A new method for lithium-ion battery's SOH estimation and RUL prediction

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***Abstract*—State of health (SOH) estimation and remaining useful lifetime (RUL) prediction are important for a battery management system (BMS). This paper presents a new method to estimate SOH by taking local voltage variation and capacity variation in charging or discharging process of the battery as SOH indexes, and realizes RUL prediction based on a particle filter. The effectiveness is validated using a NCM/LTO lithium-ion battery pack.**

Keywords—SOH, RUL, Lithium-ion Battery

I. Introduction

Lithium-ion batteries are widely used in electric vehicles and energy storage systems for their good qualities of high energy density, low self-discharge rate and no memory effect. The available capacity of the battery decreases with use, therefore it is important for a BMS to estimate and predict the SOH of the battery accurately, providing users with suggestions for operating and maintaining the battery system [1,2].

The most commonly used definition of SOH of a battery is the ratio of fully charged/discharged capacity at present to the initial capacity [2], so capacity is the direct measurement for SOH estimation. However, the fully charged/discharged capacity can hardly be acquired under certain constant current working conditions. Thus it is necessary to acquire external measurable data, such as voltage, current, temperature and internal resistance of the battery to extract SOH indexes relating to the capacity fading trends.

Electrochemical impedance spectroscopy (EIS) has been used to characterize the state of batteries since its invention [3-5]. A typical EIS measurement is usually carried out by a Frequency Response Analyzer (FRA), which is complex and expensive, so EIS measurements can only be implemented in laboratory.

Internal DC resistance of battery at certain SOC and temperature has strong correlations to the SOH of battery [6]. Internal DC resistance can be measured online by applying a current interruption to the battery and calculating the ratio of voltage variation to current variation at that moment. This method has a high demand for data acquisition, and the consistency through multiple measurements is poor.

The algorithms used for predicting the trends of capacity or SOH indexes could be Auto-Regressive and Moving Average (ARMA), Extended Kalman Filter (EKF), Particle Filter (PF), and so forth. Among them PF is a kind of Sequential Monte Carlo method and is widely seen as an ideal tool for system's state tracking and prediction [7,8].

This paper presents a SOH estimation method using local voltage variations and capacity variations in charging or discharging process of the battery as SOH indexes, and predicts RUL of the battery on this basis. The main content of this paper is as follows. First, the definitions of new SOH indexes are proposed. Second, four SOH indexes are extracted from voltage and current profiles measured on an ageing NCM/LTO lithium-ion battery pack. Then the relevance between each SOH index and capacity of battery is analyzed, and the quantitative association model is derived. Finally, SOH of another battery pack of same kind is estimated. RUL is also predicted based on particle filter algorithm and results of SOH estimation. The experiment results show that the method presented in this paper is accurate and can be easily implemented in the BMS.

II. SOH Indexes Extraction

It is easy to conclude that capacity variation at same voltage interval tends to decrease with the battery's ageing. Similarly, when the battery is charged or discharged with same amount of capacity, voltage variation tends to increase with battery's ageing. These phenomena not only manifest not only in the full but also in the local charging or discharging process.

A. Definition of SOH Indexes

In this paper, we propose two kinds of SOH indexes, i.e., capacity variation at same voltage interval and voltage variation at same capacity interval. Each kind of SOH index has two definitions with respect to charging and discharging.

The capacity variations at the same voltage interval during discharging and charging are denoted as $Q_{\text{V-D}}$, and $Q_{\text{V-C}}$ respectively, which are the integrals of the current and time from one voltage point to another while the battery is discharged or charged.

The voltage variations at the same capacity interval during discharging and charging are denoted as $V_{\text{O-D}}$ and $V_{\text{O-C}}$ respectively, which are the voltage differences while the battery is discharged or charged with the same specific capacity.

The method of obtaining SOH index of $Q_{\text{V-D}}$ is illustrated as an example. The voltage curve schematic when the battery is discharged is shown in Fig. 1.

