An Online State of Health Estimation Method for Lithium-ion Batteries Based on Integrated Voltage

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***Abstract*—A fundamental function of a battery management system is state of health estimation. While there are numerous methods to make this estimation, the constant current-constant voltage charge phase can be used, and in fact, the integrated voltage over time within the terminal voltage of 3.85 V–4.2 V during the charge phase has a strong linear correlation with state of health. To test this hypothesis, data from batteries which were run through accelerated aging tests were assessed with various methods. Estimates were made to demonstrate the effectiveness and accuracy of the developed method.**

Keywords—state of health; estimation; lithium-ion batteries; charging phase; integrated voltage

I. INTRODUCTION

Lithium-ion batteries have been widely applied in automobile, aviation, aerospace and other industries due to their high energy density, high galvanic potential, excellent low-temperature performance, low self-discharge rate, and long lifetime [1]. However, the performance of lithium-ion batteries deteriorates over time due to loss of active material and cyclable lithium and increase in resistance [2-4]. Because performance failure may cause inconvenience and even catastrophic damage to battery-powered systems, it is important to estimate batteries' state of health (SOH).

In recent years, extensive research has been done on SOH estimation of lithium-ion batteries. Generally, capacity and resistance are widely used as the health indicators to measure SOH [5]. In terms of capacity, SOH is quantitatively described by the ratio of present cycles' maximum capacity to the rated capacity. The methods for SOH estimation can be classified into three general categories: direct, adaptive, and model-based.

Direct methods obtain the health indicator through an extremely simple calculation or measurement. For example, the coulomb counting method integrates the current over time throughout the entire discharge phase to derive capacity [6]. Because batteries are seldom fully discharged or charged, this method is not applicable for on-board utilization. Electrochemical impedance spectroscopy (EIS) can be used to detect the battery internal impedance parameter to calculate the capacity based on the high degree of linear correlation between them [7]. Nevertheless, EIS requires special instrumentation, which is expensive.

Adaptive methods employ a state space equation derived from an equivalent circuit model to obtain health indicators such as charge transfer resistance, based on which SOH is calculated. Yuan et al. used charge transfer resistance derived from a single-time-constant equivalent circuit model to estimate SOH [8]. Zhang et al. presented an SOH estimation method by identifying the bulk capacitance, which has a linear relation with SOH in an equivalent circuit model [9]. Guo et al. used an equivalent circuit model to characterize the voltage curve during the constant charging phase and derive a time-based parameter that is the reciprocal of SOH to make an estimation [10].

Model-based methods use measured battery performance variables as the input of a pre-constructed model to directly calculate SOH. Yang et al. used interval capacity within a voltage range of 3.95 V-4.15 V to estimate SOH by a linear model [11]. Yang et al. used hybrid pulse power characterization to obtain parameters, such as ohmic resistance, polarization resistance, polarization capacity, and state of charge, which were used by a back-propagation neural network to estimate SOH [12]. Goh et al. used the charging time of the first peak of second-order differential voltage to estimate SOH by linear function [13]. Zhang et al. used adaptive multi-kernel relevance vector machine (RVM) to estimate SOH based on six novel features extracted from the charge/discharge period [14]. In [15], fully discharged voltage and internal resistance were adopted as aging parameters in a polynomial model to estimate SOH. Liu et al. found that both the time interval corresponding to a certain discharge voltage difference and the discharge voltage difference of the equal time interval have a highly linear correlation with the capacity [16, 17], based on which SOH can be obtained. Hu et al. used five features extracted from charge voltage and current measurements as the input of RVM to estimate SOH [18]. Laplacian Eigenmap was used to estimate SOH with the input of four features extracted from charge/discharge measurements [19]. Five charge-related features extracted from the charge phase were used as the k-nearest neighbor (kNN) regression input to obtain SOH [20].

Almost all the papers above were focused mainly on the discharge phase and used data obtained from experiments under extremely simple loading conditions. In real application, batteries are run under complexly dynamic conditions, and thus the current and voltage fluctuate dramatically. Therefore, the

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applicability of these methods based on the discharge phase with constant current is questionable. Hence, this paper concentrates on the standard constant current/constant voltage charge phase to estimate SOH. In addition, considering the low computational capability of the battery management system (BMS) which manages the rechargeable battery, such as battery cell voltage measurement, battery states estimation, battery uniformity and equalization, battery fault diagnosis [21-23], a simple method such as the linear estimation model is preferable.

