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Short communication

A fast estimation algorithm for lithium-ion battery state of health

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HIGHLIGHTS

- A new SoH estimation algorithm has been proposed for lithium-ion batteries.
- Concepts of regional capacity and voltage are introduced based on ICA.
- SoH models are developed as linear functions of the regional capacity.
- Experimental results show that the estimation errors are less than 2.5%.

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ABSTRACT

This paper proposes a novel and computationally efficient estimation algorithm for lithium-ion battery state of health (SoH) under the hood of incremental capacity analysis. Concepts of regional capacity and regional voltage are introduced to develop an SoH model against experimental cycling data from four types of batteries. In the obtained models, SoH is a simple linear function of the regional capacity, and the R-square of linear fitting is up to 0.948 for all the considered batteries with properly selected regional voltage. The proposed method without using characteristic parameters directly from incremental capacity curves is insensitive to noise and filtering algorithms, and is effective for common current rates, where rates of up to 1C have been demonstrated. Then, a model-based SoH estimator is designed and shown to be capable of closely matching battery's aging data from NASA, with the error less than 2.5%. Furthermore, such a small scale of error is achieved in the absent of state of charge and impedance which are often used for SOH estimation in available methods.

1. Introduction

Lithium-ion (Li-ion) batteries are playing an important role in many applications, such as electrified transportation and smart electric grids [1,2]. These batteries undergo a persistent aging process once manufactured. If inappropriately utilized due to overcharging, over-discharging, and/or overheating, the battery will be prematurely degraded or even cause fire and explosion, leading to dramatically deteriorated state of health (SoH) [3]. It is therefore imperative to monitor the battery's SoH for safety and health-aware management.

Due to its unmeasurable property, various prediction/estimation algorithms have been proposed for the SoH of Li-ion batteries. The first type of algorithms relies on model-based estimation techniques. For example, physical models have been used for battery health estimation by quantifying the electrochemical states/parameters, such as the total number of active lithium, resistance of the solid-electrolyte interface (SEI) film, and diffusion coefficients [4,5]. In the paradigm of equivalent circuit models, Wei et al. [6] and Hu et al. [7] obtained the SoH through estimating the capacity and internal resistance. However, the model-based algorithms are complex, and furthermore, the development of a precise and general health model is still ongoing [8,9]. To sidestep complex battery models, Hung et al. [10] explored and exploited the impedance to reflect SoH. Whereas the impedance approach can be error-prone as many uncertain factors, including state of charge (SoC) changes, load conditions, temperature, and measurement noise, can influence the health estimation results significantly. Data-driven approaches, such as support vector machine [11] and Gaussian process regression [12], have also been used to estimate the battery's health, but are subject to heavy online computations.

Incremental capacity analysis (ICA) has recently emerged to track

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the aging behavior of Li-ion batteries, using the differentiation of the battery capacity over its terminal voltage, dQ/dV, typically under constant-current charging conditions. By using a current rate of 0.04C to discharge a $LiFePO_4$ battery, up to five peaks can be observed from its IC curve [13,14]. These authors then predicted the battery's degradation characteristics using electrochemical information extracted from some of these IC peaks, especially the two close to terminals of IC curves. It has been further justified that the values of different IC peaks [15], corresponding peak voltages [16], and peak areas [14] can also be used to estimate battery SoH. However, in the existing ICA methods, the current rates are limited to be very low for extracting detailed electrochemical properties, because small IC peaks are often submerged at large current rates. This is contradictory to requirements of fast charging from terminal users. Moreover, due to the derivative nature, the ICA results can be sensitive to noise, thus the filtering approach. Besides, these IC curves can be quite different in different battery types, as seen in Ref. [17], so that the result obtained for one type may not be generalizable to others.

To enhance the ICA method, a novel and extremely simple method under the hood of ICA is proposed for real-time SoH estimation, using the constant-current profile in a charging process. In particular, the concepts of *regional capacity* and *regional voltage* are introduced and adopted to develop an SoH model against battery experimental cycling data. It is found that SoH is a linear function of the specified regional capacity. As the proposed method is independent of characteristic parameters directly from IC curves, its sensitivity to noise or filtering algorithms can be reduced significantly. It is demonstrated that estimation results built on this developed model are able to closely match publicly available battery aging data from NASA. Although only the cases with up to 1C rates have been studied, the proposed algorithm appears promising for battery health estimation at a large range of current rates.

