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Lifetime of self-reconfigurable batteries compared with conventional batteries

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ABSTRACT

This article provides a lifetime and performance study for a novel multi-cell lithium-ion storage system, named self-reconfigurable battery. In such a battery the load of each cell can be optimized due to a power control unit connected to the cell. An iterative algorithm is developed to outline the influence of the novel battery architecture on the aging trend of each cell and thus on the battery life. In order to quantify this lifetime enhancement, a semi-empirical aging model, which involves both cycling and calendar aging factors, is established and coupled afterwards to the electrical battery model. To improve the model accuracy, the aging behavior spread within a multi-cell battery is assumed to fit a normal distribution whose parameters are identified based on experimental aging tests. A lifetime study is conducted for both the novel hardware topology and the conventional topology using a realistic power profile and an optimal balancing strategy. The simulation results proof the aging benefit of the self-reconfigurable topology and show a lifetime enhancement of more than 16%. This improvement yields to a performance enhancement with respect to energy throughput of 16.8% compared to the conventional storage system.

1. Introduction

The energy storage system is a key factor for Battery Electric Vehicles (BEV) as it defines the performance of the entire vehicle. Most of today's used batteries are lithium-ion batteries. Therefore, the lifetime estimation of lithium-ion cells is important to improve the efficiency and reliability of BEV. To this end, extensive research on the degradation of lithium-ion cell has been carried out the last few years. Due to high financial costs and the long duration of laboratory aging experiments, the main research works are conducted to develop accurate aging models that describe the battery aging behavior under different cycling and storage conditions in order to predict the battery lifetime and to optimize the system design. A review of the literature shows that different modeling approaches are used. In [1–3] electrochemical aging models were presented. On the one hand those models are suitable to investigate the key parameters that influence the cell aging and to optimize the future cell design. On the other hand such models are complex and computationally intensive. To address this issue, other studies have attempted to develop semi-empirical battery lifetime models which represent a trade-off between network models and electrochemical models. Based on experimental test matrices, the influence of each aging factor is investigated and a mathematical function is determined and fitted to the set of data. Note that for this type of approach the systematic modelling effort has to be performed for each cell type. While Wang el al. represented the cycle and the calendar aging study for Li(NiMnCo)O_2 cell (NMC) [4], cycling caused capacity fade of a $LiFePO_4$ cell was investigated in [5] where factors such as depth of discharge, temperature and C-rate were considered. In order to investigate the lifetime of a lithium-ion cell, the authors in [6] established a composed model which consists of an electrical-thermal sub-model that calculates the stress factors and cell states which are the input parameters for the aging sub-model. The model output is the capacity fade and resistance rise of one cell over time. Few studies are reported in the literature to investigate the aging of the whole battery. To determine the lifetime of the entire system, some works used single cell approach and scale the behavior of a single cell to the entire cell pack. In contrary to this assumption the cells within the battery do not perform equally as shown in [7]. Based on a conducted experimental study, Lehner et al. [7] investigated the cell aging spread and shown its negative effect on the system performance. This is especially critical in a series configuration as the available energy of the storage system is restricted by the aging behavior of the worst cell. In [8] datamining algorithms were used

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to investigate the relationship between the selected initial cell attributes and aging behavior. Paul et al. used the Monte Carlo method to consider the cell disparity within the storage system [9] and established a holistic model to determine the life of the entire system. However, all these preceding studies are done for conventional battery systems, where different cell balancing circuits are used. An overview of active equalization methods is provided in [10]. While the passive balancing dissipates the excess energy through shuntresistors in the form of heat, the active balancing equalizes the battery cells by transferring the excess energy between battery cells. Among the diverse active balancing topologies [11], the switched capacitor based balancing systems are widely reported due to the circuit reliability [12]. Nevertheless, a single cell fault leads obligatory to a fault of the whole battery or the energy battery efficiency is reduced in case of high imbalanced cells due to the limited balancing current. To solve this issue self-reconfigurable batteries are presented in the literature as an effective solution. This novel battery architecture consists of power modules connected in series. They each include a lithium-ion cell and a control unit as shown in Fig. 1. While Huang et al. [13] suggested using DC/DC converters as control units to adjust the current in each cell, a self-reconfigurable battery including power semiconductor devices was presented in [14]. Some studies have given more attention to improvements on the hardware and proposed rule-based control algorithms [15,16]. In our previous researches we are focusing on optimizing the control strategy by using dynamic programming method [17,18].