SOH estimation and prognostics are both key components of prognostics and health management (PHM). While many remaining life prognostics methods concern the prediction uncertainty [24-27], few SOH estimations deal with the estimation uncertainty. Thus, one of the prominent contributions of this paper is that we provide confidence intervals for the estimations.

After analyzing batteries' experiment data, we found that the integrated voltage (IV) over time during the charging phase has a strong linear relationship with SOH, and thus this relation can be used to construct a simple linear model for SOH estimation. The effectiveness of this method is demonstrated by computer simulation with the data of accelerated aging test.

The remaining sections of this paper are organized in the following order: The accelerated aging test and findings are introduced in Section Ⅱ. Section Ⅲ presents the SOH estimation. Finally, some conclusions are given in Section Ⅳ.

II. EXPERIMENT

Four lithium-ion batteries with $LiCoO_2$ cathode were tested with Arbin BT2000 equipment under room temperature. All of the batteries went through the full charge/discharge procedure and were charged with a standard constant current (0.5C)-constant voltage (4.2 V) protocol and discharged at 1C rate until the voltage reached 2.7 V. The four batteries have the same specifications with a rated capacity of 1.1 Ah.

Fig. 1 shows the SOH degradation with the charge/discharge cycle. The batteries share a similar degradation trend, and the SOH shows an increasing degradation trend after it drops below 80%. Fig. 2 shows how the voltage changes with the constant current/constant voltage charge protocol. At the beginning of the charge phase, the voltage rose rapidly and then increased gradually to 4.2 V. Then, the charge phase went into the constant voltage charge stage and the voltage remained constant. Fig. 2 also illustrates the definition of IV, which is the dark area. It should be noted that the IV also contains the area right below the dark area and above the voltage at 0 V. More specifically, the IV is defined as follows:

$$IV = \int_{t_0}^{t_1} v dt \tag{1}$$

where v is the battery terminal voltage. t_0 and t_1 correspond to the time instant when the terminal voltage reaches 3.85 V and 4.2 V, respectively.

At different SOHs, the charging voltage curve is different, as shown in Fig. 3. Batteries in electric vehicles are usually replaced when their SOH drops below 80%, and thus there are only SOHs above 80% in Fig. 3. According to Fig. 3, the voltage interval 3.85 V–4.2 V always covers the state of charge (SOC) interval 12%-89% which is common for driver behavior. Therefore, the voltage interval 3.85 V–4.2 V was chosen to calculate IV.

In statistics, the widely-used Pearson correlation coefficient is a measure of the linear correlation between two variables. It has a value between +1 and −1, where 1 is total positive linear correlation, 0 is no linear correlation, and −1 is total negative linear correlation. The relationship between SOH and IV is shown in Fig. 4 and the Pearson correlation coefficient between them is 0.9967, which demonstrates that there is a strong linear correlation between IV and SOH. Therefore, the IV can be used to construct a simple linear SOH estimation model.

