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Remaining useful life assessment of lithium-ion batteries in implantable medical devices

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HIGHLIGHTS

- A data-driven/model-based method to lithium-ion battery prognostics is proposed.
- It employs sparse Bayesian learning (model-based) to infer capacity from features.
- It adopts particle filters (data-driven) to predict remaining useful life (RUL).
- RUL prediction involves the use of single or multiple capacity fade models.

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ABSTRACT

This paper presents a prognostic study on lithium-ion batteries in implantable medical devices, in which a hybrid data-driven/model-based method is employed for remaining useful life assessment. The method is developed on and evaluated against data from two sets of lithium-ion prismatic cells used in implantable applications exhibiting distinct fade performance: 1) eight cells from Medtronic, PLC whose rates of capacity fade appear to be stable and gradually decrease over a 10-year test duration; and 2) eight cells from Manufacturer X whose rates appear to be greater and show sharp increase after some period over a 1.8-year test duration. The hybrid method enables online prediction of remaining useful life for predictive maintenance/control. It consists of two modules: 1) a sparse Bayesian learning module (data-driven) for inferring capacity from charge-related features; and 2) a recursive Bayesian filtering module (model-based) for updating empirical capacity fade models and predicting remaining useful life. A generic particle filter is adopted to implement recursive Bayesian filtering for the cells from the first set, whose capacity fade behavior can be represented by a single fade model; a multiple model particle filter with fixed-lag smoothing is proposed for the cells from the second data set, whose capacity fade behavior switches between multiple fade models.

1. Introduction

Lithium-ion (Li-ion) batteries are widely used in consumer electronics, such as cell phones and laptops, and in transportation applications, such as hybrid and electric vehicles. Recently, Li-ion batteries have found use in implantable medical devices such as neurostimulators for the relief of chronic pain and deep brain stimulators for the treatment of Parkinson's disease. As a Li-ion battery cell ages, the decrease of capacity and the increase of internal resistance degrade the electrical performance of the cell by means of energy and power losses [1]. Capacity, which quantifies the total amount of energy stored in a fully charged cell, is an important indicator of the state of health (SOH) of the cell [1–3]; remaining useful life (RUL), also called remaining longevity, refers to the available service time left before the capacity fade reaches an unacceptable level [4]. Accurately tracking these parameters allows battery management system (BMS) to perform predictive maintenance/control of a cell through concurrent estimation of the cell SOH (diagnostics) and prediction of the cell RUL (prognostics).

Recent literature reports a variety of approaches to estimating the capacity of a Li-ion battery cell in operation. In general, these approaches can be categorized into 1) adaptive filtering approaches [1,2,5–11], 2) coulomb counting approaches [12–15], 3) neural network approaches [16–18], and 4) kernel regression approaches [19–21]. The capacity estimation of a cell by most of these existing approaches only requires readily available measurements (i.e., voltage, current and temperature) acquired from the cell. A more recent

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development in the kernel regression category was a sparse capacity estimator based on sparse Bayesian learning [22], and the estimator is a kernel regression model that approximates the relationship between the capacity of a battery cell and five characteristic features extracted from a capacity versus voltage function, $Q(V)$, or charge curve [22,23]. The capacity estimator, as a highly sparse regression model, was applied to infer the capacity of Li-ion battery designed for use in implantable medical devices, and achieved satisfactory estimation accuracy on lab and post-explant Li-ion cells cycled with a nominally weekly discharge rate [22].

Extensive research has been conducted on RUL assessment of a general engineered system with an emphasis on modeling the RUL distribution. In general, three categories of approaches have been developed that enable continuous updating of system health condition and RUL distribution: (i) model-based approaches [24–26], (ii) data-driven approaches [27–29], and (iii) hybrid approaches [30,31]. These approaches, although not developed specifically for Li-ion battery prognostics, can generally be adapted for RUL assessment of Li-ion battery. Research devoted to developing new approaches for Li-ion battery prognostics was mainly conducted by researchers in the prognostics and health management (PHM) society. A Bayesian framework with particle filter was proposed for RUL prediction of Li-ion battery based on impedance measurement and by updating an empirical capacity fade model that employs a single exponential function [32]. A similar attempt with impedance measurement was later made with the use of recurrent neural network [33]. In order to eliminate the reliance of battery prognostics on impedance measurement equipment, researchers developed various model-based approaches that predict RUL by extrapolating a capacity fade model [14,34–39]. An empirical capacity transition model was created to capture the degradation (via the use of coulombic efficiency) and self-recharge (via the use of an exponential function) of a battery cell, and the capacity transition model was updated using particle filter for RUL prediction [34]. Two interesting attempts on battery prognostics were made to improve the accuracy of the single exponential function in capacity fade modeling [35,36]. The first attempt developed a new empirical model consisting of two exponential functions and applied the new model to enable accurate RUL prediction with particle filter [35]. The second attempt employed relevance vector machine (RVM) to assist an empirical model (i.e., a sum of exponential and power functions) with accurately representing the capacity fade behavior of Li-ion battery [36]. Particle filter often directly treats the transition prior (i.e., without the use of prior measurements) as the proposal importance density used for drawing new particles. This treatment makes the implementation of particle filter convenient and computationally efficient but may cause a rapid loss of particle diversity, known as particle degeneracy. To mitigate particle degeneracy and ensure effective model updating and accurate RUL prediction, researchers have made attempts to derive better proposal importance densities by incorporating recent measurements of cell capacity. These attempts generated proposal importance densities by employing unscented Kalman filter [37], Gauss-Hermite Kalman filter [14], and spherical cubature integration-based Kalman filter [38]. In particular, the integration of Gauss-Hermite Kalman filter with particle filter resulted in the so-called Gauss-Hermite particle filter, which was applied to predict the RUL distribution of implantable Li-ion battery [14]. This model-based prognostics approach produced accurate prediction of how long a Li-ion battery cell will perform in an implantable application before the cell capacity fades to an unacceptable level. More recently, sigma-point Kalman filter was proposed to update empirical capacity fade models for RUL prediction in the presence of additive Gaussian (process and measurement) noises [39] whose variances may differ from one cell to another. Under this Gaussian assumption, the use of particle filter that would require more computational effort than Kalman filter was shown to be unnecessary and may lead to less accurate RUL prediction [39].

