A State-of-Health Estimation Method of Lithium-ion Batteries using ICA and SVM

2021 Global Reliability and Prognostics and Health Management (PHM-Nanjing) | 978-1-6654-0131-9/21/$31.00 ©2021 IEEE | DOI: 10.1109/PHM-Nanjing52125.2021.9613069

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***Abstract*—Maximum available capacity is often used as the health indicator for the state-of-health estimation of lithium-ion batteries. However, the incomplete charging and discharging process in the field usually is encountered. They are resulting in the maximum available capacity not being measured by the ampere-hour integral method. To improve the state-of-health estimation accuracy, we first propose four new fade features based on incremental capacity analysis. Then support vector machine is utilized to model the non-linear function between features and health index. Finally, a case study is conducted to verify the effectiveness and performance of the proposed method.**

Keywords—state-of-health; incremental capacity analysis; support vector machine; lithium-ion battery

I. INTRODUCTION

Lithium batteries have the excellent advantages of high energy density, high discharge voltage, low self-discharge, good cycle performance, and little ecological pollution[1]. They are widely used in military and civilian systems or equipment such as satellites, spacecraft, aircraft, high-speed rail, energy storage power stations, and smart phones[2].

Lithium batteries work under cyclic charging and discharging profiles. Due to the irreversible physical and chemical reactions during the charging and discharging process, the active materials inside the lithium batteries continue to decrease, and the SEI film gradually thickens[3]. The main external manifestations are increased internal resistance and attenuation of the maximum available capacity. Retire when failing to meet the power supply requirements of the equipment. It is generally believed that the battery fails when the capacity declines to 80% of the nominal capacity.

Lithium battery state-of-health (SOH) is generally defined as the ratio of the maximum available capacity of the current cycle to the nominal capacity, which can characterize the real-time discharge capacity and change the trend of the lithium battery. Accurate health status assessment is of great significance for judging the endurance of the system or equipment, planning system tasks, and arranging maintenance activities.

To improve the accuracy and robustness of the state-of-health estimation method, we propose a new feature set containing four shape characteristics in the incremental capacity (IC) curve and utilize a support vector machine (SVM) to establish the mapping function between curves features and health index. The proposed method can accurately estimate the state-of-health using very short discharge data.

The rest of the paper is constructed as follows. Section II introduces the feature extraction method based on the incremental capacity analysis (ICA). Section III gives a strategy to estimate the state-of-health of lithium-ion batteries using the SVM algorithm. Section IV shows one case study.

II. FEATURE EXTRACTION BASED ON INCREMENTAL CAPACITY ANALYSIS

A. Incremental Capacity Analysis

Incremental capacity analysis (ICA) is a favorable choice for estimating the state-of-health of lithium-ion batteries. IC curves contain abundant features which can characterize essential information about the aging mechanism and SOH of the battery[4]. The original IC curve, i.e., dQ/dV~V, can be obtained by performing the derivative operation to the Q~V curve. The derivative operation can be approximated by the difference operation given by [5]:

$$\left.\frac{dQ}{dV}\right|_k \approx \frac{\Delta Q_k}{\Delta V_k} = \frac{Q_k - Q_{k-1}}{V_k - V_{k-1}} \tag{1}$$

In (1), Q is the instantaneous discharged capacity, and V is the instantaneous discharged voltage. Generally, the generated IC curves require to be further denoised using the filtering method to achieve smoothness. In this paper, empirical mode decomposition (EMD) is employed to smooth the IC curves. The discharged capacity Q could be calculated by the Ah-counting method:

$$Q(k) = \sum_{j=0}^{k} I(k) \cdot \Delta T \tag{2}$$

In (2), I is the instantaneous discharging current and ΔT is the sampling time interval.

The IC curve represents the change rate of capacity with voltage during the process of charging and discharging. Consequently, the internal health state of the battery could be revealed by extracting the features of the curve for modeling. The solution of the IC curve can be obtained by Eq. (3)[6].

$$\frac{dQ}{dV}=\frac{dQ}{d\tau}\cdot\frac{d\tau}{dV}=I\cdot\frac{d\tau}{dV} \quad (3)$$

B. *Feature Extraction of IC Curve*

The IC curves of different discharging cycles are shown in Fig. 1. In the figure, the peaks of IC curves show a downward trend with increasing cycle numbers, which indicates the loss of the active materials of the battery electrodes. Moreover, the peaks shift towards the low voltage part with increasing cycles.

