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AN ADAPTIVE CAPACITY ESTIMATION METHOD BASED ON INCREMENTAL CAPACITY ANALYSIS FOR LITHIUM-ION BATTERIES

Bo Jiang[1,2], Haifeng Dai[1,2,*], Xuezhe Wei[1,2], Jingan Chen[3]

1 National Fuel Cell Vehicle & Powertrain System Research & Engineering Center, Shanghai 201804, China

2 Collaborative Innovation Center for Intelligent New Energy Vehicles, Tongji University, Shanghai 201804, China

3 Shanghai Tonzhan New Energy Sci-tech Co., Ltd., Shanghai 201804, China

ABSTRACT

Accurate capacity estimation is of vital importance for lithium-ion battery management. In this paper, an adaptive battery capacity estimation method based on incremental capacity analysis (ICA) is proposed. First of all, the second-order central least squares method is employed to smooth the charging data and obtain the incremental capacity (IC) curve. Then some battery experiments, including the complete charging and partial charging, are designed and conducted. For the complete charging, the relationship between the features of IC curves and battery capacity fading is investigated. For the limitation of ICA on partial charging, the correction method considering the charging initial SOC and battery aging status is proposed. Finally, the algorithm framework of the adaptive capacity estimation based on ICA is put forward.

Keywords: capacity estimation, ICA, lithium-ion battery, partial charging, central least squares

NOMENCLATURE

Abbreviations	
BMS	Battery management system
SOC	State of charge
ICA	Incremental capacity analysis
CLS	Central least squares
Symbols	
Q	Battery charging capacity
V	Battery terminal voltage
H	The height of the peaks or valleys

1. INTRODUCTION

Under the trend of development for new energy vehicle, the lithium-ion battery has been deemed as the research focus due to its superior performance [1]. Meanwhile, battery management is considered as the key technology to realize the high efficient utilization of battery. The accurate acquisition of battery internal parameters and states is the core function of the battery management system (BMS). As a parameter to characterize the battery performance, battery capacity is the preliminary information to estimate the battery state of charge (SOC), battery state of health, and so on, indicating that it is necessary and essential to estimate the battery capacity online. However, the battery capacity decays nonlinearly during vehical application, which will challenge the battery management and estimation method.

Efforts of many researchers have been done to investigate an accurate and adaptive capacity estimation algorithm [2]. Many studies prefer to estimate the capacity based on battery SOC due to their close relationship. Wei et al. [3] constructed a second-order estimator to realize the union estimation of battery SOC and capacity with the help of extended Kalman filter for vanadium redox flow battery. To account for the nondeterminacy in both battery model and measurement, the total least squares algorithm was employed in capacity estimation [4]. Besides the above kind of capacity estimation method, some intelligent data-driven algorithms have also attracted researchers' attention [5]. The shortcoming is that a great deal of battery experimental data is the fundamental of the data-driven method.

The incremental capacity analysis (ICA) is a capacity estimation method related to battery aging mechanism. From the analysis of the half-cell voltages curves presented in ref [6], the voltage curves of cathode and anode demonstrate different flat regions caused by the two-phase transition phenomena, and the flat regions in half-cell voltages will eventually contribute to the plateaus in the full battery voltage curve. Despite the plateau information of full battery voltage curve can be employed to estimate battery capacity, it is not easy to capture the curve difference caused by capacity attenuation [7]. The ICA method is a more intuitive way to estimate the capacity loss, through calculating the derivatives of the charged/discharged capacity with respect to battery voltage. The foundation of the ICA method is to find the incremental capacity (IC) features which have a strong relationship with battery capacity fading [8]. However, the battery voltage-charging capacity curve will be influenced by measurement noise. Therefore, the proper data processing method shall be adopted to denoise the data to obtain a smooth IC curve. Feng et al. [9] proposed a smoothing method based on support vector regression, and improvements in terms of algorithm speed, adaptability, and estimation accuracy have been made. The Gaussian filter also has superiority in smoothing charging data and was employed in ref [10]. After obtaining the IC curves under different battery aging statuses, the position of IC peaks was adopted to estimate battery capacity. To enhance the adaptability of ICA method in the battery module, Weng et al. [11] extended the ICA based capacity estimation method from a single cell to battery module which has parallel-connected cells with various aging statuses. The previous researches on the ICA method to estimate battery capacity have achieved great progress. However, an essential limitation among the current ICA researches is that the battery must be charged from the 0% SOC, and in vehical application, it is rare to discharge the batteries fully. Since that the battery charging current during vehical application is relatively large (standard charging current is 0.5C), the battery polarization process leads to a great voltage difference between the battery open circuit voltage and terminal voltage, and the difference is related to charging initial SOC. The battery polarization process challenges the adaptability of traditional ICA method. Therefore, it is necessary to investigate the effectiveness of the ICA method during battery partial charging.