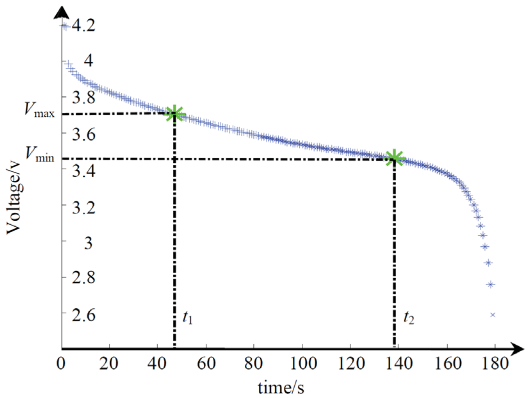

Fig.1 Voltage vs. time schematic when battery is discharged.

During the process of discharging, a voltage interval is set as [$V_{\min}$, $V_{\max}$]. The current is accumulated with time while the voltage is in the interval. Specially, the value is product of the current and the time when the current is constant as shown in Eq. 1.

$$Q_{\text{V-D}} = I \cdot \left(t_2 - t_1\right) \tag{1}$$

With the ageing of the battery, the capacity of discharging will decrease when the same voltage interval is selected.

B. SOH Indexes Extraction

According to the aforementioned method, the four SOH indexes of a NCM/LTO type lithium-ion battery pack are extracted. The battery pack is in form of 4-parallel and 12-serie with rated capacity of 20 Ah. Cyclic ageing experiment is carried out at room temperature. After charged to 30V with constant current rate of 1C, the pack is charged at constant voltage until the charging current is less than 4A. After that, the pack is discharged to 21.6V at 1C. The resting time after charging and discharging is 30 minutes.

Normally, cycle life of LTO battery is usually as long as up to several thousand and even tens of thousands of cycles. The pack used for SOH indexes extraction showed a rapid capacity fading after aged 85 cycles. Analysis afterwards reveals electrolyte leakage in one of the cells of the pack. To some extent, this accelerated the ageing process and saved testing time.

Which is the most suitable voltage interval for the extraction of $Q_{\text{V-D}}$ and $Q_{\text{V-C}}$, which is the most suitable SOC interval for the extraction of $V_{\text{Q-D}}$ and $V_{\text{Q-C}}$, have significant influence to the accuracy of SOH estimation and need to be optimized.

a) Determination of $V_{\min}$ and $V_{\max}$

First, according to the open circuit potential curve, the voltage values corresponding to SOC=30% and SOC=90%, denoted as $V_{\text{SOC=30\%}}$ and $V_{\text{SOC=90\%}}$ are determined.

Second, in order to ensure the measurement accuracy, the SOC variation between $V_{\min}$ and $V_{\max}$ should not be too small, otherwise the measurement error will have a greater impact on the method. Therefore, the SOC variation is set as no less than 5%. $Q_{\text{V-D}}$ and $Q_{\text{V-C}}$ are extracted in all the voltage intervals satisfying the above conditions with 0.1V step in the voltage interval [$V_{\text{SOC=30\%}}$, $V_{\text{SOC=90\%}}$].

Finally, the correlations between the extracted features and the battery's effective capacity are analyzed. The voltage interval that has strongest linear correlation to effective capacity is selected as the optimal interval, [$V_{\min}$, $V_{\max}$], for use of SOH indexes extraction.

b) Determination of $SOC_{\min}$ and $SOC_{\max}$

First, the SOC should be between 30% and 90%.

Secondly, in order to guarantee the measurement precision, the voltage variation at $SOC_{\min}$ and $SOC_{\max}$ should not be too small.

Next, $V_{\text{Q-D}}$ and $V_{\text{Q-C}}$ are extracted in all SOC ranges satisfying the condition with 1% step in the SOC interval [30%, 90%]. The SOC interval that has strongest linear correlation to effective capacity is selected as the optimal interval, [$SOC_{\min}$, $SOC_{\max}$], for use of SOH indexes extraction.

