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A multi time-scale state-of-charge and state-of-health estimation framework using nonlinear predictive filter for lithium-ion battery pack with passive balance control

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HIGHLIGHTS

- A multi time-scale SOC/SOH estimation framework for battery pack is presented.
- The battery pack is in series topology with passive balance control.
- The estimation framework is performed based on pack-level state definitions.
- Nonlinear predictive filter is used to provide accurate estimation results.
- UDDS profiles are used to validate the performance of the proposed framework.

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ABSTRACT

With respect to cell-to-cell variation in battery packs for electric vehicles (EVs), the estimation of state of charge (SOC) and state of health (SOH) of battery systems remains a challenging problem that needs to be solved under the strict computational limitations of battery management system. This paper aims at proposing a stable and accurate SOC/SOH estimation framework for battery pack with multi-cells connected in series with passive balance control. First, the concepts of cell-level and pack-level state definitions, which clearly describe the relationship between the states of the battery cells and those of the battery pack, are introduced. Then a multi time-scale framework for estimating the SOC/SOH of pack is developed. Within the framework, the SOH values (slow dynamics) are estimated with long time interval, while the SOC (fast dynamics) is estimated in real-time. For the framework implementation, nonlinear predictive filter (NPF) is used as the estimation algorithm to provide accurate estimates of SOC and SOH. Finally, experiments are conducted on a battery pack under UDDS driving cycles to validate the performance of the proposed framework. The experimental validation indicates that the SOC and SOH of the battery pack can be accurately estimated using the proposed framework.

1. Introduction

With the development of electric vehicles (EVs) in recent years, the lithium-ion batteries, as the energy source for EVs, attract more and more attentions for its high energy and power density and long lifespan [1,2]. For an intelligent monitoring of the lithium-ion battery, a battery management system (BMS) is required to accurately estimate the state of charge (SOC) and state of health (SOH) of the battery pack. The SOC is a crucial factor that indicates the residual capacity of battery system and helps predicting the remaining driving range of EVs [3]. Also, an accurate SOC estimation plays an important role in preventing the battery pack from over-charge and over-discharge which damage battery [4]. The SOH is another important aspect which should be estimated by the BMS [5,6], it is usually described by some battery parameters correlated with its aging such as resistance and capacity, indicating the 'power fade' and 'capacity fade' of battery pack, respectively.

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For EV applications, in order to meet the high capacity requirement and provide the desired voltage, the battery pack usually consists of hundreds of cells, which are connected in series and parallel [7]. Many SOC estimation methods have been developed based on the assumption that all the cells in the pack behave equally, and therefore, the battery pack can be conveniently modeled as a unit cell with higher voltage and larger capacity. These approaches include current integration method [8,9], open circuit voltage method [10,11], black-box model based method [12,13] and model based filtering method [14–19]. Each method has its own advantages and disadvantages. The current integration method is simple to implement with a low computational effort, but the estimation accuracy will decrease due to the accumulative errors caused by current sensor noises. Therefore, this method is often corrected by open circuit voltage method. The black-box model based method usually uses a data-trained black-box model, such as neural networks [12] and support vector regression [13], to estimate the battery SOC. The estimation can be quite accurate with sufficient offline training data, but the computational effort is particularly high. The model based filtering method is usually performed on a state space battery model and is viewed as the most promising way to estimate battery SOC because of the high estimation accuracy and online state error correction capability. Many optimum state estimation approaches have been investigated for the model based filtering method, such as sliding mode observer [14], extend Kalman filter (EKF)[15], unscented Kalman Filter (UKF)[16], adaptive extended Kalman filter (AEKF)[17], adaptive unscented Kalman filter (AUKF)[18] and particle filter (PF) [19]. Most of them have achieved acceptable results according to the literature. In a similar fashion (i.e. using a unit cell model to represent the entire battery pack) some of these estimation approaches have been also used to estimate the SOH of battery pack by means of estimating the resistance and capacity, such as dual sliding mode observer [20] and dual extended Kalman filter [6,15].