In this study, the IC curves will be first smoothed through the central least squares (CLS), and then the relationship between the features of IC curves and battery capacity fading will be obtained. Some experiments that battery charges with different initial SOC will be conducted to study the influence of partial charging on ICA. Finally, an adaptive capacity method based on the ICA method will be proposed for lithium-ion battery.

2. THE ICA AND DATA SMOOTHING METHOD

The constant current-constant voltage charging pattern is commonly used in electric vehicles. The battery will be first charged with a constant current pattern, and then transfers to a constant voltage pattern when the battery voltage reaches the charge cut-off voltage. Fig 1 (a) shows the curves of charging capacity with respect to battery voltage under different aging statuses during constant current (0.5C) profile. It is evident that the charging curves have a downward trend with attenuation of battery capacity because the amount of electricity that can be charged into the battery decreases. Besides, in region A and B, for a battery with a specific capacity, it can be found that the slope of the charging curve has changed because of the two-phase transition process. An inapparent phenomenon is that batteries with different capacity have different slope change. However, it is difficult to capture the difference.

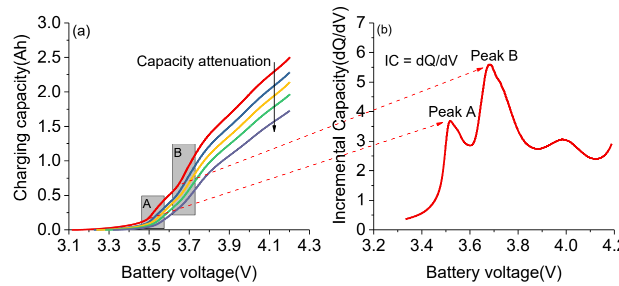

Fig 1 (a) Battery voltage-charging capacity curves under different aging statuses; (b) The diagram of IC curve

The principle ICA method is to obtain the charging capacity during tiny voltage range, or in other words, calculating the differential of the charging capacity to battery voltage. Therefore, the voltage plateaus of charging curve in Fig 1 (a) will be converted to peaks of IC curve in Fig 1 (b). Fig 1 (b) demonstrates two peaks in region A and B, and the relationship between the IC features and capacity decreasing needs to be further investigated.

The calculating of the IC curve can adopt the following equation:

$$\frac{dQ}{dV} \approx \frac{\Delta Q}{\Delta V} = \frac{Q_{k_2} - Q_{k_1}}{V_{k_2} - V_{k_1}} \quad (1)$$

where Q_k and V_k represent the battery charging capacity and voltage at sample time k separately. The problem is that if the time interval between k_1 and k_2 is small, the IC curve will be noisy, and if the time interval is large, the IC curve features will become indistinct. Thus, a more adaptive data smoothing method shall be adopted.

In this study, we will employ the CLS [12] to smooth the battery charging data and obtain the IC curve. Fig 2 shows the diagram of the CLS to smooth the data. Assume that there is a data sequence consisting of L+1 points, from ($x_{c-L/2}$, $y_{c-L/2}$) to ($x_{c+L/2}$, $y_{c+L/2}$), and a second-order polynomial function can be employed to fit the data sequence as:

$$y \approx a_0 + a_1 x + a_2 x^2 \quad (2)$$

where x and y are the measurement data, and a_0~a_2 are the polynomial coefficients.