Results of SOH indexes extraction are shown in Fig. 2 and Fig. 3.

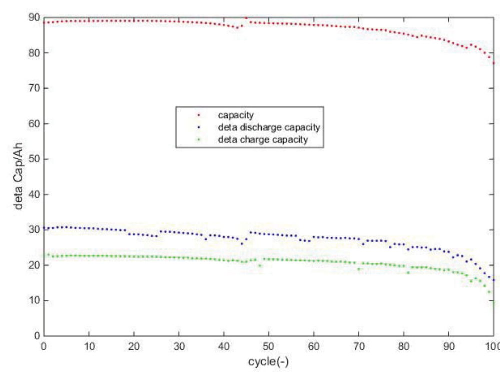

Fig.2 $Q_{\text{V-D}}$, $Q_{\text{V-C}}$ and effective capacity vs. cycle number.

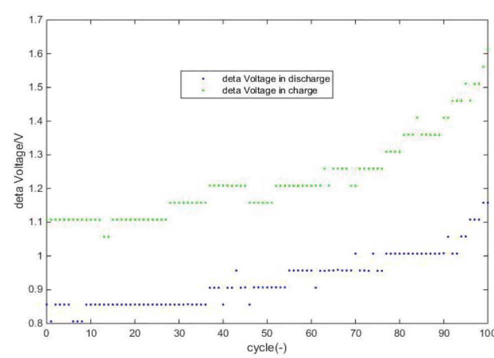

Fig.3 $V_{\text{Q-D}}$ and $V_{\text{Q-C}}$ vs. cycle number.

It can be seen from Fig. 2 that $Q_{\text{V-D}}$ is greater than $Q_{\text{V-C}}$ at all cycle numbers. The decreasing trends of both $Q_{\text{V-D}}$ and $Q_{\text{V-C}}$ are basically consistent with the capacity degradation.

In Fig. 3, $V_{Q\text{-}D}$ is greater than $V_{Q\text{-}C}$ at all cycle numbers and both of the two SOH indexes are counter correlated to the capacity fading.

Fitting the relationship between four SOH indexes and the effective capacity, profiles of which are shown in Fig. 4, Fig. 5, Fig. 6 and Fig. 7 respectively. Fitting models used are the first and the second order polynomials. The fitting errors of each fitting equation are shown in Fig. 8, Fig. 9, Fig. 10 and Fig. 11. Form of fitting equations and averaged fitting errors are also manifested, as shown in Tab. 1.

Conclusions can be drawn that all the fitting errors (or SOH estimation errors) are less than ±4% and quadratic equation are more accurate than linear equation for each SOH index.

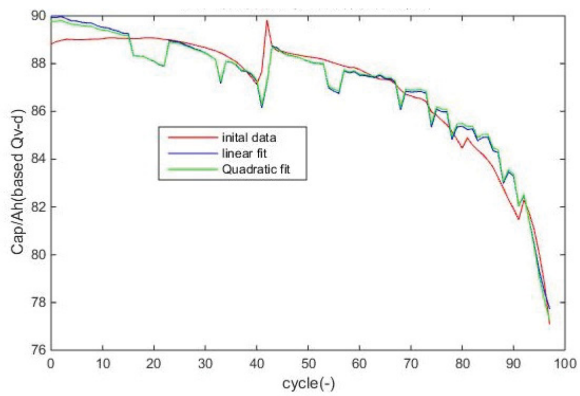

Fig.4 Linear and quadratic fitted capacity profiles based on $Q_{V\text{-}D}$.