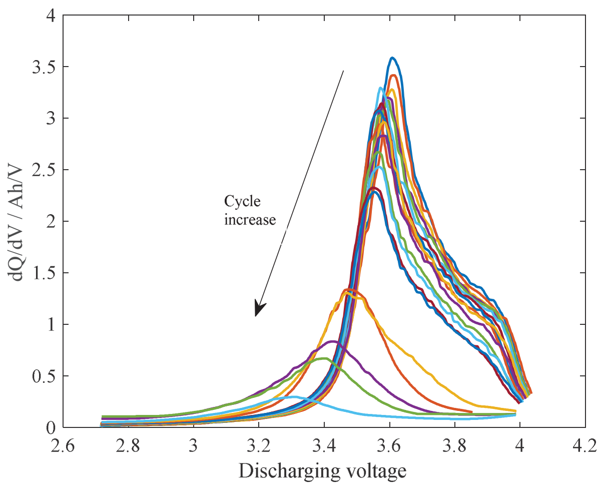

Figure 1. IC curves of different cycles

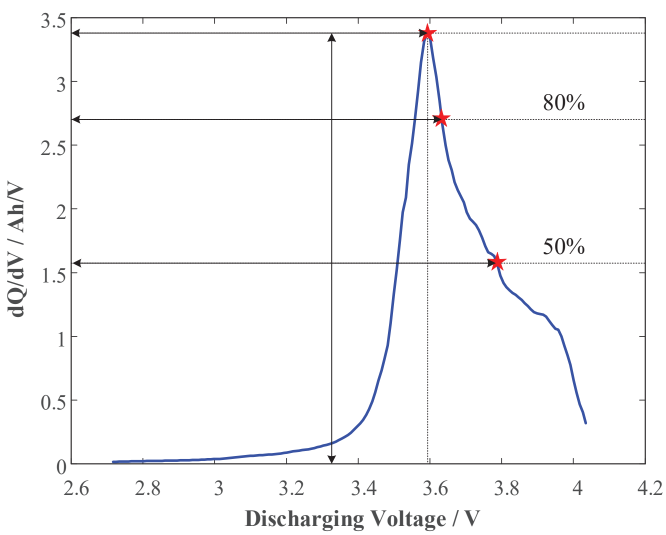

Figure 2. The features extracted from the ICA curve

The ICA is performed by extracting the peak features of IC curves, primarily the magnitude and position, which are insightful for scrutinizing the inside electrochemical processes and estimating the SOH with a pre-calibrated mapping function. In Fig. 2, we conduct a new feature sets containing four variables. The first two represent the magnitude and position of the peak, the third represents the position of the 80% peak, and the fourth represents the position of the 50% peak. It is worth noting that the more enormous voltages corresponding to the ordinates of 80% peak and 50% peak are selected considering the possibility of incomplete discharging.

This work is supported by the Foundation Strengthening Program (No.2019-JCJQ-ZD-199 and No.2020-JCJQ-JJ-215).

III. State-of-health Estimation using Support Vector Machine

A. *Support Vector Machine*

As a supervised machine learning algorithm, support vector machine (SVM) is widely applied to solve classification and regression problems. When used to solve regression problems, SVM is adapted as a regression (SVR) predicting tool[7, 8].

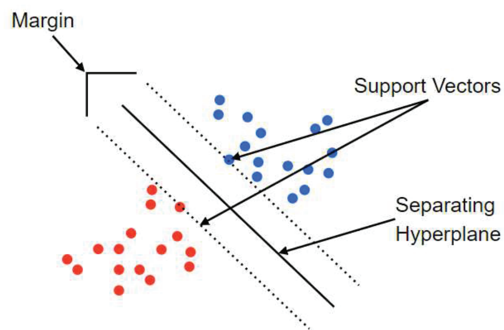

Figure 3. The principle of support vector machine

As shown in Fig. 3, a two-class classification problem can be denoted by $(x_i, y_i, i=1,2,..,n)$, where $x_i\in R^n$ and $y\in(-1,1)$. Data points are divided into two parts along a hyperplane given by:

