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State-of-health monitoring of lithium-ion battery modules and packs via incremental capacity peak tracking

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HIGHLIGHTS

- A new framework based on ICA is used to monitor SOH on-board for battery packs.
- The applicability of the framework is validated through simulation and experiment.
- The method can monitor SOH for pack consisting of cells with various aging paths.
- On-board incremental capacity analysis is realized by support vector regression.

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ABSTRACT

Incremental capacity analysis (ICA) is a widely used technique for lithium-ion battery state-of-health (SOH) evaluation. The effectiveness and robustness of ICA for single cell diagnostics have been reported in many published work. In this study, we extend the ICA based SOH monitoring approach from single cells to battery modules, which consist of battery cells with various aging conditions. In order to achieve on-board implementation, an IC peak tracking approach based on the ICA principles is proposed. Analytical, numerical and experimental results are presented to demonstrate the utility of the IC peak tracking framework on multi-cell battery SOH monitoring and the effects of cell non-uniformity on the proposed method. Results show that the methods developed for single cell capacity estimation can also be used for a module or pack that has parallel-connected cells.

1. Introduction

Battery state of health (SOH) monitoring has become an important research area [1–5]. SOH is a measure that reflects the current status of a battery, including the capacity and the capability of power output, in comparison with its fresh status [6,7]. Take electric vehicle as an example, the current capacity directly links with the driving range of the electric vehicle, whereas the capability of power output determines the dynamic property of the electric vehicle. The capability of power output is determined by both the capacity (Q) and the resistance (R) of the battery, therefore the key task for the SOH monitoring is to estimate the Q and R online [8].

The battery SOH continuously deteriorates due to irreversible physical and chemical changes in its life cycle. The aging process typically involves multiple mechanisms that affect both capacity and resistance of the battery [9], leading to the reduction of the battery's energy and power density. In the case of lithium ion cells, the performance degradation could be caused by many phenomena such as the growth of solid electrolyte interface (SEI) layers, loss of active materials, electrolyte decomposition, and electrode structural disordering [10–14]. Most of those mechanisms are coupled during the aging process and cannot be isolated and studied independently, thereby making the investigation of battery aging mechanism challenging [10]. On the other hand, good understanding of battery aging mechanisms and accurate detection of SOH are needed for design of battery management strategies to maintain performance, safety and long life cycle [15,16].

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Whereas the resistance could be assessed on-line using identification algorithms such as least squares methods [17–19], the detection of capacity fading requires columbic counting of a full charge/discharge cycle [20,21], which is hard to be satisfied in practical on-line conditions. In recent years, incremental capacity analysis (ICA) has become a popular approach for evaluating battery capacity loss in both laboratory and on-board applications [7,20,22–24].

ICA, which was first developed for studying the properties of the intercalation based battery cells [25–27], transforms voltage plateaus on the charging/discharging curve into peaks on the incremental capacity (IC) curve [28]. ICA is applicable to various battery types and was shown to be an effective tool for analyzing the capacity loss of single lithium ion cells. In practice, however, battery cells are always connected in various series-parallel configurations to form battery modules and packs, especially for high power applications such as in hybrid electric vehicles. The SOH monitoring of multi-cell battery modules is therefore crucial in practical operations.

The main difference between a single cell and a module that has parallel connected cells, when applying the ICA, is the existence of uneven current distribution due to the cell non-uniformity. Consequently, the current going through each cell in the module could be time varying even when the module is charged at a constant current [29]. Since ICA typically requires constant charging/discharging data, the uneven distribution could affect the applicability of ICA to a battery module. For parallel-connected cells, given that only the total current, rather than the individual cell currents, is measured online, performing ICA for individual cells to determine the total module capacity is not an option [30]. Therefore monitoring SOH for batteries connected in a module requires tools and algorithms beyond what have been learned for single cells.

In this paper, an IC peak tracking framework based on the ICA principles is proposed to monitor SOH on-board for battery modules and packs. The applicability of the framework is investigated using both simulations and experimental results. The investigation is based on lithium iron phosphate ($LiFePO_4$) cells with various aging conditions. Cells with different aging history are combined to form battery modules with different capacity to test and validate the proposed methodology.