However, in real world applications, in a battery pack there is some cell-to-cell variation due to manufacturing variability and inhomogeneous working environments (such as thermal imbalance) [21,22]. The cell-to-cell variation will become even larger as the cells age, which makes the unit cell model assumption unsuitable to represent battery pack. In addition to this, in a battery pack the SOC as well as the ability to store energy and deliver power, and therefore the system level SOC/SOH, highly depends on individual cell's performance, SOH, electrical topology and balance control [32]. For example, in a battery pack composed of cells in series with a passive balance control, the 'weakest cell' will firstly reach fully discharged state during the discharge operation, limiting the discharge capacity of the entire pack. A similar situation will happen during charge operation. Therefore, the 'pack states' as defined in the unit cell model do not accurately describe the battery pack SOC/SOH. As a result, an estimation based on unit cell model will be inaccurate for real world applications.

Different methods have been proposed to take into account the variability of cells in the battery SOC/SOH estimation. Plett [23] proposed a bar-delta filtering method based on SPKF to estimate the SOC and SOH values of every cell in the pack. Dai et al. [24] introduced a dual time-scale extended Kalman filtering (EKF) method to estimate the pack 'average SOC' first, and then they incorporate the performance divergences between the 'averaged cell' and each individual cell to generate the SOC estimations for all cells. Both Plett and Dai et al. use the bar-delta filter concept to reduce the computational effort of estimating the states of each individual cell in the pack. However there are still hundreds of delta filters running in the battery management system and therefore the computational effort is still significant. Kim et al. [25] proposed a stable SOC estimation method using EKF based on a screening process for improved voltage/SOC balancing of a lithium-ion series battery pack. Xiong et al. [26] also used a similar approach based on cell screening process but with AEKF to improve the estimation accuracy. Both Kim et al. and Xiong et al. preprocess the cells with a carefully defined cell screening process to make up a battery pack with good consistence. But in practical, it is almost unrealistic to get the parameters of every cell when making up the pack in mass production, thus the cell screening process is difficult to implement. Roscher et al. [27] introduced a reliable state estimation of multi-cells lithium-ion battery systems, by which cell impedance and SOC variations could be detected precisely. But how to determine the tunable correction gain was not discussed in this paper. Zheng et al. [28] introduced a cell state-of-charge inconsistency estimation for $LiFePO_4$ battery pack using mean-difference model, and SOC differences is determined with estimated OCV differences using SOC-difference/OCV-difference curve. However, to implement this method, hundreds of total least squares methods are needed to obtain the OCV differences when applying it to the battery pack in EVs, which makes its application unrealistic due to the high computational effort. Zhong et al. [29] proposed an estimation method for the battery pack state of charge based on in-pack cells uniformity analysis, the relationship between the parameters of the pack and those of in-pack cells under different balance control strategies is established in order to estimate the pack SOC, and then the pack SOC estimation can be converted into SOC estimation for the weakest cells. However, how to perform an online identification of the weakest cells is not discussed in this paper. Liu et al. [30] introduced a SOC estimation method based on minimal cell terminal voltage of the battery pack. But with the fact that the cell with minimal terminal voltage is not always the cell with the lowest capacity, the estimation can be inaccurate in some special situations.

In this paper, in order to accurately estimate the SOC and SOH of battery pack with a low computational effort, a multi time-scale nonlinear predictive filter (NPF) estimation framework is proposed. First, both cell-level and pack-level SOC/SOH definitions are presented based on series connected battery pack with passive balance control. For a battery system with these characteristics, the SOC and capacity of battery pack can be represented by the 'weakest in-pack cell' with minimum capacity, and the pack resistance is represented by the sum of all the in-pack cells' resistances. Then the multi time-scale estimation framework is presented. The framework separately evaluates the pack SOH estimate with an 'off-line' long time-scale and the pack SOC estimate with a real-time implementation with respect to the multi time-scale nature of battery systems. In the long time-scale estimation part, the resistances and capacities of all the cells in the pack are estimated with a long time interval, and the SOH of the pack are obtained based on the pack-level definitions. After that a cell screening process is implemented to select the 'weakest cell' based on the estimation results of cells' capacities. In the real-time implementation part, based on the cell screening results, the estimation of pack SOC is reduced into the SOC estimation of the 'weakest cell'. With respect to estimate every cell's SOC, the proposed framework only needs to estimate one cell which greatly reduces the computational effort. Compared to the above mentioned estimation methods using unit cell model, the proposed method has better estimation accuracy since it takes into account the cell-to-cell variation and the estimation is implemented based on pack-level SOC/SOH definitions. In comparison with the bar-delta filtering method, the proposed approach requires a lower computational effort, due to the fact that it just requires estimating the SOC of the weakest cell.

During the past years, the Extended Kalman filter (EKF) has been widely accepted as the state estimation algorithm for batteries. In