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A probabilistic approach for prognosis of battery pack aging

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HIGHLIGHTS

- A probabilistic framework is developed for the SOH prediction of Li-ion battery packs.
- Aging campaigns show that aging model alone is not sufficient for acceptable prognosis.
- Online pack level aging model parameter estimation framework is proposed.
- Proposed framework particularly considers battery packs in PHEV applications.
- Accuracy of the proposed framework is demonstrated using simulation study.

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ABSTRACT

A probabilistic framework is developed for the prognosis of battery packs. It is demonstrated using aging campaign data, that aging models alone may not be sufficient for aging prognosis, and aging model parameter estimation may further improve the accuracy of prognosis. A systematic framework that extends the aging models to battery pack aging and prognosis still remains challenging. We propose a framework that bridges the gap in cell and pack aging prognosis in a probabilistic sense, and further improves the prognosis by estimating the aging model parameters for the pack. The framework is versatile for various applications because it is not restricted to a specific cell chemistry, or a type of aging model. In addition, the proposed framework could distinguish more aged cells as compared to other cells in the pack. Numerical examples are provided to demonstrate the effectiveness of the proposed framework.

1. Introduction

Aging of dynamical systems is defined as the loss of functionality over time. Understanding of aging phenomena is critical for predicting the Remaining Useful Life (RUL) and for system design. Prognosis allows prediction of RUL using current state of the system, aging dynamics and future operating conditions. Prognosis for interconnected systems poses challenges due to the aging propagation among the components and other system interactions. Aging of one element may influence aging in the other elements, leading to faster aging of the overall system. A battery pack consists of battery cells, cooling system, and Battery Management System (BMS). Life of the battery pack affects the life-time cost of the vehicle, which includes servicing, maintenance and equipment replacement costs. Understanding the aging phenomena of the battery pack has been a research topic in the automotive industry for a couple of decades [1–3]. Prognosis methods in general are not new to the automotive industry. For example, life of engine oil is dynamically computed using actual in-use vehicle conditions and that information is used to predict the time until the next oil change. Similarly, prognosis of battery packs in electrified vehicles is important to avoid sudden power loss. Furthermore, prognostic capabilities may enable life extending functions in the vehicle control systems.

Various types of aging models have been developed and played a pivotal role in prognosis [4–7]. However, these high fidelity aging model are nonlinear and involve many model parameters required to be identified. The aging phenomena is attributed to a complicated electrochemical reaction mechanism. In order to develop an aging model for a pack for on-board prognosis, a control oriented model is necessary [8–11].

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Nomenclature

$[n]$	a sequence $1, 2, \ldots, n$
α	Collection of aging model parameters
$\overline{X}$	% capacity loss for a battery to reach the end of life
$\widehat{X}$	Estimated % capacity loss
$\mathbb{1}_{\mathscr{A}}$	Indicator function for set $\mathscr{A}$
Ω	Probability distribution function of w
Ah	Accumulated Ampere-hour current throughput
D^0	Initial distribution of α
E_{ac}	Activation energy
I	Current
p_i	Probability of cell i being most aged
R	ideal gas constant
$Ratio$	Time fraction of charge depleting
S	Capacity of a battery cell
SoC	State of charge
T	Temperature
V	Terminal voltage
V_{oc}	Open circuit voltage
w	Estimation error of pack capacity
X_c	% capacity loss of a pack
x_c	% capacity loss of a cell
X_r	% resistance loss of a pack
x_r	% resistance loss of a cell

