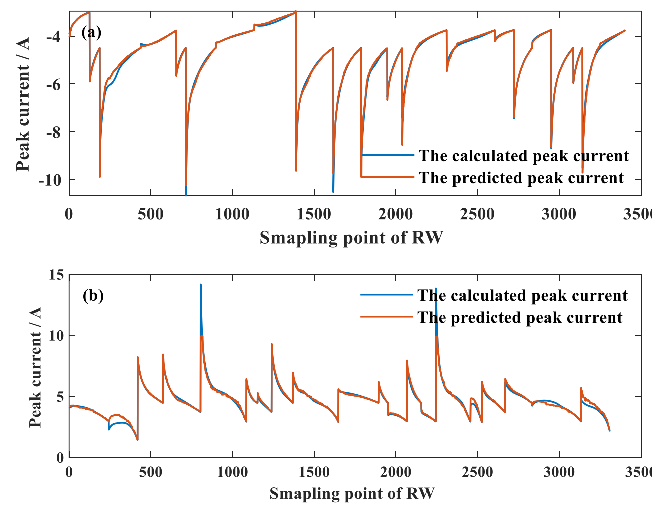

Fig. 6 The prediction result of LightGBM. (a) Charging RW steps;(b) Discharging RW steps.

CONCLUSION AND DISCUSSION

In this paper, three model parameter identifying methods are adopted and discussed for their influence on the peak current calculation. The results indicate that the parameter identified through optimization method are far more enough than offline and online method to calculate peak current accurately, further demonstrating the validity of peak current calculation approach based on voltage constraints. AI algorithm, i.e., LightGBM is also employed to predict the peak current. Results show that the prediction can greatly track the peak current with MAPE of 0.373% and 1.447% for charging and discharging process respectively, proving the potential utility of this AI algorithm in future cloud computing application.

In all, the peak current calculation method proposed in this paper can accurately calculate and predict the peak current during battery operation. Priorities for future work should focus on several limitations, e.g., 1) improve the optimization algorithm efficiency to reduce the consumption time of model parameter identification. 2) construct comprehensive battery database including input features (not limit to the SOC, voltage, temperature, capacity and current) and corresponding peak current. In this case, it could be practical to employ AI technology in actual battery detection and management to realize fast and accurate calculation of the peak current.

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