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A Lithium-Ion Battery Remaining Useful Life Prediction Method with A New Algorithm Based on Incremental Capacity Analysis

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Abstract: - Safe use of lithium-ion batteries requires accurately assessing state of charge (SoC), state of health (SOH) and capacity estimation techniques. Due to numerous charge and discharge cycles, lithium ion batteries undergo a degradation process during their use leading to failures, accidents, and fire. Traditional ICA/DVA methods have been used to overcome these issues, but they are subject to changes in battery resistance and polarization processes during battery aging. Evaluation of the SoC as a function of incremental capacity is proposed in this work to overcome this problem. This article used a new algorithm to perform, through simulations carried out with Matlab® software, incremental capacity analysis for a preventive estimate of remaining useful life (RUL). In addition, the comparison between IC curves and the SoC here used fully represents the relationship between the IC values and the internal parameters of the battery. The validity of the proposed algorithm against the phenomenon of battery aging was evaluated based on experimental data from NASA's PCoE research center.

Keywords: Electric vehicles, ICA/DVA methods, lithium-ion batteries, state of charge

I. INTRODUCTION

Lithium-ion batteries have quickly spread to the world market for the advantages that characterize them, such as high performance, high energy density, high power, high practicality in use, and long application life. Over the years, they have recognized a wide use in the electronics market, particularly for hybrid and electric vehicles in the automotive market. However, due to numerous charge and discharge cycles, lithium ion batteries undergo a degradation process, leading to failures, accidents, and explosions during use.

The BMS (battery management system) is thus used to manage failure mechanisms and fire prevention strategies.

In particular, preventing remaining useful life (RUL) becomes the main goal of researchers worldwide. The prediction of RUL occurs through different methods, such as the calculation of capacitance [1]-[4] and internal resistance [5]-[6], to fully evaluate a predictive method that analyzes the state of degradation of the battery. However, assessing internal resistance is often difficult due to high monitoring and measurement costs. In addition, evaluating the maximum capacity value during the tests in the charging and discharging phases is difficult. For these reasons, numerous studies have been conducted based on battery aging indicators by analyzing the battery charge and discharge curves. To improve the efficiency in the evaluation of SOH, according to Wang [7], some studies develop methods for the continuous measurement of the efficiency of a battery obtained with special techniques accompanied by the evaluation of absolute voltage or voltage drop [8]-[9]. Other studies calculate the state of health by measurements of impedance parameters and the fuzzy logic method [10]-[11]. In addition to the state of health estimation, researchers developed SOC estimation by analyzing incremental capacity using charge and discharge tests. This type of analysis allows optimal results despite incomplete charge and discharge cycles [12]-[16]. As described in the studies by Lin [17] charge losses during charge and discharge cycles need to be considered for a more precise assessment of the SOC. Incremental capacity analysis (ICA) methods have been developed extensively in studying battery degradation mechanisms and have recently been introduced to estimate RUL [18]-[21]. A correlation between peak IC and state of charge SOC was developed by Zheng [22]. This article uses an ICA method to evaluate SOC insensitive to battery resistance and polarization during the aging process. The article has been developed as follows. Section 2 develops the SOC assessment process based on IC curves. Section 3 proposes the algorithm for estimating SOC and CI. Section 4 provides for verification of the results of the proposed approach. The conclusions are set out in Section 5.

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II. SoC Evaluation Process

A. Experimental data

This section introduced the ICA method using datasets from the NASA research center. First, a new algorithm was developed to evaluate the initial curve of incremental capacity IC. Secondly, the curve is filtered to overcome measurement errors prevalent during testing. Finally, the algorithm calculates the SoC and evaluates the correlation between the filtered IC proposed curve and the degradation process. In this work, simulations were made based on experimental data from NASA's PCoE research center.

Four cells (5#, 6#, 7#, 18#) are cycled simultaneously, charged, and discharged under different loads and environmental conditions set respectively based on the charge made and by the environmental chamber. EIS measurements were periodically made to monitor the internal status of the battery. In particular, the processes consist of charging, discharging, and recovery from the rest phase to predict the end of charge and battery life. For the development of the graphs, the experimental data are provided by NASA and are test time (s), step time (s), step index, voltage (V), current (A), and surface temperature (°C).

