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Online state of health estimation on NMC cells based on predictive analytics

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HIGHLIGHTS

- Predictive Analytics used for state of health estimation for BMS operation.
- DV and IC curves are used for specific feature selection.
- The estimation is developed from partial charging and/or partial discharging.
- Comparison of the techniques in terms of accuracy and online development for BMS.

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ABSTRACT

Accurate on board state of health estimation is a key battery management system function to provide optimal management of the battery system under control. In this regard, this paper presents an extensive study and comparison of three of commonly used supervised learning methods for state of health estimation in Graphite/Nickel Manganese Cobalt oxide cells. The three methods were based from the study of both incremental capacity and differential voltage curves. According to the ageing evolution of both curves, features were extracted and used as inputs for the estimation techniques. Ordinary Least Squares, Multilayer Perceptron and Support Vector Machine were used as the estimation techniques and accurate results were obtained while requiring a low computational effort. Moreover, this work allows a deep comparison of the different estimation techniques in terms of accuracy, online estimation and BMS applicability. In addition, estimation can be developed by partial charging and/or partial discharging, reducing the required maintenance time.

1. Introduction

The requirements and demands that batteries have to meet are ever increasing. Therefore, effective control and management is needed to ensure a safe use of the battery with the best possible performance. This is assigned to the battery management system (BMS). Among the tasks that BMS carries out, it is responsible for monitoring the State of Health (SoH) of the battery. Despite the fact that diagnosis and prognosis of the State of Health are essential in practical applications, they are neither effective nor quite accurate enough yet.

The SoH reflects the ability of a battery to store and deliver energy relative to its initial conditions considering the application energy and power requirements. This estimation is needed to identify the performance decrease (in terms of capacity and power) of the battery, to predict the remaining useful life (RUL), and to detect its end of life (EoL). While SoH takes a 100% value when the battery is fresh at beginning of life (BoL), it lowers as it ages. The EoL of the battery is defined by the application requirements. As an example, at SoH<80% the battery is often considered no longer usable for an electric vehicle and should be replaced [1].

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SoH determination is usually based either on the decrease of the battery capacity and/or the power. Capacity decrease and power fading do not originate from one single origin, but from a number of various processes and their interactions with the positive electrode (PE) and/or the negative electrode (NE) [2]. Classical methods used to study these processes requires the destruction of the cell, thus disabling any further use. According to our previous work [3] and others studies [4–6] the determination of SoH in a less aggressive way can be obtained by two different approaches: adaptive models and/or experimental techniques.

Adaptive models that include methods like Kalman Filters [7,8] Neural Networks [9], or Fuzzy Logic [10] are useful when system-specific information is unavailable. It must be mentioned that in [8], not only SoH but also the State of Charge (SoC) is estimated. The strength of the adaptive models is diagnosis but their main problem is that they need training data to determine the current capacity. Experimental techniques includes Impedance Spectroscopy (EIS) [11], Probabilistic methods [12], and Data Maps [13]. These approaches take into account the physical processes and failure mechanisms that occur in systems, enabling a prognosis of capacity. A limitation of these approaches is that they cannot detect intermittent failures [14]. In order to have a better comprehension the next table has been developed (Table 1).

Among the experimental techniques, differential voltage techniques using differential voltage curves (DV) and/or incremental capacity curves (IC) also need to be considered. These techniques have been used by many researchers [15–18] in order to reveal battery degradation mechanisms occurring in a battery cell. Recently, both curves have been used presenting accurate results not only for degradation mechanisms detection [16], but also for detection of overcharging capacity fade [19] and even online SoH estimation [20,21]. Even so, there is still work to do in this field, in order to enhance the works that already exist such as to carry out an online and on board estimation for real-time applications.

In this regard and according to our previous study [3], it seems very interesting to develop new techniques based on the use of DV and/or IC curves together with an adaptive model as neural network, fuzzy logic or other methodologies, which consider the use of predictive analytics, i.e. detecting patterns in datasets and modelling them to predict new values. The different techniques will be compared in terms of running the methods in an online way, accuracy, and BMS implementability.

The paper is structured as follows: Section 2 presents the experimental content in terms of the testing procedure, used cells, and applied estimation techniques. Next section details the results, which were obtained from the testing, including the IC and DV curves and their principles. Section 4 shows the patterns and the feature selection, which are used by the estimation techniques. Results coming from the different methodologies are also explained and compared. Finally, conclusions are presented coming with the main contribution of the paper.

2. Experimental

2.1. Cycling

Four 40Ah pouch Graphite (G) based anode/LiNi1-x-yMny-CoxO2 (NMC) based cathode cells have been used for this research. It must be mentioned that three of the cells correspond to high power cells and the other one is a high energy cell, corresponding to 138 Wh/kg. Table 2 presents the technical specification of the tested cells, indicating the end of discharge voltage, maximum charge voltage and the charging and discharging rates.

The ageing tests were performed in a temperature controlled environment at 25 °C. In order to develop the tests under control a climate chambers CTS (Clime-Temperature-System, CTS/T-40/200/Li and CTS/T-40/600/Li models) and Prebatem Selecta (80 and 150 L chambers with Peltier effect) have been used. Experiments were carried out using DIGATRON MCT (Multiple Cell Tester, MCT 100-06-10 ME and MCT 50-06-24 ME models) with BTS-600 battery data acquisition software.

The cells were tested from the BoL until the EoL (20% capacity loss, if reached). Two tests were carried out on the cells, a capacity test and a full charge/discharge test:

- Capacity test: charge and discharge cycles (at current-constant voltage, CC-CV, and CC modes, respectively) at nominal conditions specified by cell manufacturer (1C-rate current and 25 °C temperature). Three full charge-discharge cycles were performed in order to assess both reversible and irreversible capacity losses and check the repeatability of the results.
- Cell full charge/discharge test: Prior to the discharge of the cells are fully charged in CC-CV mode at 1C. Discharge were performed at a C/5 rate. This C-rate was chosen as it was the fastest one that enabled observing the voltage plateaus in view of implementation in real application where low rate cycling is impractical. Galvanostatic voltage profiles were used for examining electrode phase changes and understanding degradation phenomena.

In order to have the first characterization when the SoH is 100% a capacity test and a full charge/discharge test were performed before starting the cycling. All tests were regularly performed after each cycling period until 80% capacity loss was reached (considered as the (EoL). The SoH was calculated from the capacity test according to Equation (1) were Q is the capacity in Ah (1).

Table 2
Technical specification of the tested cells.

Technical specification	
Charging rate	0.2C (8.0 A)
Discharging rate	0.5C (20 A)
End of discharge voltage	3.0 V
Max. charge voltage	4.15 ± 0.03 V

Table 1
Differences between experimental techniques and adaptive methods [3].

	SoH estimation	
	Experimental techniques	Adaptive methods
Based on	Storing the lifetime data and the use of the previous knowledge of the operation performance of the cell/battery	Calculation of the parameters, which are sensitive to the degradation in a cell/battery
Advantages	- Low computational effort - Possible implementation in a BMS	- High accuracy - Possible to be used as in situ estimation
Drawbacks	- Low accuracy - Not suited for in situ estimation	- High computational effort - Difficult in BMS implementation