The solution of equation (2) can be obtained by defining a cost function $T = \sum_{c-L/2}^{c+L/2} (y_i - a_0 - a_1 x_i - a_2 x_i^2)$, and then minimize the cost function T with a_0~a_2. By solving $\frac{\partial T}{\partial a_0} = 0$, $\frac{\partial T}{\partial a_1} = 0$, and $\frac{\partial T}{\partial a_2} = 0$, the following equation will be derived:

$$\begin{bmatrix} L+1 & \sum_{c-L/2}^{c+L/2} x_i & \sum_{c-L/2}^{c+L/2} x_i^2 \\ \sum_{c-L/2}^{c+L/2} x_i & \sum_{c-L/2}^{c+L/2} x_i^2 & \sum_{c-L/2}^{c+L/2} x_i^3 \\ \sum_{c-L/2}^{c+L/2} x_i^2 & \sum_{c-L/2}^{c+L/2} x_i^3 & \sum_{c-L/2}^{c+L/2} x_i^4 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \sum_{c-L/2}^{c+L/2} y_i \\ \sum_{c-L/2}^{c+L/2} x_i y_i \\ \sum_{c-L/2}^{c+L/2} x_i^2 y_i \end{bmatrix} \quad (3)$$

By solving the equation (3), the polynomial coefficients of the equation (2) will be obtained. If we adopt y as the battery charging capacity, and x is the battery voltage, the IC at the central point (x_c, y_c) can be obtained as:

$$\frac{dQ}{dV} \approx a_1 + 2a_2 x_c \quad (4)$$

It should be noticed that to ensure the smooth IC curve, the moving CLS shall be adopted from the charging beginning to the end.

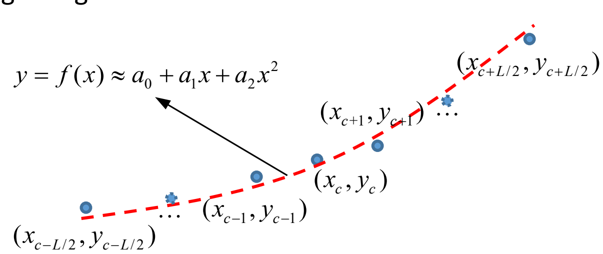

Fig 2 Diagram of the central least squares

3. EXPERIMENT DESIGN

To obtain the relationship between IC features and capacity attenuation, battery experiments shall be designed and conducted. A kind of NMC/Graphite cylindrical battery with the nominal capacity of 2.750Ah is used in this study. The battery charge and discharge cut-off voltage are 4.2V and 2.5V, respectively. The experiment setup includes a battery test system, an environmental chamber, and a computer. All the experiments are conducted at 25°C.

A total of 6 batteries (#1~#6) are used for the ICA experiments, which is showed in Table 1, and to enhance the accuracy, there different aging status of battery #1~#6 are taken into account, including Test 1~Test 3. The accelerated aging is employed during different tests.

Table 1 Batteries for the ICA experiments

Battery No.	Test 1	Test 2	Test 3
#1	2.872Ah	2.872 Ah	2.871 Ah
#2	-	2.670 Ah	2.589 Ah
#3	2.598 Ah	2.517 Ah	2.363 Ah
#4	2.332 Ah	2.280 Ah	2.183 Ah
#5	2.735 Ah	2.659 Ah	2.578 Ah
#6	2.870 Ah	2.724 Ah	2.555 Ah

As mentioned above, the adaptive ICA method to estimate battery capacity, including complete charging and partial charging, is the purpose of this study. In the complete charging experiments, each battery (#1~#6) under different aging statuses will be charging from 0% to 100% SOC at two or three times with the 0.5C current, and the sampling frequency is 10Hz. In the partial charging experiments, the test flow is shown in Fig 3.