B. Simulation of NASA datasets

Following a charging process of the #5, #6, #7, and #18 constant current (DC) batteries equal to a value of 1.5 A, a voltage of 4.2 V was reached, and a constant voltage (CV) mode was switched to a constant voltage (CV) mode until a charge current value of 20mA was reached. The estimated value represents a phenomenon of aging of the battery, as shown by the graphs processed through simulation with the Matlab® software. The trend illustrated by the diagrams shows how the SOC value is mainly influenced by current, voltage, and temperature values. Mathematically, the curve IC is the derivative of capacitance (Q) concerning voltage (V) obtained using (1).

$$dQ/(dV) \approx \Delta Q/(\Delta V) \qquad (1)$$

The IC curve during the DC charging process at different aging levels is shown in Fig. 1. Fig. 1 shows how the incremental capacity curves are proportional to the aging process. The cause of this trend is that the increase in resistance and the phenomenon of polarization have no effect on the IC curves, leading to difficulties in identifying the application characteristics of the IC curve. Thus, in Fig. 2, the voltage curves have been developed as a function of different SoC values.

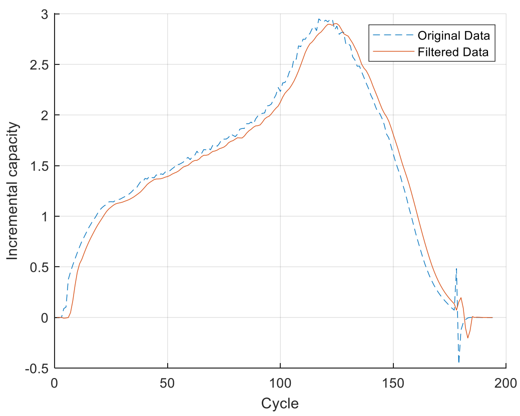

Fig. 1 – Comparison of the incremental capacity curve for battery #5 of the NASA dataset between simulated and measured data in case of discharge.

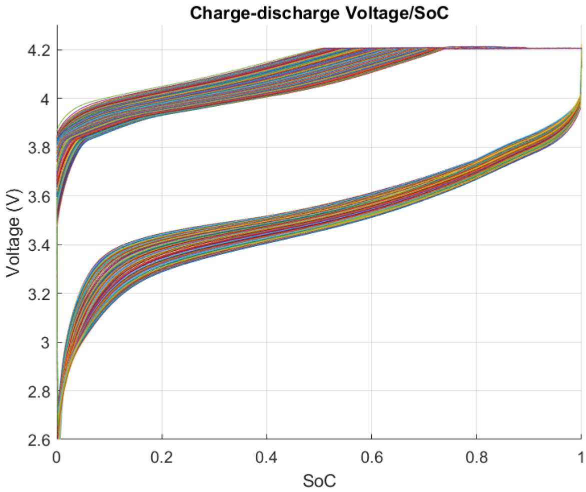

Fig. 2 – Battery #5, curves with voltage values compared to the SoC.

In Fig. 4, the representation of ICs as a function of the SoC shows that the IC curves do not vary as a function of polarization and resistance during battery aging.

Fig. 1 compares the incremental capacity curve and the filtered data for battery #5 in the NASA dataset. In the graph, it is possible to see how the blue curve corresponds to a value of the incremental capacity while the fuchsia curve represents the value of the filter. It is possible to see how the filtered data can filter the measurement error well, and the characteristics of the IC curve are well represented.

Fig. 3 shows the incremental capacitance values compared to the SOC for charging (blue) and discharging (red) cases. It is interesting to note that depending on the cycles, the trend varies considerably depending on the SOC. In particular, in this article, the peak value and the area below the peak are considered important factors that reflect the aging state of the battery. The definition of the region below the peak takes place thanks to the analysis of the voltage trend between a maximum value of 4.2 V and a minimum of 2.6 V for cases of charge and discharge, visible in Fig. 3.

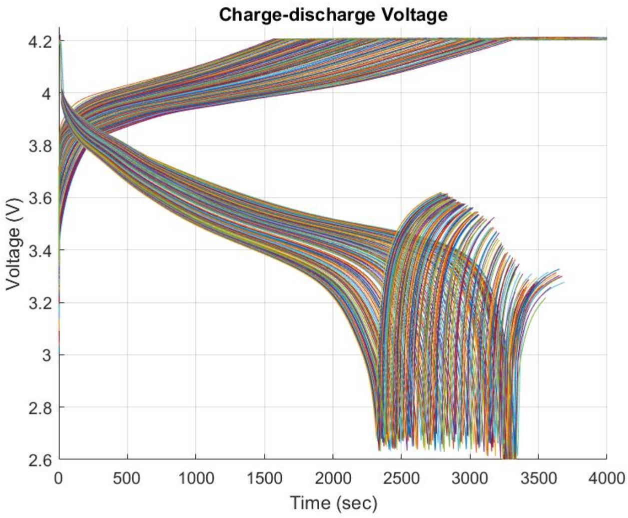

Fig. 3 – Battery #5: Voltage trend (V) as a function of time.