$$(\omega,x)+b=0 \quad (4)$$

where *w* is a vector of hyperparameters and (‘,’) denotes a dot product. The optimal hyperplane must meet a constraint:

$$y_i\left[\left(\omega,x_i\right)+b\right]\geq 1-\varepsilon_i \quad (5)$$

In (5), ε_i is a non-negative error term. The optimal hyperplane can be defined with:

$$\phi(\omega,\xi)=\frac{1}{2}\|\omega\|^2+c\sum_i\xi i \quad (6)$$

within the constraints given in (5). Here, *c* is a user-defined parameter. The optimum of Lagrangian multipliers with the saddle point is applied to solve the optimization problem.

$$\begin{aligned}&\phi(\omega,b,\xi,\alpha,\beta)\\&=\frac{1}{2}\|\omega\|^2 c\sum_i\xi i\\&-\sum_i\alpha_i\left(y_i\left[\omega^T x_i+b\right]-1+\xi_i\right)\\&-\sum_i\beta_i\xi_i\end{aligned} \quad (7)$$

In (7), α and β are Lagrange multipliers. Except for a small subset of input vectors, namely the support vectors (SVs), the values of other input vectors are zero. A variant algorithm of SVM called SVR is used to find the best fit line (the hyperplane) with the maximum number of data points. The optimal function of SVR is given by:

$$(\omega,x)+b=f(x) \quad (8)$$

The max deviation of $f(x)$ from the training data must be less than ε, with the maximum flatness possible. Therefore, the optimization problem is given by:

$$\phi(\omega,\xi)=\frac{1}{2}\|\omega\|^2+c\sum_i \xi_i \tag{9}$$

within the following constraints:

$$y_i-(\omega,x_i)-b\le\varepsilon+\xi_i \tag{10}$$

The Lagrangian function is:

$$\begin{aligned}&\phi(\omega,b,\xi,\alpha,\beta)=\\&\frac{1}{2}\|\omega\|^2+c\sum_i \xi i\\&-\sum_i\alpha_i\left(\left[\omega^T x_i+b\right]-y_i+\varepsilon+\xi_i\right)\\&-\sum_i\beta_i\xi_i\end{aligned} \tag{11}$$

The optimized objective function is given by:

$$f(x)=\sum_{i=1}^{l}\alpha_i(x_i,x)+b \tag{12}$$

In (12), x_i represents support vectors.

The main advantage of SVR algorithms for regression problems is the formation of support vectors. The method has low computational complexity. These advantages make SVR a widely applied data-driven modeling algorithm.

B. Health Assessment Modeling

As shown in Fig. 4, we use SVR to establish the non-linear function mapping between the degradation features and the health index. The input of the model is four features extracted from ICA curves, namely dQ/dV_{peak} V_{peak}, $V_{80\%\text{peak}+}$ and $V_{50\%\text{peak}+}$. The output of the model is the health index (SOH).

IV. CASE STUDY

A. Data Introduction

In the paper, the lithium-ion battery cycle-life data collected by the CALCE® research group was employed. A battery cell with a rated capacity of 1.1Ah named CS2_36 was utilized for testing cycle life performance[9]. The experiments were carried out under ambient temperature of 25~30°C. The cell was charged using the standard constant current - constant voltage (CC-CV) protocol with a constant current of 1C till 4.2V, and the voltage of 4.2 V was kept until the charging current decreased steadily to 0.05A. The battery was discharged at a constant current (CC) of 0.45A until the voltage dropped to the cutoff voltage of 2.7V. The battery was cycled multiple times under the conditions mentioned above. The protocol of battery charging and discharging is shown in Fig. 5.

