Energy 103 (2016) 784–796

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

State of health estimation algorithm of $LiFePO_4$ battery packs based on differential voltage curves for battery management system application

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ARTICLE INFO

Article history:
Received 7 September 2015
Received in revised form
16 January 2016
Accepted 27 February 2016

Keywords:
State of health estimation
Differential voltage curves
Battery management system application
LFP/Graphite cells

ABSTRACT

This paper discusses a novel differential voltage curve capacity estimation to determine the state of health of $LiFePO_4$ cells. Differential voltage curves are used because of their ability to detect and quantify degradation mechanisms. The estimation is carried out through partial charging or discharging tests, and is specifically designed for battery management systems, due to the trade off between accuracy and low computational effort. This means the method can be effectively executed online, in a real application. The technique is also able to accurately detect the end of life of the cells.

Aging datasets of 18 cells with identical chemistry were used for both parametrization and validation. The cells were subjected to a wide range of cycling and storage conditions, including temperature, state of charge, charging and discharging rate, depth of discharge and state of health. The performance and robustness of the estimation are validated by means of the degradation datasets from more than 25 different scenarios at the cell and battery pack level. The related results indicate that the proposed health management strategy has an average relative error of 1.5% at the battery pack level.

1. Introduction

The requirements and demands that batteries must meet are constantly increasing. Therefore, effective control and management is needed to ensure the safe use of batteries, with the best possible performance. Despite the fact that the diagnosis and prognosis of the SoH (State of Health) is essential for practical applications, so far they are neither effective nor accurate. The BMS (Battery Management System), among the technical tasks that it carries out, is responsible of monitoring the State of Health of the battery.

The SoH reflects the ability of a battery to store and supply energy relative to its initial conditions, considering the energy and power requirements of the application. This estimation is needed to identify any decrease in the performance (in terms of capacity and power) of the battery and to detect its end of life. SoH reflects the current condition of the battery in terms of a percentage, referenced to a fresh cell. While SoH has a value of 100% when the battery is fresh, at its BoL (begin of life), it decreases with age until it reaches its EoL (end of life). The EoL of the battery is defined by the application requirements. For example, at SoH < 80%, the battery is considered no longer usable by an electric vehicle and should be replaced [1].

SoH determination is usually based on either the decrease of battery capacity or the increase in internal resistance. A decrease in capacity and power fading do not originate from one single cause, but rather from a number of different processes and their interactions on the positive or negative electrodes [2]. Traditional methods used to study these processes require the destruction of the cell, rendering any further use of the cell impossible. As previously published in our previous work [3], a less aggressive determination of SoH is possible through two different approaches: adaptive models and experimental techniques.

Experimental methods record the historical cycling data of the battery. This information, combined with previously obtained knowledge about the influence of the main parameters affecting the battery lifetime, make it possible to estimate the SoH. This approach requires a good insight into the interrelation between operation and degradation of the battery cell, obtained through either physical analysis or the evaluation of large historical operation data sets in connection with SoH tests on the battery cell. This category could be considered to include methods such as sample entropy [4], data fitting [5] or probabilistic methods [6]. In the case of sample entropy [4], the SoH is estimated using a Bayesian predictive technique and sample entropy. The sample entropy of short

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http://dx.doi.org/10.1016/j.energy.2016.02.163
0360-5442/

voltage sequences is used as an effective signature of capacity loss. The Bayesian prediction establishes the correlation between the loss of capacity and the results from the sample entropy. Several experimental data sets have been used, taking into consideration the effect of the temperature. In data fitting [5], the estimation is based on the battery cycle number, using the ECE 15 driving cycle. This is of great importance in order to conduct realistic experiments on electric vehicles. Consequently, the method is independent from the battery parameters, which are difficult to obtain while driving. The author in Ref. [6] proposes a probabilistic method for estimating the SoH by analyzing the charge and discharge data of electric storage batteries. The method has its origins in classic probability theory. It consists of calculating the probability of the number of times when the same voltage would be measured, according to the discharge curves for new and aged batteries.