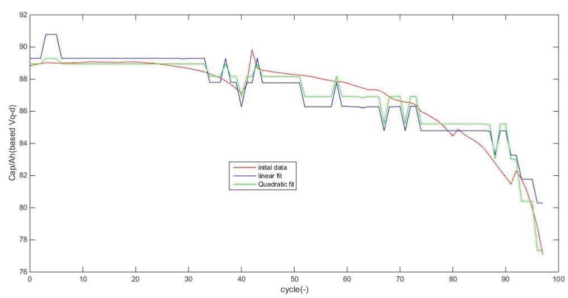

Fig.5 Linear and quadratic fitted capacity profiles based on $V_{Q\text{-}D}$.

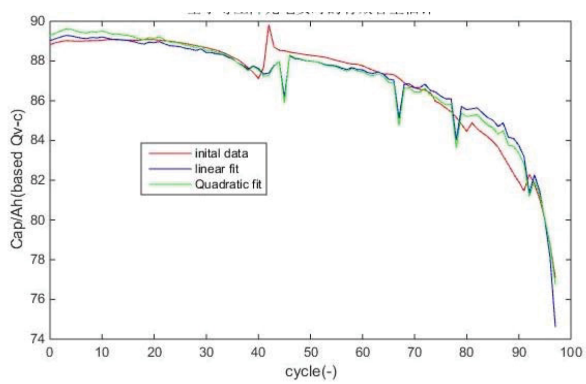

Fig.6 Linear and quadratic fitted capacity profiles based on $Q_{V\text{-}C}$.

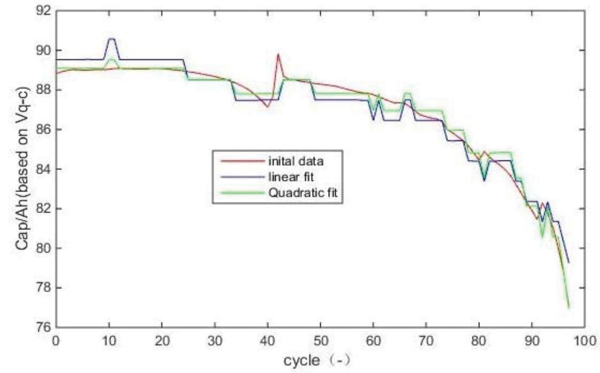

Fig.7 Linear and quadratic fitted capacity profiles based on $V_{Q\text{-}C}$.

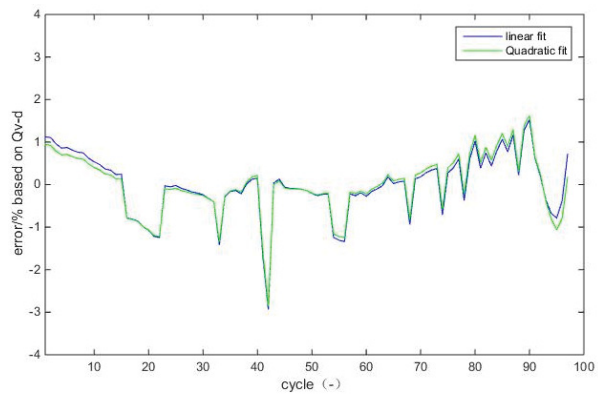

Fig.8 Fitting error profiles based on $Q_{V\text{-}D}$.

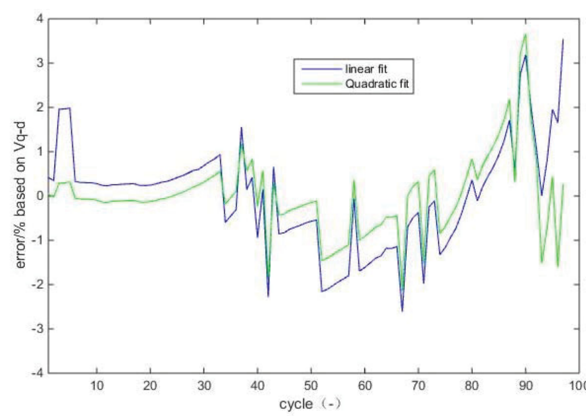

Fig.9 Fitting error profiles based on $V_{Q\text{-}D}$.