When a Li-ion battery is used as the power source in an implantable medical device, it is very important to be able to track the capacity fade of the battery and assess its RUL throughout the lifetime. This can provide information to the patient and his/her health care provider regarding when and how a replacement of the device might be needed. The information could be crucial for ensuring device operation and minimizing therapy interruptions. The need for predictable capacity fade models and ability to predict RUL is particularly significant given long targeted lifetime of implanted devices (typically 10 years; up to 25 years in some cases) and large variation in use conditions (many cycles versus few cycles over a certain calendar time) depending on the therapy needs. Examples of implantable medical devices that may be powered by a Li-ion battery include neurological stimulators, spinal stimulators, cardiac stimulators such as pacemakers and defibrillators, and diagnostic devices such as cardiac monitors. In this paper, a hybrid data-driven/model-based method is employed for online RUL assessment of Li-ion batteries in implantable medical devices. The hybrid method integrates sparse Bayesian learning (data-driven) with recursive Bayesian filtering (model-based) to enable real-time inference of capacity from charge-related features and prediction of RUL from recursive updating and extrapolation of capacity fade models. A generic particle filter is adopted to implement recursive Bayesian filtering for batteries whose capacity fade behavior can be represented by a single fade model, and a multiple model particle filter (MMPF) with fixed-lag smoothing is proposed for batteries whose capacity fade behavior switches between multiple fade models. The effectiveness of the proposed method is demonstrated by leveraging daily cycling data from eight fresh cells from Medtronic, PLC (hereafter referred to as the MDT cells) as well as eight fresh/post-explant cells from Manufacturer X (hereafter referred to as the Mfg. X cells). A large difference in the capacity fade behavior is seen between the two manufacturers' data sets used in this paper and hence these data sets serve as excellent test cases for developing robust prognostic techniques applicable to wide variety of fade characteristics.

The reminder of this paper is organized as follows. Section 2 presents the fundamentals of the proposed method. The method is applied to online capacity estimation and RUL prediction of Li-ion batteries used in implantable applications. Section 3 discusses the experimental results of this application. The paper is concluded in Section 4.

2. Technical approach

Given the current and voltage signals measured from a cell operating under a typical use condition and a discrete-time state space model that describes the capacity fade behavior of the cell, we aim at estimating the capacity of the cell at every charge/discharge cycle and predicting its RUL, i.e., how long the cell is expected to operate before its capacity falls below an unacceptable level (or a capacity threshold). The subsequent sections present our proposed prognostic method to accomplish this online task. As shown in Fig. 1, the proposed prognostic method consists of two essential modules: 1) sparse Bayesian learning, which automatically learns (from a training data set) a mapping from charge-related features to capacity measurement; and 2) recursive Bayesian filtering, which recursively updates an empirical capacity fade model with the capacity measurement and extrapolates the model for prediction of RUL. In what follows, the two modules will be explained in further detail. Section 2.1 describes the sparse Bayesian learning scheme for capacity estimation; and Section 2.2 presents the recursive Bayesian filtering technique for RUL prediction.

2.1. Sparse Bayesian learning of capacity (module 1)

Sparse Bayesian learning or RVM [22,40] will be employed to train a sparse capacity estimator that learns the complex mapping from the feature ($\mathbf{z}$) space to the capacity measurement (y) space (see Fig. 2). Suppose we have a training data set $\{\mathbf{z}_j, y_j\}$, $j = 1, 2, \ldots, M$, consisting of M input-output pairs from training cells. The sparse measurement