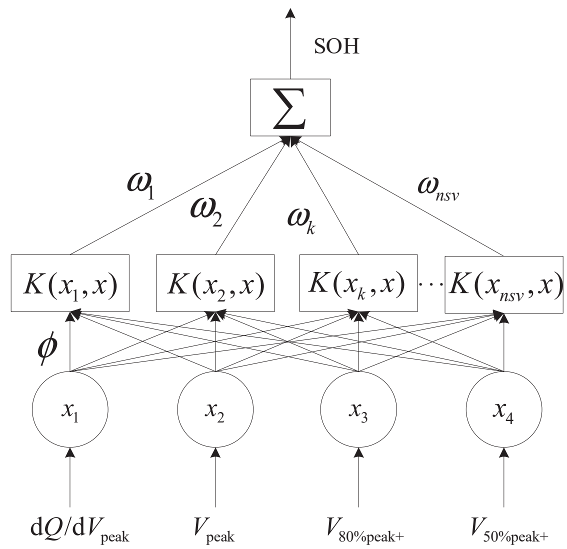

Figure 4. Health assessment model using SVM

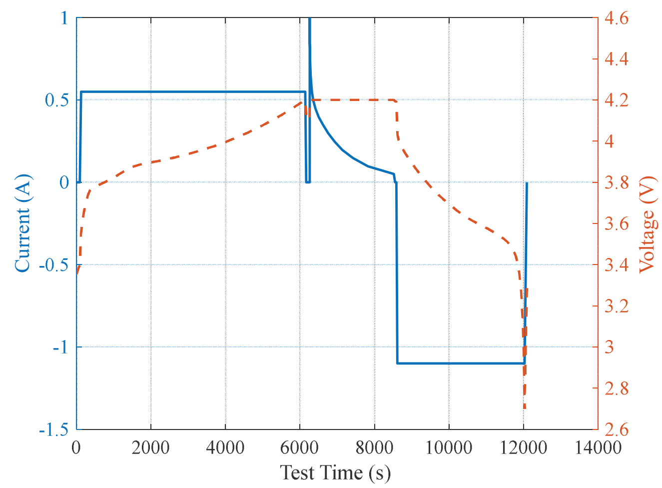

Figure 5. Battery charging and discharging protocol

B. Results Analysis

The framework of SOH estimation is shown in Fig. 6. First, the discrete integration method is used to obtain the curve of capacity to voltage. Second, the ICA method combined with curve smoothing is utilized to get the curve of dQ/dV to voltage. Third, four degradation features are extracted from the peak of the IC curve. Finally, SVM is employed to model the map between degradation features and health index.

Generally, the peaks of an IC curve can characterize the two-phase transformation process of positive and negative active materials[10]. To quantify the level of degradation, the four features relative to the peak dQ/dV_{peak}, V_{peak}, $V_{80\%\text{peak}+}$ and $V_{50\%\text{peak}+}$ are extracted from the IC curves. The four variables show the same downward trend with the increased cycle number. The curves of these features are shown in Fig.7 ~ Fig. 10.

We utilized SVM to model the function between the features mentioned above and the health index. The result is shown in Fig. 11. According to the figure, we conclude that the SOH model can capture the degradation trend very well. Moreover, the root mean square error (RMSE) and Pearson correlation coefficient (R^2) is computed to measure the performance of the proposed method. TABLE I. shows the RMSE and R^2 of battery CS_36. According to the analysis results, the method proposed in this paper has a high accuracy of SOH estimation with little discharge data.