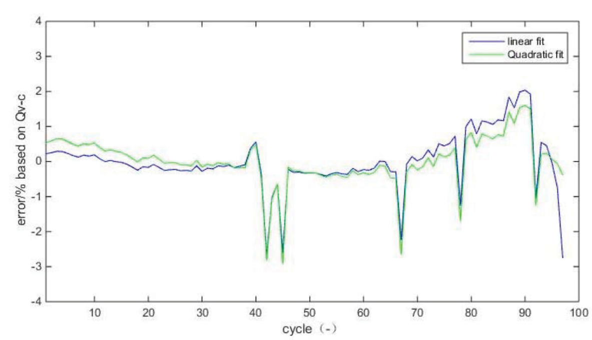

Fig.10 Fitting error profiles based on $Q_{V\text{-}C}$.

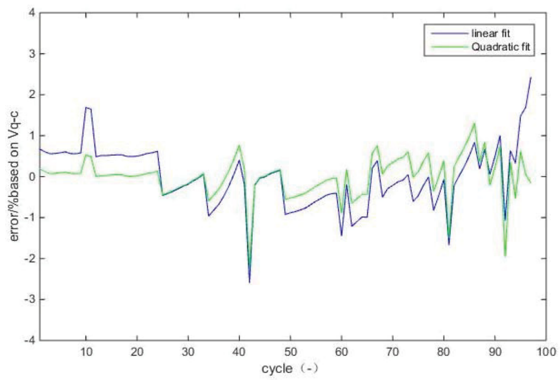

Fig.11 Fitting error profiles based on $V_{Q\text{-}C}$.

Tab. 1 Fitting equations and errors of SOH indexes.

SOH indexes	Linear fitting equations	Fitting errors (%)
$Q_{V\text{-}D}$	$Q = 0.8418Q_{V-D} + 64.0124$	0.857
$Q_{V\text{-}C}$	$Q = -30.0496Q_{V-C} + 114.9267$	1.1121
$V_{Q\text{-}D}$	$Q = 1.0245V_{Q-D} + 65.7621$	0.8216
$V_{Q\text{-}C}$	$Q = -21.2633V_{Q-C} + 113.1131$	0.7816
SOH indexes	**Quadratic fitting equations**	**Fitting errors (%)**
$Q_{V\text{-}D}$	$Q = -0.0240Q_{V-D}^{2} + 2.0053Q_{V-D} + 50.3549$	0.7954
$Q_{V\text{-}C}$	$Q = -36.0476Q_{V-C}^{2} + 41.8246Q_{V-C} + 79.5450$	0.9754
$V_{Q\text{-}D}$	$Q = 0.0129V_{Q-D}^{2} + 0.5955V_{Q-D} + 69.0271$	0.7618
$V_{Q\text{-}C}$	$Q = -24.8214V_{Q-C}^{2} + 44.3311V_{Q-C} + 70.4139$	0.4765

III. SOH Estimation And RUL Prediction

A. SOH Estimation

The SOH estimation method is applied to another battery pack of same type with the previous one. The new pack has been aged for 335 cycles and the actual SOH is still above 95%. Taking $V_{Q\text{-}C}$ and $V_{Q\text{-}D}$, which show relative smaller fitting errors in Tab. 1, as the SOH indexes, estimation results and the error curves are shown in Fig. 12 and Fig. 13. It is observed that SOH estimation errors are all less than ±4% and even less than ±2% if $V_{Q\text{-}C}$ is used, which proves that the fitting models constructed through previous pack can be used for the new pack with excellent accuracy.