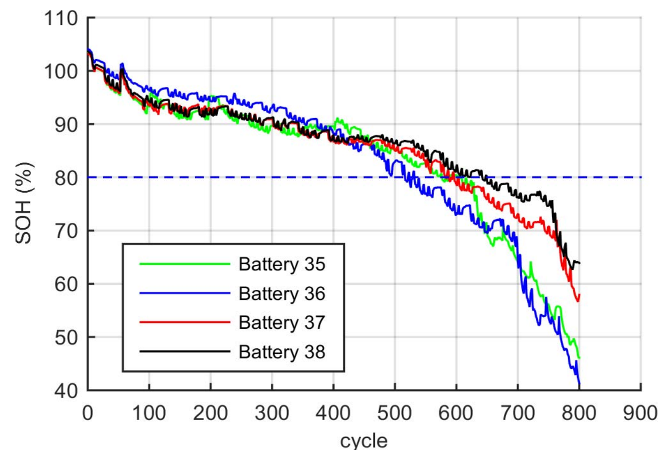

Fig. 1. SOH degradation of four batteries

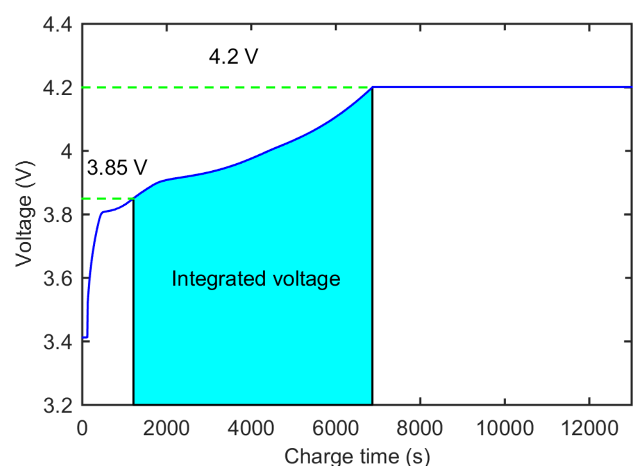

Fig. 2. Charging voltage of battery 35 and illustration of integrated voltage

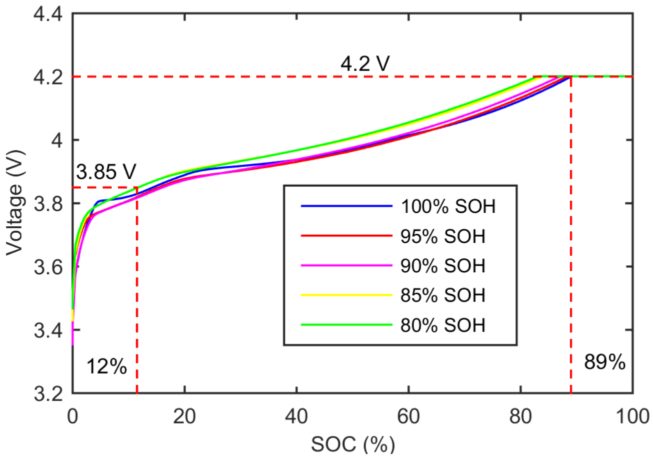

Fig. 3. Charging voltage curve at different SOHs

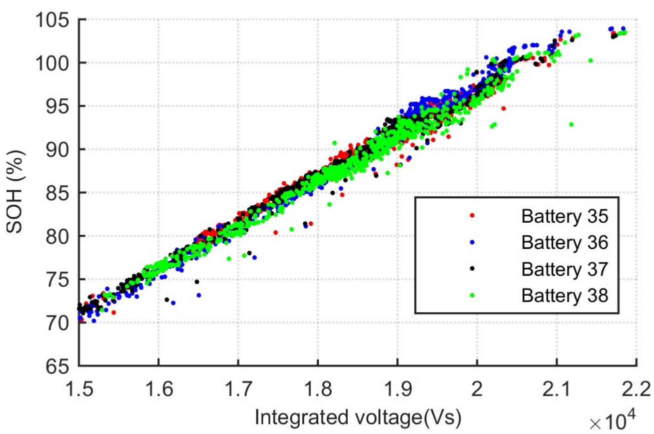

Fig. 4. Relationship between SOH and integrated voltage

III. SOH Estimation

The linear relationship between SOH and IV is described as follows:

$$y = \alpha + \beta x \tag{2}$$

where y and x represent SOH and IV, respectively. α and β are the parameters to be determined by the least squares (LS) method based on the batteries' experiment data. Denote the estimated parameters $\hat{\alpha}$ and $\hat{\beta}$,then the new estimation $\hat{y}_h$ corresponding to new input x_h is $\hat{y}_h = \hat{\alpha} + \hat{\beta} x_h$, and the $100(1-\theta)\%$ confidence interval is:

$$\hat{y}_h \pm t_{(\theta/2,n-2)} \times \sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n-2} \times (1+\frac{1}{n}+\frac{(x_h-\overline{x})^2}{\sum_{i=1}^{n}(x_i-\overline{x}_i)^2})}\ .$$

$t_{(\theta/2,n-2)}$ is student's t-distribution with n-2 degrees of freedom. n is the sample size. $\hat{y}_i$ is the estimation corresponding to the x_i and y_i is the SOH measurement. $\overline{x}$ is the mean of all the integrated voltage x_i .

Because there is data for four batteries, the data for three batteries is used to determine the parameters α and β in (2), and then another battery's data is used to verify the constructed model. Obviously, there are four SOH estimations for every battery, and they are shown in Figs. 5–8. Table 1 shows the estimation evaluation criteria such as root mean square error (RMSE), coefficient of determination (R^2), mean absolute error (MAE), mean absolute relative error (MARE), and maximum absolute error (ME). The definitions of MAE and MARE are as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right| \tag{3}$$

$$MARE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|y_i - \hat{y}_i\right|}{y_i}\times 100\% \tag{4}$$

where $\hat{y}$ is SOH estimation and N is the number of data points.