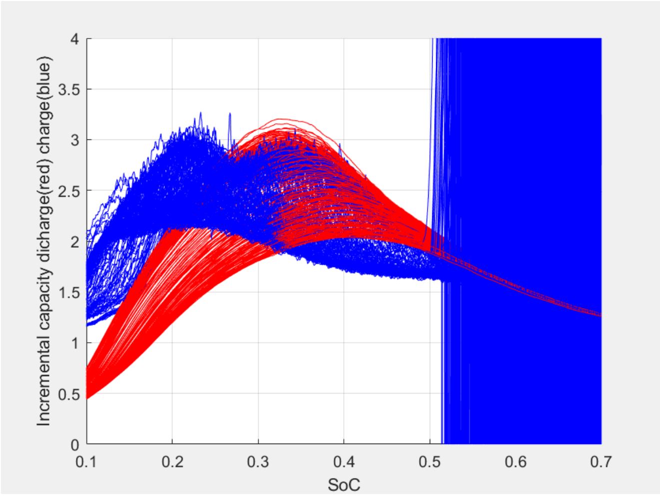

Fig. 4 - Battery #5: Incremental capacity values compared to SOC for charge (blue) and discharge (red) cases.

III. Statement of contribution/Methods

Incremental capacity curve analysis is an essential method for analyzing battery aging. This article considered constant current charge and discharge phase data to calculate voltage curves – SoC and incremental capacitance – SoC.

For the development of incremental capacity graphs, the experimental data provided by the NASA research center are test time (s), step time (s), step index, voltage (V), current (A), and surface temperature (°C).

The measured data is loaded through the Data-load script through which it is possible to extrapolate from a .xslx, .csv, or .mat file only the data concerned.

The code calculated the SoC with the following equation:

$$\mathrm{SoC} = \int_{t0}^{tn} I \qquad (2)$$

In which appear:

I: current (A);

t0: initial instant (s);

tn: final instant (s).

From the Fig. 2 in which the voltage (V) and the SoC are graphed, it can be seen how the no-load voltage remains dependent, especially in the final parts of the state of charge, at very high SoCs and then descends in the discharge phase as the SoC decreases. In addition, it does not undergo variations depending on the temperature used in the tests.

The incremental capacity is then calculated in the case of charging and discharging with the formulas:

$$\mathrm{ICc(j)} = \frac{[(\mathrm{SoCc(j+fw)} - \mathrm{SoCc(j-fw)}]}{(\mathrm{Voltage(f+fw)} - (\mathrm{Voltage(j-fw)}))} \qquad (3)$$

$$\mathrm{ICd(j)} = \frac{[(\mathrm{SoCd(j+fw)} - \mathrm{SoCd(j-fw)}]}{(\mathrm{Voltage(f+fw)} - (\mathrm{Voltage(j-fw)}))} \quad (4)$$

In (3) and (4), the following items appear.

SoCc: State of Charge value in case of charge [%];

SoCd: State of Charge value in case of discharge [%];

Voltage: voltage value (V).

ICc: the value of incremental capacity in the case of charge;

ICd: the value of incremental capacity in case of discharge.

A filter has been applied to the incremental capacity value.

Filters are data processing techniques that can mitigate high-frequency fluctuations or remove periodic trends of a specific frequency from data. In Matlab®, the filter function filters a data vector x according to the following difference equation, which describes a filter with an intercepted delay line.

$$a(1)y(n) = b(1)x(n) + b(2)x(n-1) + \cdots + b(N_b)x(n - N_b + 1) - a(2)y(n-1) - \cdots - a(N_a)y(n - N_a + 1) \quad (5)$$

In (5), the following items appear:

a and b: vectors of filter coefficients;

Na: order of the feedback filter;

Nb: order of feedforward filter;

n: The index of the current item of x.

The output y(n) is a linear combination of the current and previous elements of x and y.

The filter function uses the specified coefficient vectors a and b to filter input data x.