Adaptive methods determine the SoH through calculations based on parameters that are sensitive to the degradation of the battery cell. The necessary data must be measurable or examined throughout the operation of the battery. The advantage of this option is that a large number of tests and simulations of the battery behavior is not required. It will ensure better adaptability to different battery types and chemistries, but there is also the drawback that it has a high computational load, which complicates the online running of the model on a real application [7]. Another limitation of these approaches is that they cannot detect intermittent failures [8]. Methodologies like Kalman filters [9], neural networks [10] and fuzzy logic [11] can be considered adaptive methods. Authors in Ref. [9] based their research on the use of two extended Kalman filters with different time scales, in order to estimate both SoH and SoC (state of charge). A method in which a neural network has been used for SoH estimation is also indicated in the references [10]. This work describes the SoH monitoring of a high-power-density Li-ion cell, using recurrent neural networks to predict the deterioration of battery performance. Many other authors use fuzzy logic techniques in combination with EIS (Electrochemical impedance spectroscopy) to estimate SoH [11]. In this work, different conditions of temperature and SoC are studied in lithium ion batteries. In order to obtain a clearer view of the main differences between the experimental and adaptive methods, the following table was developed. It clearly indicates the main advantages and drawbacks of the different methods (Table 1).

Differential voltage techniques using DV (differential voltage) curves and/or IC (incremental capacity) curves also need to be considered, as they might be very beneficial for SoH estimation. These techniques have recently emerged and have been used by many researchers in order to reveal battery degradation mechanisms occurring in a battery cell. M. Dubarry et al. [12] combine modeling and experimental techniques in order to develop a universal tool for diagnosis and prognosis. The model consists of a modified equivalent circuit model capable of simulating the different degradation modes via a synthetic approach based on the behavior of electrodes reflected by the study of the DV and IC curves. On the contrary, it seems difficult to implement this technique online. Researchers such as Bloom [13] have illustrated how the capacity loss of cells can be shown based on DV curves. Tests were conducted for 18650-sized cells. These high-power Li-ion cells were characterized in terms of performance of both cycle and calendar life at 45 °C. The research showed that the capacity fade of these cells was due to side reactions at the anode. In a later work [14], $LiNi_{1-x-y}Mn_yCo_xO_2$ (NMC) positive electrodes were tested using the same technique. This analysis indicated that lithium-capacity-consuming side reactions were occurring primarily at the negative electrode. In Ref. [15], the author uses DV and IC curves in order to study aging mechanisms of five commercial lithium-ion batteries. Nevertheless, the author mentions that further research is still required to achieve the on-board identification of the aging mechanism. Although very accurate results have been obtained from these studies, there is still no method to carry out an online estimation for real-time applications.

After providing an overview of the different techniques proposed in literature, this paper then focuses on a specific method, which is based on the use of differential voltage curves. It is considered that this technique can be very beneficial in order to estimate the SoH of a cell and battery pack. Indeed, the technique reported in this work estimates the SoH based on DV curves with an average error at the cell level of less than 1%. The tested cells are made up of $LiFePO_4$ (LFP)-based active material on the PE (positive electrode) and graphite intercalation compound (G)-based active material on the NE (negative electrode). Due to the fact that each has its own chemical characteristics, their operational modes are also different. Therefore, their DV and IC curves will also be different, accordingly. For this reason, the method that has been developed is only valid for LFP cells or batteries.

The method employs the DV curves to detect not only the SoH itself, but also the EoL of the cells. Furthermore, the benefit of this procedure is that it can be implemented in a BMS and run in real time. The process developed to validate this method covers 29 different scenarios, in order to deal with a wide variability of cycling parameters, and it also stores the scenarios at cell and at battery pack level.

The paper is organized in the following manner: Section 2 presents the basic principle of DV and IC curves, including how the parameterization is performed. For this purpose, the cells and equipment used in the present case are introduced. The following section explains in depth how the SoH estimation technique works. Section 4 presents the results of the validation stage, the great variability of scenarios in which the method has been tested, and the results obtained at the cell and battery pack level. Finally, Section 5 presents the main conclusions, followed Section 6, which details further steps to be taken in order to expand this technique to other chemistries.

2. Characterization

2.1. Differential voltage curves

It is well established that dominant aging mechanisms on graphite anodes are caused by SEI (Solid Electrolyte Interphase)

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

	SoH estimation methods	
	Experimental techniques	Adaptive methods
Based on	Recording the lifetime data and the use of previous knowledge about the operational performance of the cell/battery.	Calculation of parameters sensitive to degradation in a cell/battery.
Advantages	- Low computational effort - Possible implementation in a BMS	- Highly accurate - May be used for in situ estimates
Drawbacks	- Not very accurate - Not suited for in situ estimates	- High computational effort - Difficult to implement in a BMS