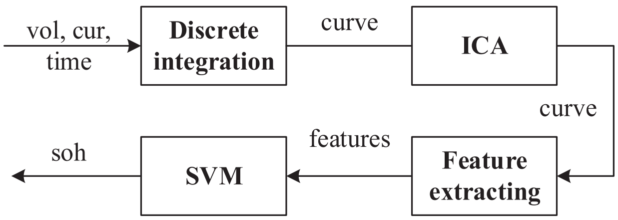

Figure 6. The framework of implementing SOH assessment

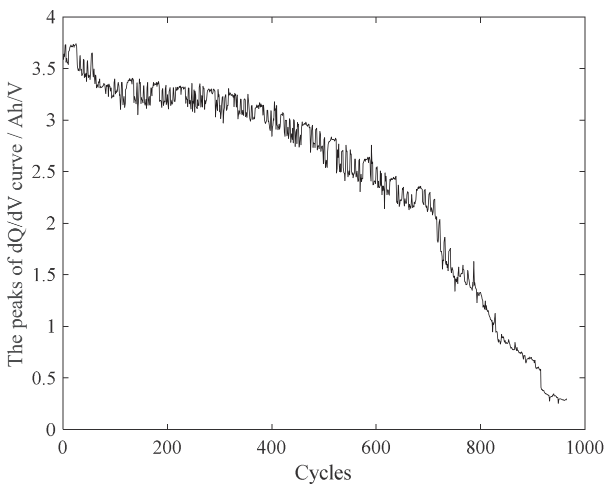

Figure 7. The peak of the dQ/dV curve under cycling

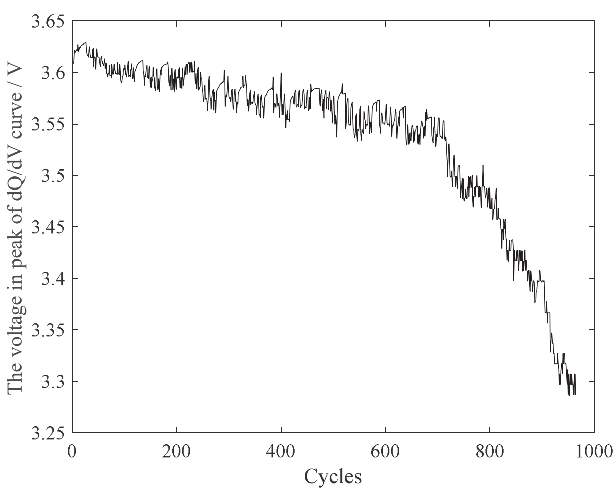

Figure 8. The voltage in the peak of the dQ/dV curve under cycling

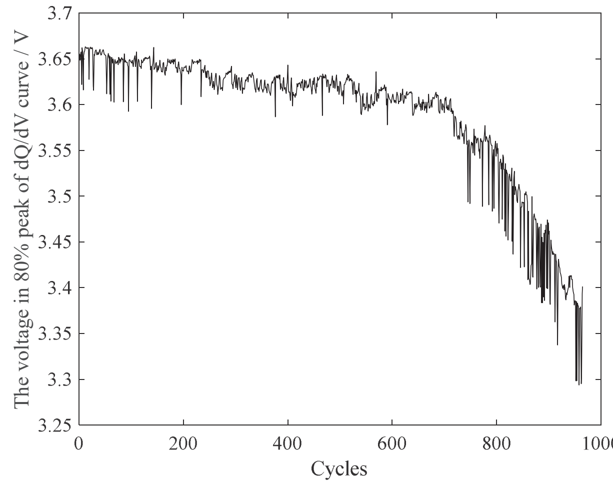

Figure 9. The voltage in 80% peak of dQ/dV curve under cycling

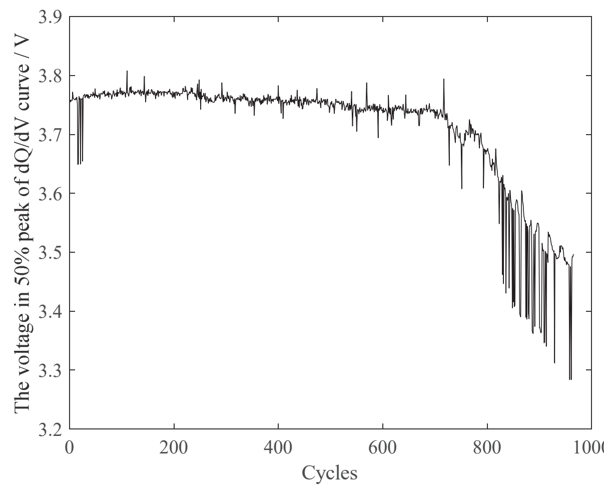

Figure 10. The voltage in 50% peak of dQ/dV curve under cycling

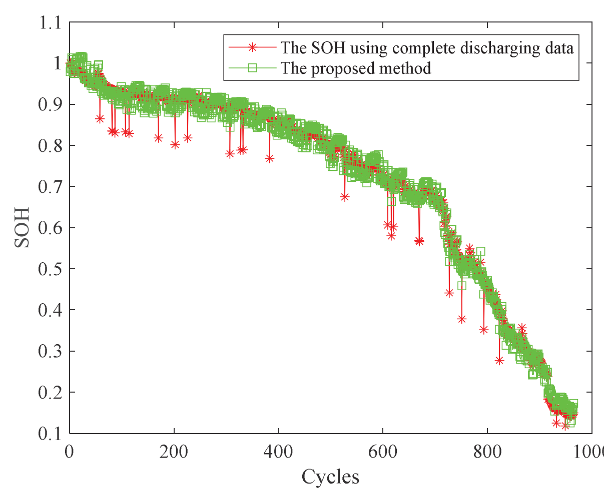

Figure 11. Results of SOH estimation using the proposed method

TABLE I. PERFORMANCE EVALUATION OF THE PROPOSED METHOD

Battery No.	RMSE	R^2
CS2_36	0.0205	0.9925

V. CONCLUSION

This paper proposes four new fade features based on incremental capacity analysis and utilizes these features and the SVM method to estimate the SOH of batteries, improving the accuracy of SOH estimation, especially under incomplete charging and discharging conditions. An alternative topic of further research may be the applicability and variations of the proposed method to ICA curves with multiple peaks.

ACKNOWLEDGMENT

The authors wish to express sincere appreciation to the reviewers and the Editor-in-Chief for their valuable comments and suggestions.

This work is supported by the Foundation Strengthening Program (No. 2020-JCJQ-JJ-215 and No. 2019-JCJQ-ZD-199).

REFERENCES

[1] J. F. Peters, M. Baumann, B. Zimmermann, J. Braun, and M. Weil, "The environmental impact of Li-Ion batteries and the role of key parameters – A review," *Renewable and Sustainable Energy Reviews,* vol. 67, pp. 491-506, 2017, doi: 10.1016/j.rser.2016.08.039.

[2] A. Fly and R. Chen, "Rate dependency of incremental capacity analysis (dQ/dV) as a diagnostic tool for lithium-ion batteries," *Journal of Energy Storage,* vol. 29, 2020, doi: 10.1016/j.est.2020.101329.

[3] X. Han *et al.*, "A review on the key issues of the lithium ion battery degradation among the whole life cycle," *eTransportation,* vol. 1, 2019, doi: 10.1016/j.etran.2019.100005.