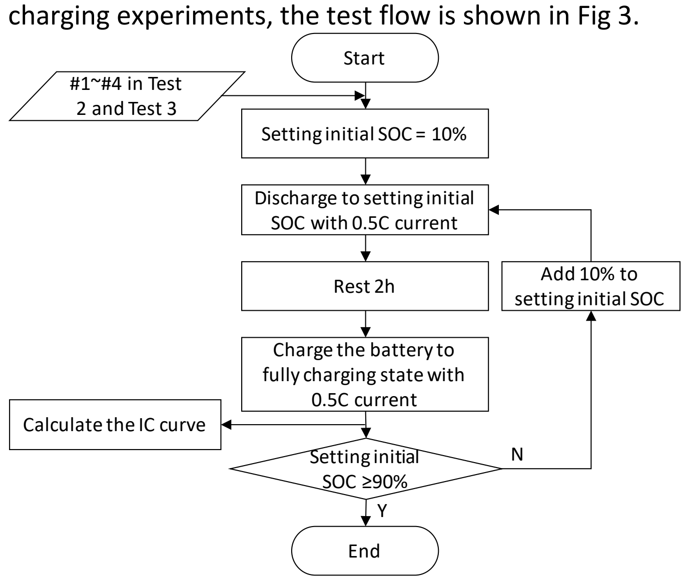

Fig 3 The experiment flow for partial charging

In the partial charging experiment, battery #1~#4 in Test 2 and Test 3 will be charging from a setting initial SOC (10%, 20%, …90%) to 100% with the 0.5C current. After obtaining the charging data, all the IC curves will be analyzed for capacity estimation.

4. RESULTS AND DISCUSSION

4.1 The ICA method for complete charging

Fig 4 shows the IC curves under different battery aging statuses. It is evident that the IC curves are smooth and without much noise, which can be used in the analysis of capacity estimation. From the IC curves of battery with a capacity of 2.871Ah (new battery) to that of battery with a capacity of 2.183Ah (aged battery), three peaks and three valleys of curves can be clearly seen, as shown in Fig 4. In fact, a tiny peak is on the right of Peak B, and it is ignored in this study.

When the battery capacity decreases, it can found that Peak A, B, and C have a downward trend and move toward the right, so do the Valley A, B, and C. It means that the change of these IC features has a close relationship with battery capacity attenuation and can be employed to perform the estimation. In this study, we simply adopt the height of the IC peaks and valleys to describe the capacity decreasing.

The relationship between battery capacity and the height of peak and valley is fitted by a one-order polynomial function, and the fitting results with the bigger coefficient of determination (R-square) are shown in Fig 5. Fig 5 shows fitting results of Peak B, Valley B, and Peak C, and it can be concluded that the correlation between these three features and battery capacity is strong (R-square≥0.9). Moreover, the correlation is adaptive to different batteries (#1~#6), which enhance the promise of ICA method to estimate the battery capacity. It can be confirmed that the position of Peak B, Valley B, and Peak C under different battery aging statuses are 3.675~3.715V, 3.865~3.920V, and 3.975~4.015V, respectively. Therefore, the data smoothing and IC curve derivation can be performed in the above voltage range to reduce the computation load.