With the Matlab® script, you assigned a value to the two vectors a and b.

a = 1

b=[-0.0888 0.0426 0.31222 0.45502 0.31222 0.0426 -0.0888]

Finally, the value of the SoC and the incremental capacity for the charging case was plotted.

IV. Result and Discussions

Fig. 5, 6, 7, and 8 show the trends in incremental capacity compared to cycles and the value of Q for battery #5, #6, and #7. In particular, it is easy to see how incremental capacity and Q characteristics reflect battery degradation well and can be considered indicators.

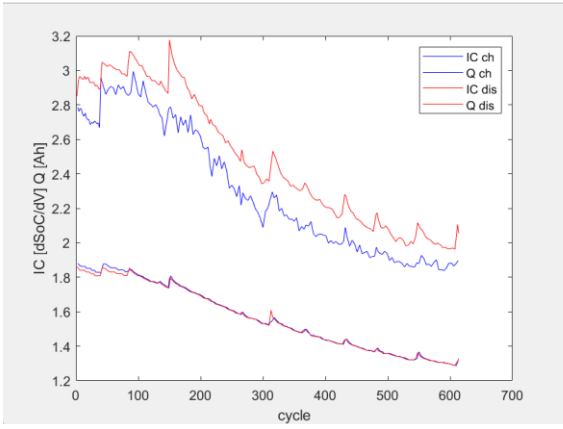

Fig. 5 – Battery #5:Trend of incremental capacity and Q value compared to cycles.

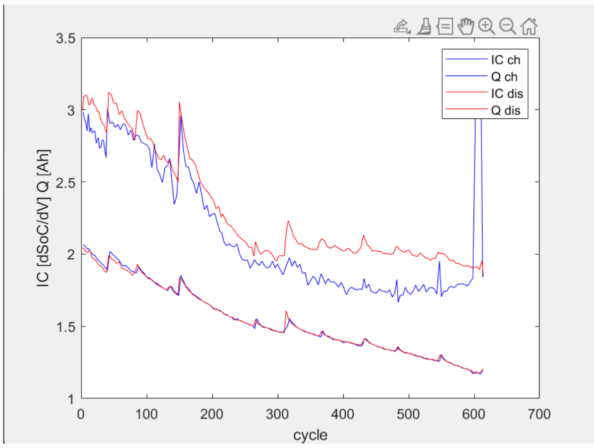

Fig. 6 – Trend of incremental capacity and the value of Q compared to the cycles for the battery #6.

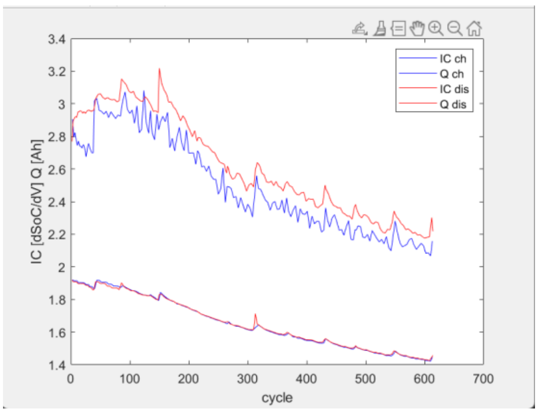

Fig. 7 – Trend of incremental capacity and the value of Q compared to the cycles for battery #7.

The Q and incremental capacity estimates for battery #5, #6, #7 are compared in Fig. 5, 6, and 7.

The Fig.4 shows how the correlation between the SoC and the incremental capacitance is influenced by the charge/discharge current rate and the ambient temperature. In addition, cell tension measurements are affected by errors made during measurements, adversely impacting the accuracy of the algorithm used for evaluating the CI. Consequently, the use of software filters is recommended to reduce the effect of noise on voltage measurements in the BMS.

The Fig. 8, 9, and 10 show the correlation between the capacity and the current integral of the battery #5, #6, and #7 in the charge and discharge phase.

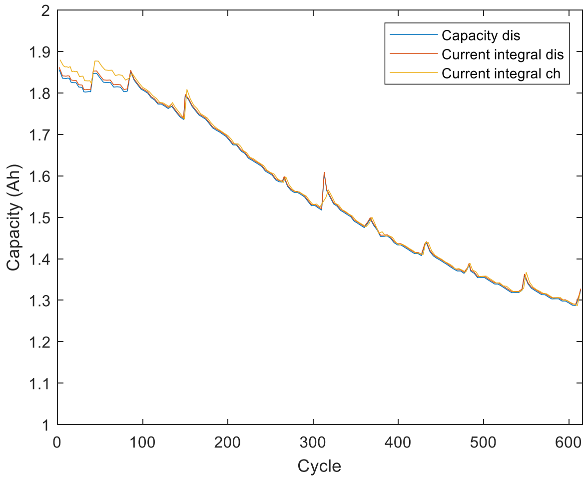

Fig. 8 – Trend of capacity and the value of current integral compared to the cycles for the battery #5, in the charge and discharge phase.