[4] J. He, X. Bian, L. Liu, Z. Wei, and F. Yan, "Comparative study of curve determination methods for incremental capacity analysis and state of health estimation of lithium-ion battery," *Journal of Energy Storage,* vol. 29, 2020, doi: 10.1016/j.est.2020.101400.

[5] J. P. Christophersen and S. R. Shaw, "Using radial basis functions to approximate battery differential capacity and differential voltage," *Journal of Power Sources,* vol. 195, no. 4, pp. 1225-1234, 2010, doi: 10.1016/j.jpowsour.2009.08.094.

[6] T. Sun, B. Xu, Y. Cui, X. Feng, X. Han, and Y. Zheng, "A sequential capacity estimation for the lithium-ion batteries combining incremental capacity curve and discrete Arrhenius fading model," *Journal of Power Sources,* vol. 484, 2021, doi: 10.1016/j.jpowsour.2020.229248.

[7] J. C. Álvarez Antón, P. J. García Nieto, F. J. de Cos Juez, F. Sánchez Lasheras, M. González Vega, and M. N. Roqueñí Gutiérrez, "Battery state-of-charge estimator using the SVM technique," *Applied Mathematical Modelling,* vol. 37, no. 9, pp. 6244-6253, 2013, doi: 10.1016/j.apm.2013.01.024.

[8] V. M. Nagulapati *et al.*, "A novel combined multi-battery dataset based approach for enhanced prediction accuracy of data driven prognostic models in capacity estimation of lithium ion batteries," *Energy and AI,* vol. 5, 2021, doi: 10.1016/j.egyai.2021.100089.

[9] W. He, N. Williard, M. Osterman, and M. Pecht, "Prognostics of lithium-ion batteries based on Dempster–Shafer theory and the Bayesian Monte Carlo method," *Journal of Power Sources,* vol. 196, no. 23, pp. 10314-10321, 2011, doi: 10.1016/j.jpowsour.2011.08.040.

[10] Y. Jiang, J. Jiang, C. Zhang, W. Zhang, Y. Gao, and Q. Guo, "Recognition of battery aging variations for LiFePO4 batteries in 2nd use applications combining incremental capacity analysis and statistical approaches," *Journal of Power Sources,* vol. 360, pp. 180-188, 2017, doi: 10.1016/j.jpowsour.2017.06.007.