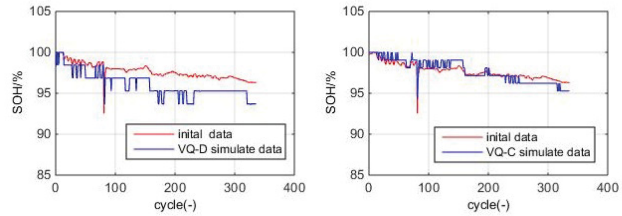

Fig.12 SOH estimation.

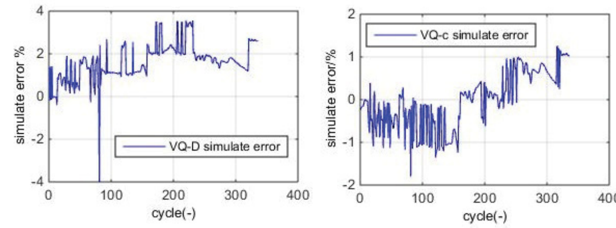

Fig.13 the error curve.

B. RUL Estimation

PF algorithm has been widely used on the lithium-ion battery life prediction, the specific steps can be reference in many literatures and will not be addressed in this paper.

The model used in the PF framework is

$$Q_k = \beta_1 + \beta_2 e^{(\beta_3 / k)} \tag{2}$$

Where Q_k is the discharging capacity of kth cycle, β_1, β_2, β_3 are state values.

Capacity fading tendency of the battery pack is predicted based on the SOH estimation result taking $V_{Q\text{-}C}$ as SOH index, which has the smallest estimation error, as shown in Fig. 14. Fig. 15 is the zoom-in view before cycle 500.

By setting 80% of the initial capacity as lifetime threshold, the battery's RUL is 20,100 cycles, with total lifetime being 20,435 cycles. To some extent, this prediction can reflect a LTO battery pack's actual lifetime. The more solid validation work will be done after more experimental data is acquired.

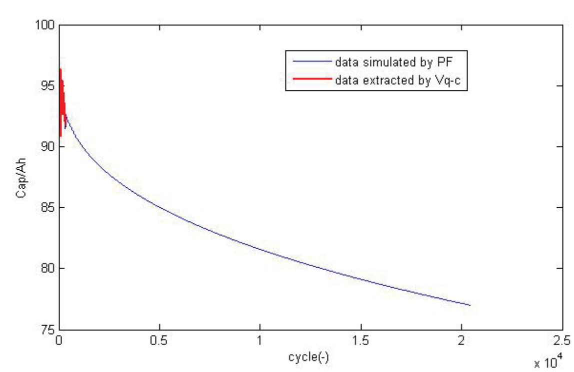

Fig.14 Capacity predicted vs. cycle number.

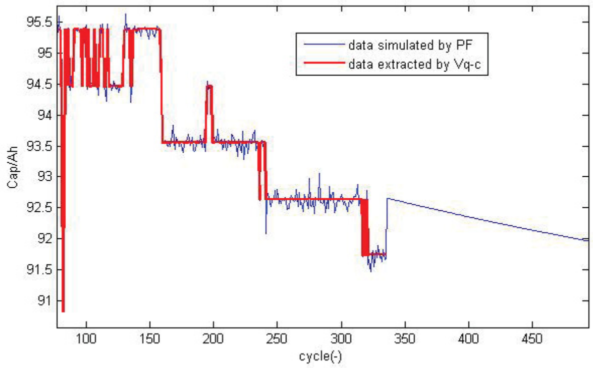

Fig. 15 Zoom-in view of before cycle 500 in Fig. 14.

IV. CONCLUSIONS

In this paper, the local capacity variations and voltage variations during charging and discharging are correlated to lithium-ion battery's state of health, and the new SOH indexes are used for SOH estimation and RUL prediction of battery pack. The merits of the work are:

(1) The SOH estimation error is less than ±4%, the RUL prediction can reflect the actual lifetime of the battery.

(2) No additional battery monitoring circuit is needed and the algorithm is esay to be implemented in a BMS.

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