Past research at the Center for Automotive Research (CAR), at the Ohio State University (OSU) has established an aging model for lithium-ion pouch cells containing blended spinel and layered-oxide positive electrodes. These aging models were then extended for packs by appropriate consideration of electrical and thermal balancing as well as the differences among individual cells [12]. A semi-empirical aging model is adopted in the work to reach a balance between model complexity, computational efficiency and physical understanding of the aging mechanism for a cell. Such a model may be implemented for pack-level prognosis when the aging model of every cell in the pack is known. However, the manufacturing variability may cause heterogeneity between the interconnected cells, making identification of the aging model for all the cells challenging. One way of addressing this issue is to consider aging model parameters as the state variables and implement dynamic estimation methods such as Extended Kalman Filter (EKF) or Nonlinear Predictive Filter (NPF) to estimate both State Of Health (SOH) and the aging model. However, in most experimentally validated aging models [13,14], the SOH appears as a nonlinear static function of measured or estimated variables, such as State Of Charge (SOC) or temperature. Those filtering techniques may not be directly applicable for on-board prognosis due to computational complexity. These approaches require a separate filter for each cell or module in series. Another approach is to identify the aging model on line using machine learning and data driven algorithms, for example, Artificial Neural Networks (ANNs) [15,16].

In this paper, we propose a model based estimation framework that is specifically developed for the algebraic aging models in order to improve both accuracy and computational complexity. The proposed framework updates the aging model of the cells with only the knowledge of SOH and SOC estimation of the entire pack. Cell-to-cell heterogeneity due to manufacturing variability and exposure to different temperatures in a pack can be probabilistically quantified using measurements or estimations of physical parameters of cells. The aging model of the pack can then be derived by combining cell aging models in probabilistic sense. The proposed framework is suitable for on-board prognosis of a Plug-in Hybrid Electric Vehicle (PHEV) battery pack. It is not restricted to any specific cell chemistry or a type of aging model. In addition, the proposed framework updates the parameters of the aging model of the pack if physical parameter measurements and estimations of SOC and SOH are available, which is generally true in practical usage of PHEV. It is worth mentioning that the probability of one cell being most aged (or the probability of being the "weakest" cell) is naturally included in the framework. This information is valuable to improve the BMS control scheme, rebuilding the battery pack, and replacing aged modules to prolong the life time of the pack. Hence, we believe the paper makes important contributions that are not available in the literature:

1. extension of the cell-level aging model to pack aging model in a probabilistic sense
2. identification of a the semi-empirical aging model that can be used with measurements available in a typical production PHEV
3. identification of the most aged cell in a battery pack

The rest of the paper is organized as follows. In section 2, we review the aging model of a cell. A motivating example based on experiment data is also provided to illustrate the necessity of aging model parameter estimation. Section 3 establishes the probabilistic framework to aging characteristics of the battery packs. Simulation studies and experiments are demonstrated in Section 4 to show the effectiveness of the proposed method.

2. Aging model —background

In this section, we will first review typical aging models for a battery cell, and how degradation of single cell affects the aging of a pack. A realistic method for identifying the aging model for battery cell is also described. Using single cell aging campaign data, we demonstrate that the aging model parameter estimation improves the predictive capabilities of the aging model. This example provides motivation for pack level aging model parameter estimation to improve prognosis of a pack.

2.1. Aging model of single cell

The aging of a battery cell is characterized by the capacity fade and resistance growth. For the aging attributed to resistance growth, we will only focus on the ohmic resistance instead of detailed second order equivalent resistance model [5,13]. Let x_c and x_r be the percentage capacity loss and resistance growth respectively. The aging model of cell i can be written in the following form in general

$$\begin{cases} x_{c,i}(t) = f_c(z_i, \alpha_i, t) \\ x_{r,i}(t) = f_r(z_i, \alpha_i, t) \end{cases}, \; z_i = \left[SOC_i, T_i, V_i, I_i \right] \tag{1}$$

where T_i is the battery internal temperature, V_i is the terminal voltage, I_i is the input current, and $\alpha_i \in \mathbb{R}^n$ is the vector collecting the aging model parameters [17]. The z_i, also called as stress factors, are time dependent, and aging of the cell depends on the time history of these inputs. However, it has been shown using Palmgren-Miner rule that the aging is cumulative and does not depend on the cycling sequence, provided certain conditions are