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Research Paper

# State of health estimation of battery modules via differential voltage analysis with local data symmetry method

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ABSTRACT

Cyclic voltammogram (CV) and differential voltage analysis (DVA) are two effective techniques to analyze the aging mechanism and estimate the aging state of a battery. However, the effectiveness of the two methods reported previously is based on single battery cells. In this paper, a comparison of the two methods is stated, and the equivalent relation is further derived. Besides, a local data symmetry method is introduced to calculate the differential voltage (DV) curve. The DV curves calculated by the proposed method are much smoother than that by the numerical-derivative method. Based on the location interval of two inflection points in the DV curve, a new method is inferred for lithium iron phosphate ($LiFePO_4$) battery cells, and is applied to estimate the state of health (SOH) of battery modules. The applicability of the method is further verified via battery module simulation and experimental data. The results show that the DV curves fluctuate and do not overlap in the voltage plateau region due to the uneven currents flowing through each in-parallel battery cells. There is also a good linear regression of the two inflection point location interval versus battery module capacity within 2% error bounds, suggesting that the DVA method inferred from battery cells can be directly applied to battery modules.

## 1. Introduction

The growing concern over energy and environmental crisis has greatly stimulated the research and development of electric vehicles (EVs) [1,2]. Lithium-ion batteries (LIBs), as an essential part of EVs, have been intensively preferred because of their high energy density and safety [3,4]. However, the short cycle life of LIBs remains tremendous challenge to the further commercialization of EVs. The battery cycle life continuously deteriorates due to irreversible physical and chemical reactions [5]. A great insight to battery chemical reactions and aging mechanisms is conducive to design optimal battery management strategy [6]. The cyclic voltammogram (CV) has become a popular approach to analyze aging mechanisms within the battery. The locations of the CV peaks are related to battery aging state [7]. But the CV is generally measured by electrochemical workstation, which seems to be unsuitable for on-board implementation with in-situ operational data.

To describe the aging state of a battery, the state of health (SOH) is promulgated by the battery management system (BMS) [8–10]. SOH is a 'measure' that reflects the current state, including capacity and impedance, in relative to the original state of the battery [11]. A series of model-data fusion approaches are proposed for on-line SOH evaluating. Generally, these are the Recursive Least Square (RLS) method [12], Extended Kalman Filtering (EKF) method [13], Multivariate Adaptive Regression Splines (MARS) method [14], Support Vector Machine (SVM) method [15] and Particle Filter (PF) method [16]. However, the above mentioned methods are highly dependent on the adopted battery model and the accuracy of the model's parameters [1].

In recent years, incremental capacity analysis (ICA) and differential voltage analysis (DVA) are available to estimate the aging state and SOH of a battery [17–26]. The two methods originate from the study of intercalation process of battery materials [6]. ICA can be achieved by differentiating charged or discharged capacity ($dQ/dV$) with respect to terminal voltage ($V$). The aging mechanisms are then described by the peak amplitude and position of the $dQ/dV$–$V$ (IC) curve [17–19]. Moreover, the adaptability of the ICA to analyze aging mechanisms of different LIBs from different manufactures is reported previously [20]. Correspondingly, DVA studies the aging state by using the relation of charged or discharged capacity ($Q$) to differential voltage ($dV/dQ$). As for ICA, many researchers have studied how the DV curve changes during battery cycle life [21–24]. Furthermore, the

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**Table 1**
Specifications of equipment and parameters of battery cells.

| Item | Model | Manufacturer | Characteristics |
|---|---|---|---|
| Temperature and humidity test chamber | BE-TH-225L8 | Dongguan Bell Experiment Equipment Co., Ltd. | Temperature: $-70 \sim 150\,^{\circ}C$ ($\pm 1\,^{\circ}C$); Humidity: $20 \sim 98\%$ |
| Battery performance tester | NBT5V10A | NingBo BaTe Technology Co., Ltd. | Voltage: $0 \sim 5$ V (0.05% FS); Current: 150 mA $\sim$ 10 A (0.05% FS) |
| Battery performance tester | NBT5V100A | NingBo BaTe Technology Co., Ltd. | Voltage: $0 \sim 5$ V (0.05% FS); Current: 300 mA $\sim$ 100 A (0.05% FS) |
| LiFePO$_4$ battery | JL-8Ah | Jiuli Energy Co., Ltd | Rated capacity: 8 Ah; Rated voltage: 3.2 V |

possibility of the two methods has been validated for on-line SOH estimation [25,26]. And a battery SOH monitoring framework is also inferred to realize effective on-line SOH estimation.