Since the recent works regarding lifetime prediction of the entire system focused on non-reconfigurable batteries, there is a need to establish a new lifetime prediction model that takes into consideration the features of this novel battery architecture. The purpose of this work is to feature how controlling cell current enhances the battery lifetime by comparing the aging behavior of a self-reconfigurable battery with that of a conventional non-configurable battery. For this objective, an iterative algorithm is established to reveal the favorable influence of the reconfiguration flexibility on cells aging rates. Thereafter, to quantify this lifetime enhancement a semi-empirical aging model is developed using aging test results and coupled afterwards with electrical-thermal model to describe the capacity fade and resistance increase of the lithium-ion battery.

2. System architecture and motivation

In this section more insight in the self-reconfigurable architecture is provided. As mentioned in the introduction, the cells are not directly connected to each other but each one is associated to a cell control unit that allows controlling the discharge rate of each cell during battery operation to maximize the energy efficiency of the system. Thus the battery cells are not discharged in the same manner. The implemented energy management strategy determines the discharge rate of each cell. In [19] the discharge rate of just the worst cell in the pack is set to zero. This strategy did not ensure the optimal energy efficiency of the battery. An alternative strategy was presented in [17] that optimizes the discharge rate of each cell based on cell spread, actual cell state and the power request in order to achieve cell balancing accompanied by maximal system energy efficiency. Due to its better performance, the latter control strategy will be considered in this research.

2.1. The influence of the control strategy and battery architecture on system aging

The control strategy activates cells with more energy content more often than worse performing cells in order to balance the battery during operation. Hence, all battery cells are fully discharged at the end of the discharge cycle. This leads to the fact that the charge throughput of each cell over one discharge cycle $\Delta Q_{\mathrm{Th},i}$ is equal its capacity at the beginning of the discharge cycle:

$$\Delta Q_{\mathrm{Th},i}(z) = C_i(z-1), \tag{1}$$

where z is the cycle number and C_i is the capacity of ith cell.

The cell charge throughput $Q_{\mathrm{Th},i}(z)$ after z cycles is calculated as follows

$$Q_{\mathrm{Th},i}(z) = \sum_{j=1}^{z} \Delta Q_{\mathrm{Th},i}(j) = \sum_{j=1}^{z} C_i(j-1). \tag{2}$$

Once the cumulated charge throughput $Q_{\mathrm{Th},i}(z)$ corresponding the ith cell is known, its actual capacity $C_i(z)$ is determined using the cycle life function F which describes the impact of charge throughput on the actual cell capacity

$$C_i(z) = F(Q_{\mathrm{Th},i}(z)). \tag{3}$$

Eqs. (1), (2) and (3) reveal that the calculation of the actual capacity is an iterative process which is summarized in Fig. 2.

The algorithm starts with setting the initial capacity for each cell to the nominal value. Next, the cummulated cell charge throughput is calculated. Thereafter, the actual cell capacity is determined afterwards using the cycle life function presented in [5]. The loop is executed until the end of life criteria (EoL) is reached which is when 80% of nominal capacity remains.

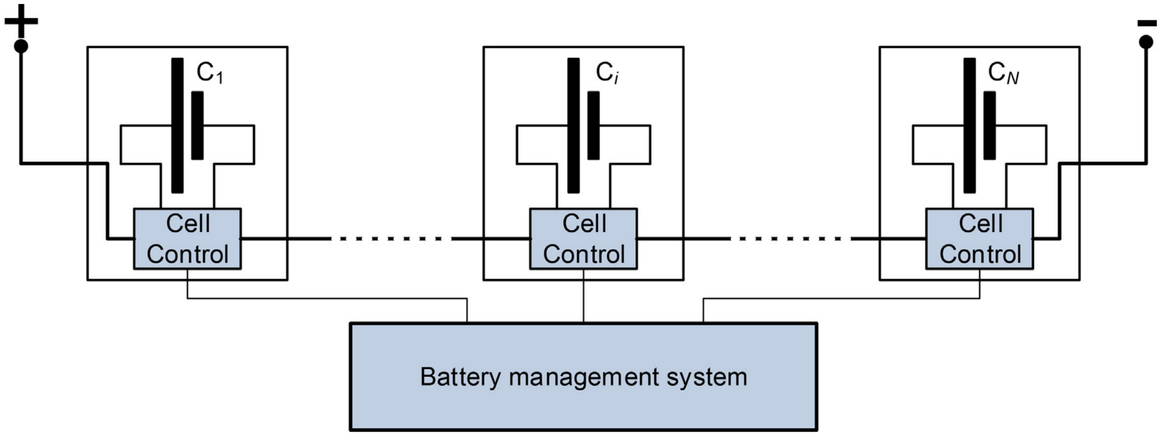

Fig. 1. Self-reconfigurable battery architecture.