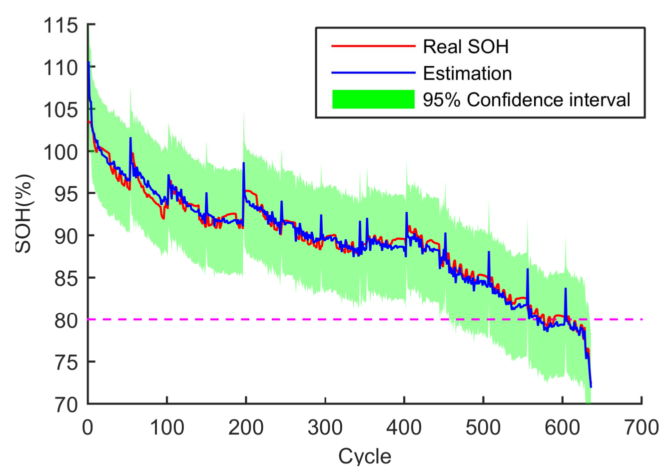

Fig. 5. SOH estimation for battery 35

Figs. 5–8 show that all the SOH estimations are close to the real data. More specifically, all the RMSE and R^2 are below 0.013 and above 0.97, respectively, and thus the constructed model properly describes the linear relation between SOH and IV. The biggest mean absolute error is only 0.95%. The biggest mean absolute relative error is 1.04%, which means the estimate made by the established model has a high accuracy. The average of maximum error of the four estimations is only 7.42%, which is acceptable for real applications. Besides, all the real data are within the 95% confidence intervals of the estimation. Therefore, the effectiveness and accuracy of this method are demonstrated by Figs. 5–8 and Table 1.

Battery 33 under different discharge rate (0.5C) is used to validate on-line SOH estimation. The SOH estimation model is constructed by the data of batteries 35-38 and the estimation result is shown in Fig. 9 and the estimation performance is listed in Table 1. Fig. 9 shows the estimated SOH follows the trend of the real data and all the real data are within the 95% confidence intervals of the estimations.. The maximum error for estimation is just 5.99%. The mean absolute error and mean absolute relative error are only 1.55% and 1.71%, respectively. Therefore, the developed method is applicable to on-line SOH estimation.

TABLE I. SOH ESTIMATION PERFORMANCE OF FOUR BATTERIES

BATTERY NUMBER	**Estimation Performance**				
	RMSE	***R^2***	***MAE***	***MARE***	***ME***
35	0.0095	0.972	0.72%	0.80%	6.99%
36	0.0123	0.975	0.95%	1.04%	5.92%
37	0.0089	0.981	0.65%	0.72%	6.41%
38	0.0115	0.970	0.80%	0.90%	10.36%
33	0.0184	0.944	1.55%	1.71%	5.99%