Since the measured voltage contains noise, it is inevitable that the disturbance is brought into the calculated IC or DV curve [25,26]. There is difficulty in identifying the peaks lying within the plateau region of *V*-*Q* curve, where the peaks are submerged by the measurement noise. A solution is to use a fifth order polynomial to fit the measured *Q*-*V* curve. The IC curve is then calculated from the fitted curve [25]. Similarly, a second order polynomial is used to smooth the DV curve calculated from the numerical-derivative method [26]. The results of the polynomial fitting method are constrained by the selected data range and the order of the polynomial. Although high-degree polynomial order achieves higher fitting precision, a higher computing time is the greatest cost. Currently, the support vector regression method is also introduced to calculate the IC curve [25]. However the computational efficiency of the method is also low, as it involves a matrix element. Therefore, a higher efficiency method is needed for obtaining the IC or DV curve.

In applications, a battery module generally consists of several small battery cells connected in parallel to meet the capacity requirement. The battery modules are then assembled in series to achieve the required voltage in EVs [27,28]. If there is no difference among the in-parallel battery cells, a battery module could be regarded as a single large capacity battery. Unfortunately, due to the inconsistent manufacturing processes and operating environments, battery cell variations cannot be eliminated [1,29]. The inconsistency among in-parallel battery cells will lead to uneven current flowing through each battery cell branch even if the battery module is charged or discharged using a constant current [30]. In addition, the current of in-parallel battery cell cannot be directly measured. Therefore, the applicability of ICA or DVA methods for SOH estimation of a battery module should be explicitly researched.

In this paper, the CV and DVA method is initially compared. Then the local data symmetry method is introduced to calculate the DV curve. Subsequently, a new method is proposed to estimate the SOH of battery modules based on the two inflection points in the DV curve. Finally, the applicability of the proposed method is validated by battery modules with different capacities, which are assembled by four lithium iron phosphate (LiFePO$_4$) battery cells in parallel.

## 2. Comparison of IC/DV and CV curve

A fixed voltage sweep rate is set to measure a battery within a certain limited voltage range. The relation between the reaction current and the sweep voltage is called CV, which can be described as [5]:

$$I = f_{CV}(V) \tag{1}$$

Where, $I$ is the reaction current, and $V$ represents the sweep voltage.

A fundamental function of a BMS is to monitor battery voltage, current and temperature [31]. Assuming the current following through a battery is constant, the (dis)charged capacity $Q$ can be expressed as:

$$Q = It \tag{2}$$

Where, $t$ is (dis)charge time.

Then the relation of (dis)charged capacity and voltage can be demonstrated as:

$$V = f(Q), \;\; Q = f^{-1}(V) \tag{3}$$

According to the principle of the ICA method, the IC curve can be described by Eq. (4).

$$(f^{-1})' = \frac{dQ}{dV} = \frac{d(It)}{dV} = \frac{Id(t)}{dV} = \frac{I}{dV/d(t)} = g(V) \tag{4}$$

Then the battery current can be deduced from Eq. (4):

$$I = \frac{dV}{dt} \cdot g(V) = f_{IC}(V) \tag{5}$$

Comparing Eq. (1) and Eq. (5), the two formulas are of the same form and type. The CV curve is subjected to the sweep voltage and reaction current. And the IC curve is dependent on the current and differential voltage *dV/dt*. In addition, the sweep rate of voltage in the CV is constant, whereas the *dV/dt* in the ICA method is varying with time. The ICA or DVA method presents the similar qualitative results as the CV based on the same mathematical derivation [6].

## 3. Cycle test and data analysis for battery cells

### 3.1. Testing system and schedule

Four LiFePO$_4$ battery cells with different aging states from a same manufacturer are randomly selected. For description purposes, the four battery cells are named from No. 1 to No. 4 battery cell, respectively. Table 1 lists the specifications of equipment and parameters of the battery cells. The four battery cells are performed cycle life test under the environmental temperature (25 °C), as described in Table 2. The battery cell voltage, current and (dis)charged capacity data are sampled synchronously with the sampling frequency of 1 Hz.

**Table 2**
Battery cycle test profile.

| Step number | Step name | | Stop condition |
|---|---|---|---|
| 1 | Rest | Duration: 30 min | |
| 2 | Charge | Current: 1C | Voltage >=3.65 V |
| 3 | Charge | Voltage: 3.65 V | Current <=1/10C |
| 4 | Rest | Duration: 30 min | |
| 5 | Discharge | Current: 1C | Voltage <=2 V |
| 6 | Rest | Duration: 30 min | |
| 7 | Cycle | Step 2 to 6 | |