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Online estimation of lithium-ion battery capacity using sparse Bayesian learning

Chao Hu*, Gaurav Jain, Craig Schmidt, Carrie Strief, Melani Sullivan

Medtronic Energy and Component Center, Brooklyn Center, MN 55430, USA

HIGHLIGHTS

- We propose a sparse Bayesian learning method for battery capacity estimation.
- The method is applicable to Li-ion batteries used in implantable medical device.
- Five features indicative of battery capacity are extracted from charge curves.
- RVM regression approximates mapping from feature space to capacity state space.
- Cycling data from lab and field cells are used to verify the performance.

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ABSTRACT

Lithium-ion (Li-ion) rechargeable batteries are used as one of the major energy storage components for implantable medical devices. Reliability of Li-ion batteries used in these devices has been recognized as of high importance from a broad range of stakeholders, including medical device manufacturers, regulatory agencies, patients and physicians. To ensure a Li-ion battery operates reliably, it is important to develop health monitoring techniques that accurately estimate the capacity of the battery throughout its life-time. This paper presents a sparse Bayesian learning method that utilizes the charge voltage and current measurements to estimate the capacity of a Li-ion battery used in an implantable medical device. Relevance Vector Machine (RVM) is employed as a probabilistic kernel regression method to learn the complex dependency of the battery capacity on the characteristic features that are extracted from the charge voltage and current measurements. Owing to the sparsity property of RVM, the proposed method generates a reduced-scale regression model that consumes only a small fraction of the CPU time required by a full-scale model, which makes online capacity estimation computationally efficient. 10 years' continuous cycling data and post-explant cycling data obtained from Li-ion prismatic cells are used to verify the performance of the proposed method.

1. Introduction

Capacity, as an important indicator of the state of health (SOH) of Li-ion battery [1,2], measures the maximum amount of electric charge that a fully charged battery can deliver. Online estimation of battery capacity raises awareness of the present battery health condition and enables early detection of an incipient fault and timely implementation of maintenance actions. Recent literature reports a variety of approaches to estimating the capacity of Li-ion battery. In general, these approaches can be categorized into the adaptive filtering approach [1–6], the coulomb counting approach [7–9], the neural network (NN) approach [10–12] and the kernel regression approach [13–17].

Joint/dual extended Kalman filter (EKF) [1] and unscented Kalman filter [2,3] were employed to estimate the state of charge (SOC), capacity and/or resistance of Li-ion battery. To improve the performance of joint/dual estimation, adaptive measurement noise models of Kalman filter were developed to separate the sequence of SOC and capacity estimation [4]. A multiscale scheme with EKF [5] was developed that decouples the SOC and capacity estimation with respect to both the measurement- and time-scales and employs a state projection schedule for accurate and stable capacity estimation. Most recently, a data-driven multi-scale EKF algorithm was developed that leverages the fast-varying characteristic of SOC

* Corresponding author.
E-mail addresses: chao.x.hu@medtronic.com, huchaostu@gmail.com (C. Hu).

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and the slowly-varying characteristic of capacity, with an aim to achieve accurate SOC and capacity estimation in real-time [6].

The coulomb counting approach estimates the capacity by a simple integration of current over time. An enhanced coulomb counting approach was developed to estimate the capacity of a Li-ion cell with dynamic re-calibration after the cell is fully charged or discharged [7]. The coulomb counting approach offers a simple way to compute the capacity. But it requires accurate current measurement and, often, a full charge/discharge cycle to be exercised. This approach is typically used, in a well-controlled experiment, to provide a benchmark for evaluating a more sophisticated capacity estimation approach. Two recently developed approaches employed the coulomb counting approach to estimate the battery capacity based on the difference in the SOC values before and after partial charge/discharge [8,9].

The NN approach builds a network structure of interconnected “neurons” to model the dependency between the input features (e.g., cell terminal voltage, current and temperature) and the output (i.e., cell capacity). The recurrent NN were employed to estimate the two SOH-related parameters, namely the capacity and equivalent series resistance, of a high-power-density Li-ion cell based on the temperature, current, SOC variations and historical cell behavior [10] and achieved good accuracy in SOH estimation over hundreds of accelerated ageing cycles. The Hamming NN was applied to identifying the representative capacity pattern (from a set of training cells with known capacities) that most closely matches that of a testing cell whose capacity is unknown and to be estimated [11]. A very recent study developed a data-driven approach that integrates NN with dual EKF for online estimation of Li-ion battery [12]. In this approach, an NN model was built as a battery dynamic model that utilizes the SOC, current and capacity to estimate the terminal voltage, and dual EKF was used to jointly estimate both the SOC and capacity.