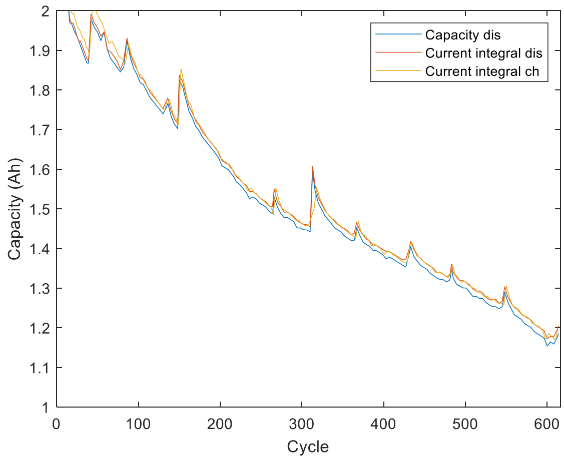

Fig. 9 – Trend of capacity and the value of current integral compared to the cycles for the battery #6, in the charge and discharge phase.

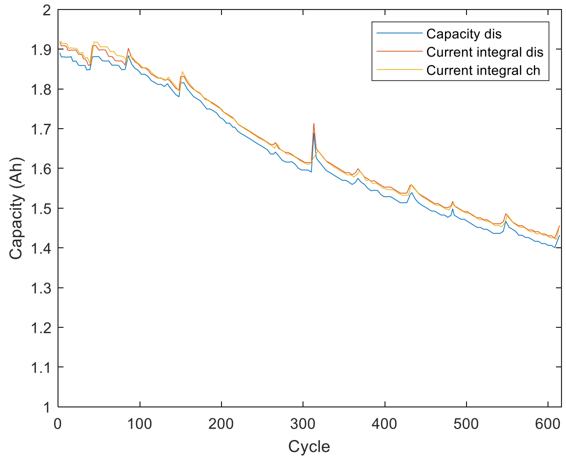

Fig. 10 – Trend of capacity and the value of current integral compared to the cycles for the battery #7, in the charge and discharge phase.

Table I briefly compares the proposed method and existing techniques for estimating SOC and capacity.

Table I – Comparison between SOC and capacity estimation methods.

	Methods	Complexity	Accuracy
SoC estimation	The FP-based methods OCV based methods Model-based methods	Low Low High	High Low High
Capacity estimation	The FP-based methods The ICA/DVA based methods Model-based methods	Low Medium High	High High High

Furthermore, Table I compares the proposed method with the existing one for SOC and capacity estimation. From the table, it is possible to see how the proposed ICA/DVA based methods present a high complexity associated with a high accuracy, in comparison with the other traditional methods used.

CONCLUSION

The prediction of RUL occurs through different methods, such as the calculation of capacitance and internal resistance to fully evaluate a predictive method that analyzes the state of degradation of the battery. However, assessing internal resistance is often difficult due to numerous factors such as high monitoring and measurement costs. In addition, evaluating the maximum capacity value during the tests in the charging and discharging phases leads to suboptimal results. For these reasons, in this article simulations have been conducted based on battery aging indicators by analyzing the battery charge and discharge curves with the goal of safe battery usage through precise assessment of SoC and incremental capacity. The robustness of the proposed algorithm against the phenomenon of battery aging was evaluated for several cells in the NASA dataset. The validity in calculating and analyzing the incremental capacity is also demonstrated compared to other methods which have the disadvantage of not being applicable in cases of incomplete cycles of the charging and discharging phases of the batteries. The proposed method calculating the SoC state of charge using the IC/DV curve has numerous advantages. First of all, the most obvious we find is that it fully represents the relationship between the IC values and the internal parameters of the battery. Secondly, from the simulations carried out we observe how the proposed algorithm eliminates the effect of battery resistance in calculating the SoC comparing IC and SOC while realizing the prediction of the RUL of the proposed lithium-ion batteries.

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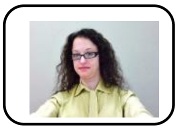

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