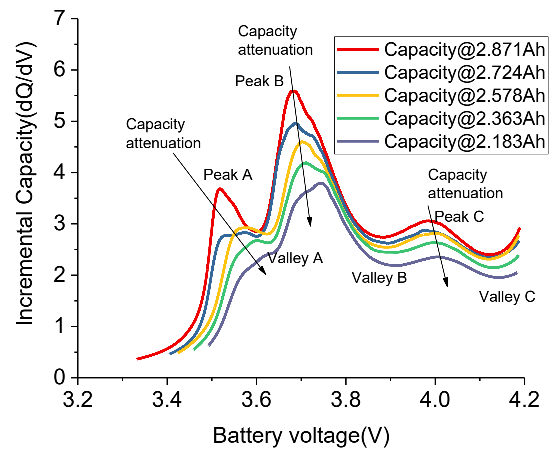

Fig 4 IC curves under different battery aging statuses

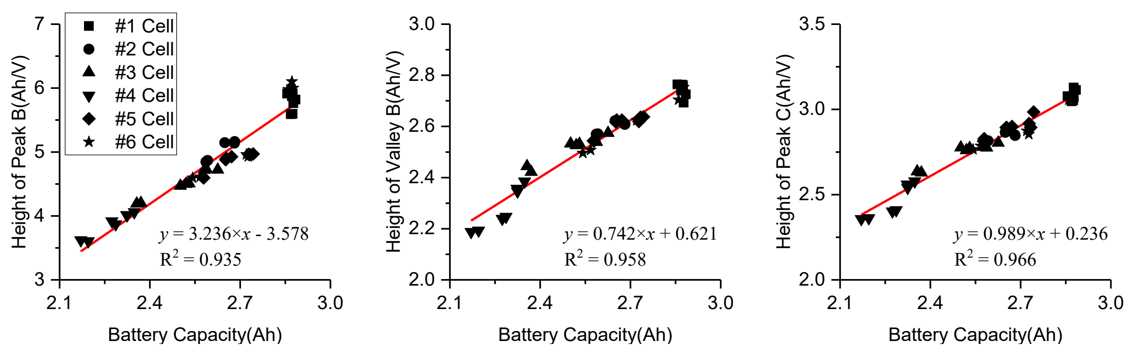

Fig 5 Fitting results of IC features with the battery capacity

Hence, for the battery complete charging, the capacity estimation based on ICA method can be obtained as:

$$\begin{cases} \mathrm{Cap}_1 = 0.289 \times H_{\mathrm{Peak,B}} + 1.205 \\ \mathrm{Cap}_2 = 1.291 \times H_{\mathrm{Valley,B}} - 0.691 \\ \mathrm{Cap}_3 = 0.977 \times H_{\mathrm{Peak,C}} - 0.142 \end{cases} \quad (5)$$

where $H_{Peak,B}$, $H_{Valley,B}$, $H_{Peak,c}$ are the height of Peak B, Valley B, and Peak C, respectively, and Cap_1, Cap_2, Cap_3 are the estimated capacity.

The final estimated capacity can be average of the above Cap_1, Cap_2, Cap_3, or the weighted average of them, where the weight coefficient is adjusted according to the quality of correlation.

4.2 The ICA method for partial charging

As discussed above, it is rare to charge the battery from 0%, and battery polarization process will influence the IC curves if the battery is charging from different initial SOCs.

Fig 6 shows the IC curves with different charging SOC_{init} (initial SOC) ranging from 0% to 100%. In Fig 6 (a), it can be found that even the new battery (#1), the IC curve will be distorted if the battery is not charging from 0%. Due to initial charging voltage increasing, besides the complete charging IC curve, only the IC curve with the SOC_{init} = 10% has the feature of Peak A. For IC curves with the SOC_{init} from 10 to 40%, the feature of Peak B can be found. However, the difference between these deformed peaks is irregular. For IC curves the with the SOC_{init} from 10 to 60%, it can be found that the height of Peak C in different IC curves remains unchanged, which is promising to employed in capacity estimation.

For the aging battery, as shown in Fig 6 (b), the same characteristic of Peak A and Peak B can be concluded. However, for the Peak C, peaks in different IC curves with different SOC_{init} have a downward trend. Hence, for # 3 battery in Test 2, the correlation of the height the Peak C and SOC_{init} is shown in Fig 7. It can be confirmed that the height of Peak C has a strong relationship with the initial charging SOC. Because the IC curve with the SOC_{init} bigger than 60% is very deformed, so it is out of consideration. The slope (-0.0108) of the fitting result shown in Fig 7 is called SOC correction coefficient.

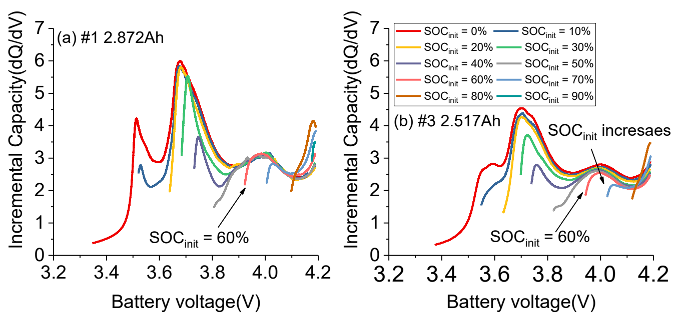

Fig 6 IC curves with different charging initial SOC: (a) # 1 battery in Test 2; (b) #3 battery in Test 2