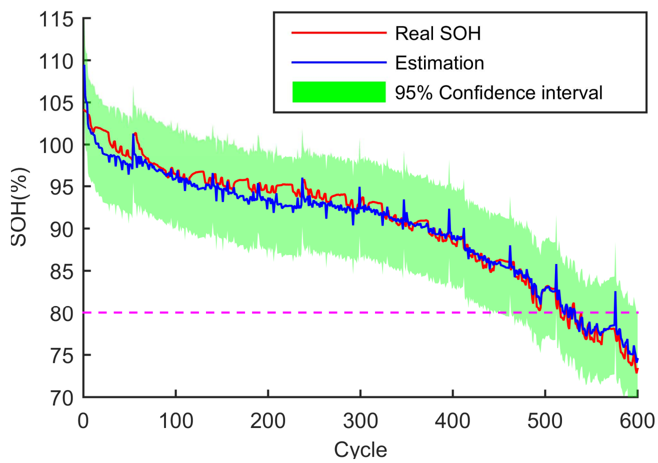

Fig. 6. SOH estimation for battery 36

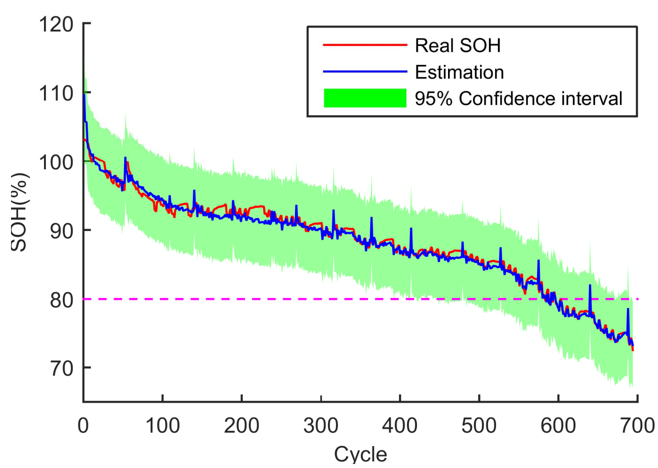

Fig. 7. SOH estimation for battery 37

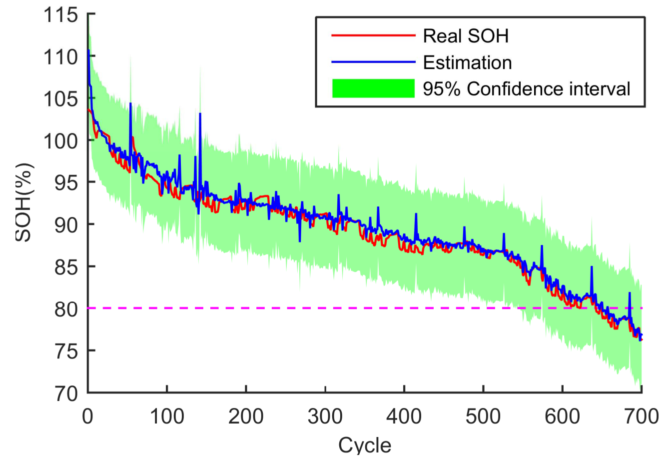

Fig. 8. SOH estimation for battery 38

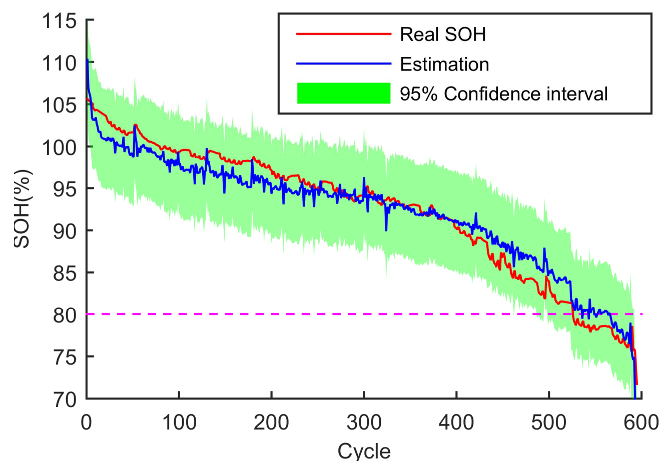

Fig. 9. On-line SOH estimation for battery 33

IV. CONCLUSIONS

A strong linear correlation between SOH and integrated voltage over time was determined from data of lithium-ion batteries which were run through accelerated aging tests, as the Pearson correlation coefficient between SOH and integrated voltage over time is 0.9967. Therefore, a SOH estimation model with low computing burden was developed using least square methods based on this linear correlation. The integrated voltage was obtained from the charging phase within the terminal voltage range of 3.85 V–4.2 V. As a result, the developed method is applicable to online SOH estimation regardless of the loading conditions.

To validate the effectiveness of the developed method, four SOH estimations for four batteries were made. The average of root mean square error is 0.01. The average of mean absolute error is 0.78%. The average of mean absolute relative error is 0.87%. The average of maximum absolute error is 7.42% . All the four estimation evaluation criteria are almost equal to zero, which means an accurate estimation was achieved. Besides, the average of coefficient of determination (R^2) is 0.97 and all the real SOH data fall into the 95% confidence interval of the estimation. Thus these estimations verified the effectiveness and accuracy of the developed method. Another battery under different discharge rate was used to validate the constructed model, and the mean absolute error for SOH estimation is only 1.55%, thus this demonstrates the effectiveness of the developed method for on-line SOH estimation.

The developed method is most applicable to batteries on the electric vehicles as these batteries are always run through dynamic loading conditions and the battery management system does not have a high computing performance. However, as different kinds of batteries have different discharge characteristics, the integrated voltage interval should be determined. When the battery is charged but the voltage range does not cover the pre-defined voltage interval, the battery management system just uses the SOH calculated herein for state of charge estimation, and updates the SOH at the next charge cycle. There are two charge protocols for electric vehicles: fast charge and slow charge. For an electric vehicle, the current in fast charge is about 14 times that of the slow charge. Thus, the effect of charge rate on SOH estimation will be investigated in the future research. If the charge rate does affect the estimation, a new estimation method will be applied based on the charge rate.

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