The remainder of this paper is organized as follows. In Sections 2 and 3, the ICA based SOH monitoring framework designed for single cells is discussed and the applicability of the framework to battery module is analyzed. In Section 4, the application of ICA for battery module SOH monitoring is verified through simulation using a module model incorporating cell aging mechanism. Then the experimental design and setup for battery module tests are presented in Section 5. The experimental ICA results are discussed and analyzed in Section 6. Finally, the conclusions are given in Section 7.

2. ICA for single Cell SOH monitoring

The concept of ICA originates from the study of the intercalation process based batteries [25–27,31]. Using graphite based lithium ion cell as an example, during the charging (or discharging) process, when the lithium ions are being intercalated into (or deintercalated from) the carbon electrode, the graphene sheets together with the solid phase lithium ions are arranged periodically to form different stage structures [32]. Those stages are associated with different energy levels in the negative electrode, and reflected as multiple voltage plateaus on the battery OCV curve. The ICA technique can be used to characterize the electrochemical properties related to the intercalation process by computing the IC curve as,

$$IC = \frac{dQ}{dOCV} \tag{1}$$

and transforming the voltage plateaus into clearly identifiable peaks, where Q represents the charged capacity. In practice, the OCV data are often substituted with voltage data (V) collected with constant current (for instance, 1/25 C rate) under slow charging/discharging, sometimes referred as close to equilibrium OCV data [22]. The dQ/dV based ICA curve could accurately reflect the characteristics of the underlying battery chemistry, given that the results are properly computed, due to the following equivalence,

$$\frac{dQ}{dV} = \frac{dQ}{d(OCV + IR)} \approx \frac{dQ}{dOCV} = IC \tag{2}$$

where V, I, R are the battery voltage, current and internal resistance, and $dIR \ll dOCV$ when dI is small.

ICA has the advantage to detect a gradual change in cell behavior during aging and degradation [22,33,34]. It is useful particularly for battery SOH monitoring as the extracted peak values and their change pattern are closely related to the battery capacity fading. Fig. 1 shows the IC curves for a series of degradation test from [7]. It can be seen that the second IC peak drops monotonically as capacity degrades. The correlation between the IC peak intensities and battery faded capacity can be used to formulate a battery capacity estimation model [20,34]. Through the identification of IC peaks using battery charging data, one can estimate the capacity and evaluate the battery health condition for single cells. One of the major difficulties in implementing ICA is the computation of the IC curve directly from the test data on-board. This issue has been addressed by different approaches including the probability density function method in [23], the support vector regression method in [7] as well as using the high precision charger [35,36].

In this paper, we will extend the methodology developed with single cells to battery modules for cells connected in parallel.

3. Multi-cell SOH monitoring with cell non-uniformity

3.1. Backgrounds

For single battery cells, the IC peak intensities and areas under the peaks are quantitatively correlated to cell capacity and therefore could be used to identify capacity degradation [7]. The ICA based capacity estimation approach (by tracking the changes of the IC peak values) could be extended from cells to packs if the same correlation between capacity and IC peaks can be established for a module or pack.

Most popular battery pack configurations connect cells in parallel first to form small modules, and then connect the modules in series to form the pack [37,38]. For instance, as shown in Fig. 2, the Chevrolet Volt's pack is made up of 96 modules with each module having 3 cells connected in parallel, and Nissan Leaf has modules that contain 2 in-series cell pairs connected in parallel [37]. The parallel connected cells can self-balance their SOC throughout the operations. The configuration also improves the overall robustness of battery pack. However, in such design, the currents going through individual cells are usually not monitored and only the terminal data can be used for battery state monitoring [29]. As the individual cell measurements are no longer available, the IC peak tracking based battery capacity estimation framework has to be performed using the terminal data. However, cell-to-cell variation is inevitable in battery productions [39–43]. The variation might grow larger, as the aging rate of each single cell could be different during operations. The non-uniformity could lead to uneven current distribution among the parallel-connected cells, thereby