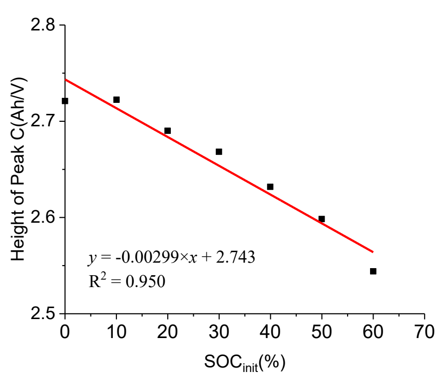

Fig 7 Fitting results of $H_{Peak,c}$ with battery SOC_{init} for #3 battery

However, from Fig 7 (a) it can be confirmed that the initial charging SOC will not influence the height of Peak C, or in other words, the SOC correction coefficient is zero. It means that the SOC correction is related to the battery aging status. Fig 8 shows the SOC correction coefficient (slope of fitting results of $H_{Peak,c}$ with battery SOC_{init}) in the partial charging experiments, and it can be concluded that, with battery capacity decreasing, the SOC correction coefficient decreases (the absolute value increases). The relationship between SOC correction coefficient and battery capacity is also fitted by a one-order polynomial function, and the result demonstrates a good fitting (R-square = 0.935). Therefore, the adjustment of the SOC correction coefficient according to battery capacity is called the aging correction. Considering that the battery capacity changes very little during two operation cycles, hence we can use the capacity estimated at the last operation cycle to perform the aging correction if the battery is partial charging.

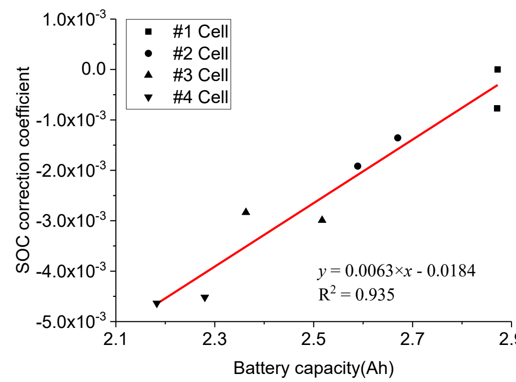

Fig 8 The relationship between SOC correction coefficient and battery capacity

Based on the above analysis about ICA of battery complete charging and partial charging, the overall adaptive capacity estimation method is shown in Fig 9. The necessary battery data includes the charging current and terminal voltage. Moreover, BMS shall read the battery capacity of the last cycle from controller memory and determine the battery charging SOC_{init}. According to the SOC_{init}, the estimation is performed as follow:

(1) If the SOC_{init} is equal to zero, meaning that it will be a complete charging, BMS will calculate the IC curve and estimate the battery capacity according to the Equation (5).

(2) If the SOC_{init} is not equal to zero but smaller than 60%, BMS will calculate the IC curve and obtain the height of Peak C. First is aging correction and BMS will determine the SOC correction coefficient according to the battery capacity at last cycle (as shown in Fig 8). Then is SOC correction and BMS will determine the corrected height of Peak C according to the SOC correction coefficient and the original height of Peak C (as shown in Fig 7). Finally, BMS will

estimate the battery capacity according to the Equation (5).

(3) If the SOC_{init} is larger than 60%, the capacity estimation will not be performed during this cycle.