The kernel regression approach models the non-linear relationship between the measureable features and the cell capacity by way of kernel functions. Kernel regression techniques that were employed to estimate the capacity of Li-ion battery include support vector machine (SVM) [13,14], relevance vector machine (RVM) [15,16] and k-nearest neighbor (kNN) regression [17], all of which are machine learning techniques. SVM was used to predict the SOC, capacity fade and power loss of Li-ion battery based on the baseline data collected from reference performance tests [13]. In a more recent study, SVM was used in combination with load cycle counting to estimate the capacity of high-power Li-ion battery used in hybrid electric vehicles [14]. The performance of the developed capacity estimation approach was verified by performing a six-month cycling test with real-world driving profiles. RVM is a sparse Bayesian approach to kernel regression and performs regression in a probabilistic manner. The extreme sparsity of the RVM regression model allows one to make estimations for new observations in a highly efficient manner. An intelligent RVM-based method was proposed to estimate the SOH of Li-ion battery based on the sample entropy feature extracted from the discharge voltage measurements [15]. A Bayesian framework combining RVM and particle filter was proposed for tracking the capacity fade and predicting the remaining useful life of Li-ion battery [16]. Unlike SVM and RVM, kNN regression is a non-parametric learning technique. The technique possesses the unique property that no explicit training step is required. Recently, kNN regression was employed to capture the complex dependency of the capacity on the charge-related features, and particle swarm optimization was adapted to finding the optimal combination of feature weights for creating a kNN regression model with the minimum estimation error [17].

As mentioned above, researchers have developed a wide range of methods to estimate the capacity of Li-ion battery. However, further research is still needed to develop efficient, accurate and robust methods that track the capacity fade of Li-ion battery based on readily available measurements (i.e., voltage, current and temperature). This paper aims to apply a statistical learning method, RVM, to the task of estimating the capacity of Li-ion battery based on the voltage and current measurements during charge. This application involves two main steps, which are presented in Section 2 and summarized as follows:

1. First, five characteristic features that are indicative of the capacity are extracted from the charge curves. These features can be easily computed based on the voltage and current measurements during a charge cycle, where a battery is fully charged from a partially discharged state. See Section 2.1 for details.
2. Then, RVM is used to learn the relationship between the capacity of a battery and its charge-related features. A RVM regression model, after being trained offline, is used to infer the unknown capacity of a battery online from a set of charge-related features. Two desirable properties that RVM possesses are (i) the generalization, i.e., the over-fitting is avoided during offline training, and (ii) the sparsity, i.e., only a sparse set of training points, namely relevance vectors, are used for online inference. The generalization property ensures good accuracy in online inference, while the sparsity property improves computational efficiency. To the best of our knowledge, the present study is the first to investigate the use of the sparse Bayesian learning method to infer the battery capacity from the charge data. See Section 2.2 for details.

The experimental verification of this application was accomplished by analyzing data from (i) a 10 years' continuous cycling test on eight Li-ion cells that were manufactured in 2002 and (ii) a post-explant cycling test on twenty-three Li-ion cells with 4–7 implant years. Section 3 presents and discusses the verification results. The paper is concluded in Section 4.

2. Technical approach

The aim of the method described in this section is to estimate the capacity of a Li-ion battery cell based on the basic measurements (i.e., voltage and current) collected from the cell during charge. Specifically, we intend to convert the voltage and current measurements during a charge cycle to a feature vector, $\mathbf{x}$, and use a trained RVM expert to infer the cell capacity based on the feature vector. Section 2.1 briefly describes the composition of the feature vector. Section 2.2 discusses the use of RVM to build a sparse kernel regression model that approximates the non-linear mapping from the multi-dimensional feature space to the one-dimensional capacity state space.

2.1. Feature extraction

Typical voltage and current curves of a Li-ion battery cell during a charge cycle is shown in Fig. 1 [17]. The cell enters the charge stage after being partially discharged to a certain SOC level. A standard charge protocol comprises of two charge steps, the constant current (CC) charge step and the constant voltage (CV) charge step. In the CC charge step, a charge current is kept at a constant until the cell terminal voltage rises up to a predefined voltage limit, V_{max}. Immediately after the cell terminal voltage reaches V_{max}, the charge process transitions from the CC charge step to the CV charge step. In the CV charge step, the cell terminal voltage is kept unchanged at V_{max} until a predefined time limit is reached. Accordingly, the total charge capacity consists of two parts, the CC charge