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# A quick on-line state of health estimation method for Li-ion battery with incremental capacity curves processed by Gaussian filter



Yi Li<sup>a,b,\*</sup>, Mohamed Abdel-Monem<sup>a,c</sup>, Rahul Gopalakrishnan<sup>a</sup>, Maitane Berecibar<sup>a</sup>, Elise Nanini-Maury<sup>b</sup>, Noshin Omar<sup>a</sup>, Peter van den Bossche<sup>a</sup>, Joeri Van Mierlo<sup>a</sup>

<sup>a</sup> Vrije Universiteit Brussel, MOBI Research Group, Pleinlaan 2, 1050, Brussels, Belgium

<sup>b</sup> ENGIE LAB Laborelec, Rodestraat 125, B-1630, Linkebeek, Belgium

<sup>c</sup> Helwan University, Faculty of Engineering, Cairo, Egypt

#### HIGHLIGHTS

- Proposed an on-line battery state of health (SoH) monitoring method for NMC cells.
- The method can monitor battery SoH with partial charging data.
- Ageing mechanisms of batteries are studied by non-destructive methods.
- Gaussian filter is used to obtain IC curves with improved smoothness.
- Established a quantitative correlation between features on IC curves and cell SoH.

#### ARTICLE INFO

Keywords: On-line SoH estimation High energy NMC batteries Ageing mechanism Incremental capacity Differential voltage Gaussian smoothing

#### ABSTRACT

This paper proposes an advanced state of health (SoH) estimation method for high energy NMC lithium-ion batteries based on the incremental capacity (IC) analysis. IC curves are used due to their ability of detect and quantify battery degradation mechanism. A simple and robust smoothing method is proposed based on Gaussian filter to reduce the noise on IC curves, the signatures associated with battery ageing can therefore be accurately identified. A linear regression relationship is found between the battery capacity with the positions of features of interest (FOIs) on IC curves. Results show that the developed SoH estimation function from one single battery cell is able to evaluate the SoH of other batteries cycled under different cycling depth with less than 2.5% maximum errors, which proves the robustness of the proposed method on SoH estimation. With this technique, partial charging voltage curves can be used for SoH estimation and the testing time can be therefore largely reduced. This method shows great potential to be applied in reality, as it only requires static charging curves and can be easily implemented in battery management system (BMS).

#### 1. Introduction

Lithium ion battery (LIB) was firstly commercialized by Sony in 1991, since then this chemistry has become the one of the most promising and fastest growing electric energy system storage (ESS) in the market due to the advantage of high volumetric/gravimetric energy density [1]. LIBs were initially applied on portable/consumer devices such as cell phones and laptops, with the achieved significant success in this market, they are recently penetrating into the field of hybrid electric vehicle (HEVs) and electric vehicles (EVs). It could be foreseen that they can largely expand their market in large scale ESS application as their costs keep dropping and the lifetime get improved [2]. The performance of LIB degrades with time, an accurate diagnosis of battery degradation is of great significance for safe and efficient battery utilization. Battery state of health (SoH) is used as an indicator to evaluate the degradation level of batteries. The battery SoH is monitored through a battery management system (BMS), it still remains a difficult and challenging topic since the ageing mechanisms of batteries are complicated and the battery degradation do not originate from one single cause, but from various processes and their interactions, like the operating modes, working environment and ageing history [3,4]. The battery SoH reflects the ability of a battery to store and supply energy in respect to its initial conditions by considering the energy and power requirements of the application, which can be defined as a state of

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<sup>\*</sup> Corresponding author. Vrije Universiteit Brussel, MOBI Research Group, Pleinlaan 2, 1050, Brussels, Belgium. *E-mail address*: li.yi@vub.be (Y. Li).

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health related to energy capability (SoH<sub>E</sub>) or/and power capability  $(SoH_P)$ . The  $SoH_E$  can be quantified by the battery capacity and impedance is used for the quantitative definition of battery SoH<sub>P</sub>. Having an accurate prediction for either one with simple approaches is particularly significant to the safety of entire systems, with this information we can adjust the operating modes to extend the battery lifetime as well as predict the appropriate time intervals for battery replacement [5]. In this work, the battery capacity is chosen as the indicator for SoH by calculating the ratio of actual cell capacity to the cell initial capacity  $(SoH = \frac{Q_{current}(Ah)}{Q_{presh}(Ah)} \times 100\%)$ . For a fresh battery, the SoH is equal to 100% and the value of SoH decreases with ageing. The battery end of life (EoL) is defined by the application requirements. For the batteries applied in EVs or HEVs, they are considered no longer usable and should be replaced when the SoH is less than 80% [6]. However, this direct calculation method requires a fully charging and discharging cycle of the battery, which is energetically inefficient as well as impractical in real application since the batteries are partially cycled in most cases.

Research on battery SoH estimation has attracted lots of attention in recent years. Different estimation methods have been proposed in this field, each technique has its own advantages and shortcomings in terms of estimation accuracy, testing time duration, feasibility for implementation. The SoH estimation techniques can be roughly classified to three groups: experimental techniques, adaptive models and incremental capacity/differential voltage analysis.

The first group is directly measured from experiments, such as hybrid pulse power characterization (HPPC) and electrochemical impedance spectroscopy (EIS). HPPC method is capable of identifying the battery dynamic power capability over its useable charge and voltage range by using a test profile that incorporates both charge and discharge pulses [5,7]. EIS is mainly used to determine the impedances of the battery and proved to be an effective tool for ageing and failure diagnosis [8,9]. Since the battery dynamics tend to affect different frequency ranges on the EIS measurement [5]. However, the experimental methods are remaining to be off-line SoH identification techniques [9].