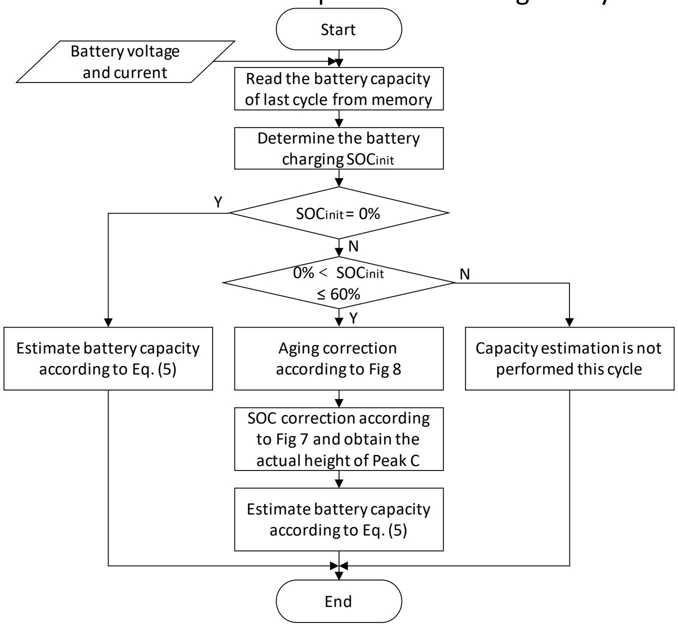

Fig 9 The adaptive capacity estimation based on ICA method

5. CONCLUSIONS

This paper presents an adaptive capacity estimation based on the ICA method, some conclusions can be drawn as below: (1) The battery charging data is noisy and the experiment results show that the CLS is an effective data smoothing method to obtain the IC curve; (2) The IC curves have a downward trend when battery capacity decreases. The height of Peak B, Valley B, and Peak C has a strong relationship with the capacity attenuation and can be employed to estimate battery capacity; (3) The battery charging initial SOC will influence the shape of IC curves, leading to the blurring of features. The proposed correction method according to the initial charging SOC and battery aging status is an adaptive method for ICA during partial charging.

Future work will focus on battery aging mechanism analysis based on ICA method, as well as the influence of battery temperature on ICA curves. Furthermore, the proposed adaptive method shall be verified by vehicular online application.

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REFERENCE

[1] Waag W, Fleischer C, Sauer DU. Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles. Journal of Power Sources. 2014;258:321-39.

[2] Xiong R, Li L, Tian J. Towards a smarter battery management system: A critical review on battery state of health monitoring methods. Journal of Power Sources. 2018;405:18-29.

[3] Wei Z, Tseng KJ, Wai N, Lim TM, Skyllas-Kazacos M. Adaptive estimation of state of charge and capacity with online identified battery model for vanadium redox flow battery. Journal of Power Sources. 2016;332:389-98.

[4] Balasingam B, Avvari GV, Pattipati B, Pattipati KR, Bar-Shalom Y. A robust approach to battery fuel gauging, part II: Real time capacity estimation. Journal of Power Sources. 2014;269:949-61.

[5] Hu C, Jain G, Zhang P, Schmidt C, Gomadam P, Gorka T. Data-driven method based on particle swarm optimization and k-nearest neighbor regression for estimating capacity of lithium-ion battery. Applied Energy. 2014;129:49-55.

[6] Marongiu A, Nlandi N, Rong Y, Sauer DU. On-board capacity estimation of lithium iron phosphate batteries by means of half-cell curves. Journal of Power Sources. 2016;324:158-69.

[7] Ansean D, Garcia VM, Gonzalez M, Blanco-Viejo C, Viera JC, Pulido YF, et al. Lithium-Ion Battery Degradation Indicators Via Incremental Capacity Analysis. IEEE Transactions on Industry Applications. 2019;55:2992-3002.

[8] Li X, Jiang J, Wang LY, Chen D, Zhang Y, Zhang C. A capacity model based on charging process for state of health estimation of lithium ion batteries. Applied Energy. 2016;177:537-43.

[9] Feng X, Weng C, He X, Wang L, Ren D, Lu L, et al. Incremental Capacity Analysis on Commercial Lithium-Ion Batteries Using Support Vector Regression: A Parametric Study. Energies. 2018;11.

[10] Li Y, Abdel-Monem M, Gopalakrishnan R, Berecibar M, Nanini-Maury E, Omar N, et al. A quick on-line state of health estimation method for Li-ion battery with incremental capacity curves processed by Gaussian filter. Journal of Power Sources. 2018;373:40-53.

[11] Weng C, Feng X, Sun J, Peng H. State-of-health monitoring of lithium-ion battery modules and packs via incremental capacity peak tracking. Applied Energy. 2016;180:360-8.

[12] Wang L, Pan C, Liu L, Cheng Y, Zhao X. On-board state of health estimation of LiFePO4 battery pack through differential voltage analysis. Applied Energy. 2016;168:465-72.