2. Experiments

The experiments were performed on three commercial 18650 Li-ion battery cells using a UPower® battery testing system (5 V, 10 A, 0.1% accuracy) with the sampling rate of 1 Hz and at the room temperature of 25°C. A constant-current constant-voltage (CCCV) profile was adopted for charging operation, where the CC rate is 1C, cut-off current rate is 0.05C, and maximum voltage is 4.2 V. A CC scheme with current rate of 1C and cut-off voltage of 2.75 V was applied in discharging. To obtain the actually rated capacity at different SoH levels, the current trajectory throughout the charging process of each cycle has been integrated over time. A publicly available dataset from NASA [18,19] has also been exploited in this work. It was generated from four $LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$ battery cells, labeled as #05, #06, #07, and #34 in the original data source. As the above tests, CCCV and CC profiles were applied to battery charge and discharge, respectively. Specifically, the current at its CC stage is 1.5 A, the cut-off current is 20 mA, and cut-off voltage is 4.2 V. The current for discharge is 2 A for #05, #06, and #07 cells, and is 4 A for #34 cell, while the cut-off voltage is 2.7, 2.5, 2.2, and 2.2 V, respectively. The key experimental setup and labels for the obtained datasets are further listed in Table 1.

Table 1
Datasets for model development and estimator validation.

Dataset	Type	Capacity	Cycles	Data Source
1	$LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$	2 A h	136/189	NASA
2	FST®-2000NCM	2 A h	150	Experiment
3	FST®-2500NCM	2.5 A h	50	Experiment
4	SONY®US18650VTC6 NCM	3 A h	100	Experiment

3. Concept definition and problem statement

SoH definition. Despite various definitions exist in this literature [3], the SoH of a Li-ion battery to be used here is defined in the following form

$$SoH(\tau) = \frac{C_n(\tau)}{C_{n0}} \tag{1}$$

where C_{n0}: $=C_n(\tau = 0)$ is the battery rated capacity taken from its specification sheet, which is taken at 25°C at the beginning of the battery's service life. Under the same temperature, $C_n(\tau)$ is the actually rated capacity at the battery's aged state at time τ. Due to the slow dynamics of a battery's SoH relative to its electrochemical dynamics over time t [9], the time τ in (1) usually represents the index of cycle number.

SoH estimation problem. For many battery-powered devices, it is inconvenient or even impossible to obtain the value of $C_n(\tau)$ during operation. This is because that the calibration of $C_n(\tau)$ requires the battery to be fully charged and discharged. Indeed, the effort for SoH calculation can be reduced significantly if it can be derived from some regional current trajectory within a charging operation [20], which is unnecessarily a complete charging process from its lowest voltage to the highest. In such an operation, the capacity resulting from integral of the regional current profile along time t is termed as *regional capacity* and denoted by $\hat{C}_n$. The open question is: can we appropriately define and calculate $\hat{C}_n$ using real-time measured current data, such that SoH relates to $\hat{C}_n$ directly?

4. Regional capacity formulation and calculation

This section addresses the open question by first proposing a five-step procedure to extract the regional capacity based on incremental capacity analysis.

4.1. Procedure to calculate the regional capacity

The peak value and position of IC curves have been widely demonstrated to have a strong relevance to the battery capacity, such as the work of [13–15]. Inspired by such a fact, before presenting the procedure, several characteristic properties of IC curves to be used in the sequel are defined. The peak value of an IC curve is the maximum value of $dQ(t)/dV(t)$ for all $t \geq 0$ in the charging operation. The terminal voltage corresponding to the IC peak is denoted by V_{peak}. A *regional voltage* ΔV_{reg} is used to determine the initial and end time points (t_0 and t_1) for counting the regional capacity. Mathematically, there exist

$$V(t_0) = V_{peak} - \Delta V_{reg}/2 \tag{2}$$

$$V(t_1) = V_{peak} + \Delta V_{reg}/2. \tag{3}$$

Intuitively, the regional capacity $\hat{C}_n$ is the capacity change over the time interval $[t_0, t_1]$ with the form of

$$\hat{C}_n(\tau) := Q(t_1) - Q(t_0) \tag{4}$$

where $Q(t)$ is the transient capacity state of a battery cell under some constant-current charging process.

Based on the above definitions, $\hat{C}_n(\tau)$ is calculated in the following steps:

Step 1: Measure the current and voltage trajectories of battery cells. These signals are recorded along the discrete-time index k. Here, k relates to t according to $t = k/f$, where f is the sampling frequency.
Step 2: Derive the IC curve, namely dQ/dV, to locate its peak point. Since the resolution of voltage sensors can be quite limited in practice, the measurements obtained in *Step 1* can be highly noisy. In this regard, dQ/dV is calculated using finite difference over N time steps