The second group is the adaptive model based methods, which can be further dived into lumped-parameter equivalent circuit based models and black-box based methods. The equivalent circuit model (ECM) with joint/dual extended Kalman Filters (EKF), also called joint estimation, have the advantages of providing high accuracy of capacity estimation [10-15]. These models have strong physical relation between the model parameters with the underlying electrochemical processes that occur within battery cells [16]. Unfortunately, the model based techniques can be computational intensive due to large matrix operations and therefore difficult to be implemented in BMS for real application [15]. The black-box based models, such as neuron network (NN) and support vector regression (SVR), do not rely on the predetermined system parameters or have any connection with the physical properties of batteries [10,17-20]. Compared to model-based approaches, they have less requirements on dedicated hardware/software [17]. Such statistical approach learns the ageing behavior of the studied system from a large amount of data and find a mathematical description to make connections between the battery features like terminal voltage, current and temperature with the cell capacity. The limitation of the machine learning based method is that they require acquisition of data covering the entire age of the battery under various utilization modes, and they are only valid within the trained data range [18].

The third group is the differential approach based on incremental capacity (IC) analysis and/or differential voltage (DV) analysis. This differential analysis have the advantages from both experimental and adaptive-model approaches, as it can be used for battery degradation identification as well as the SoH estimation with low computational effort [6]. The requirement of static charging/discharging is the main drawbacks of this method [6]. Incremental capacity is calculated by

differentiating the change in battery capacity to the change in terminal voltage during either charging or discharging, as defined in the Eq. (1). Differential voltage is defined as the inverse of differential capacity, shown in Eq. (2) [21].

$$\frac{dQ}{dV} = \frac{\Delta Q}{\Delta V} = \frac{Q_t - Q_{t-1}}{V_t - V_{t-1}} \tag{1}$$

$$\frac{dV}{dQ} = \frac{\Delta V}{\Delta Q} = \frac{V_t - V_{t-1}}{Q_t - Q_{t-1}} \tag{2}$$

where  $Q_t$  and represent the battery capacity and voltage at time t, respectively. Although both of them can provide similar information, there is a big difference between each other. The IC curve refers to the cell voltage, which can be a direct indicator of the battery state, whereas the DV refers to the cell capacity, which is a secondary indicator that can vary with aging and degradation and lose its reliability as a reference in the course of aging [22]. With this method, the voltage plateaus on the charging/discharging curve can be transformed into clearly identifiable peaks on the IC/DV curve. The peaks in IC curve represent phase equilibria, while the DV curve represents phase transitions [23]. Each peak in the curve has its unique features, like intensity and position, and it represents a specific electrochemical process taking place in the cell [24]. The extracted peak values and the shape and position variation of peaks are closely related to the battery capacity fading, and therefore can be used for monitoring battery ageing. The specific degradation mechanism can be distinguished by analyzing the progression of each peak in IC/DV curves throughout ageing, observing how the change of the active materials over time can be helpful in identifying the best operating conditions for cells.

Previous studies based on differential analysis have shown it to be an effective tool for both analyzing battery ageing mechanism and SoH estimation, e.g. in Refs. [4,6,25-32]. This method is interesting as it have many advantages: it can be easily implemented in a BMS by just monitoring two parameters (voltage and charge/discharge capacity); it is suitable for different types of lithium ion batteries like chemistries, battery size, cell designs and operating condition [5]. Bloom et al. [30] conducted DV analysis on NMC/graphite cells and found the side reactions mainly happen on negative electrode which leads to battery capacity fade. Han et al. [29] used IC curves to analyze the ageing mechanism of NMC/LTO cells and found a two-stage capacity loss, which is caused by the loss of anode material and loss of cathode material, respectively. Dubarry et al. [28] studied the aging behaviors of commercialized LiFePO4 /graphite (LFP) cells in different formats with IC analysis. Till now, most of the IC/DV analysis on Li-ion batteries have been focused on the electrochemical ageing mechanism analysis, while only a handful of research has been carried out for on-line SoH estimation [4,6,31,32]. Wang et al. [4] proposed an on-line SoH estimation method for LFP battery pack, they estimated the battery SoH by relating the location interval of two inflection points on DV curves to battery capacity fade. Berecibar et al. [6] estimated the battery SoH with DV analysis, their method is able to use partial charging curves with maximum initial SoC levels of 60% SoC but restricted to low charging current rate of  $I_t^1/5$ . Weng et al. [31] derived IC curves with the approach of support vector regression algorithm by using partial charging data and the battery capacity fade was correlated with the intensity of IC curve peaks, but it is costly to be implemented into BMS. These IC/DV based SoH estimation techniques are developed for LFP cells. Because each chemistry has its own characteristics and performs differently from the others, this means the proposed method for LFP cells might not be suitable for NMC cells. Therefore, the adaptability and validity of IC/DV analysis on NMC cells should be investigated. Goh et al. [32] proposed a capacity estimation algorithm for NMC battery by using second-order DV curves obtained in the constant charging phase,

 $<sup>^1</sup>$   $I_t$  represents the current rate as documented in the standard IEC 61434 and presented by Equation  $I_t=C/1$  h [33].

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