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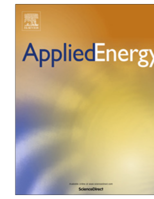

Data-driven method based on particle swarm optimization and k-nearest neighbor regression for estimating capacity of lithium-ion battery

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HIGHLIGHTS

- We develop a data-driven method for the battery capacity estimation.
- Five charge-related features that are indicative of the capacity are defined.
- The kNN regression model captures the dependency of the capacity on the features.
- Results with 10 years' continuous cycling data verify the effectiveness of the method.

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ABSTRACT

Reliability of lithium-ion (Li-ion) rechargeable batteries used in implantable medical devices has been recognized as of high importance from a broad range of stakeholders, including medical device manufacturers, regulatory agencies, physicians, and patients. To ensure Li-ion batteries in these devices operate reliably, it is important to be able to assess the battery health condition by estimating the battery capacity over the life-time. This paper presents a data-driven method for estimating the capacity of Li-ion battery based on the charge voltage and current curves. The contributions of this paper are three-fold: (i) the definition of five characteristic features of the charge curves that are indicative of the capacity, (ii) the development of a non-linear kernel regression model, based on the k-nearest neighbor (kNN) regression, that captures the complex dependency of the capacity on the five features, and (iii) the adaptation of particle swarm optimization (PSO) to finding the optimal combination of feature weights for creating a kNN regression model that minimizes the cross validation (CV) error in the capacity estimation. Verification with 10 years' continuous cycling data suggests that the proposed method is able to accurately estimate the capacity of Li-ion battery throughout the whole life-time.

1. Introduction

Capacity, which quantifies the available energy stored in a fully charged Li-ion battery cell, is an important indicator of the state of health (SOH) of the cell [1,2]; remaining useful life, also called remaining longevity, refers to the available service time that is left before the capacity fade reaches an unacceptable level [3–5]. It is important to accurately estimate these two parameters in order to monitor the present battery SOH and to enable failure prevention through timely maintenance actions.

Recent literature reports a variety of approaches to estimate the capacity of Li-ion battery. In general, these approaches can be categorized into the adaptive filtering approach [1,2,6–9], the coulomb counting approach [10–12], the neural network (NN) approach [13,14] and the kernel regression approach [15–17]. Joint/dual extended Kalman filter (EKF) [1] and unscented Kalman filter [2,6] 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 the Kalman filter were developed to separate the sequence of SOC and capacity estimation [7]. A multiscale scheme with EKF [8] 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 and the slow-varying characteristic of capacity, with an

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aim to achieve accurate SOC and capacity estimation in real-time [9].

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 [10]. The coulomb counting approach provides a simple way to compute the capacity but 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 value before and after partial charge/discharge [11,12].

The NN approach basically builds a network structure of interconnected "neurons" to model the dependency between the measureable features (e.g., cell terminal voltage, current and temperature) and the 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 previous cell behavior [13] and achieved good accuracy in the 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 [14].

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) [15] and relevance vector machine (RVM) [16,17], both 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 [15]. RVM is a Bayesian approach to kernel regression and produces estimations in a probabilistic manner. The extreme sparsity of the estimations by RVM 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 [16]. A Bayesian framework combining RVM and the particle filter was proposed for tracking the capacity fade of Li-ion battery and predicting the remaining useful life [17].

Although a large number of capacity estimation methods have been developed, research efforts are still in great need to develop simple, but accurate, methods that enable life-time tracking of capacity fade based on readily available measurements (i.e., voltage, current and temperature). In this study, we develop a data-driven method that estimates the capacity of Li-ion battery based on the charge voltage and current curves. 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. Then, the k-nearest neighbor (kNN) regression is used to build a non-linear kernel regression model, with an aim to capture the complex dependency of the capacity on the five extracted features. The kNN regression, as a similarity-based technique, predicts the response of a testing point by averaging the responses of the k-nearest neighbors to the point in a weighted manner. Finally, particle swarm optimization (PSO) is adapted to finding the optimal combination of feature weights for creating a kNN regression model that minimizes the cross validation (CV) error in the capacity estimation. 10 years' continuous cycling data obtained from eight Li-ion prismatic cells are used to verify the effectiveness of the proposed method in the capacity estimation over the life-time. This paper is organized as follows. Section 2 presents the fundamentals of the proposed data-driven method. The approach is applied to estimating the capacity of Li-ion battery used in implantable medical devices. Section 3 discusses the experimental results of this application. The paper is concluded in Section 4.

2. Technical approach

Given the basic measurements (voltage, current and charge capacity) of a Li-ion battery cell during charge, we aim at estimating the cell capacity by using a data-driven method. In the method, five characteristic features that are indicative of the capacity are extracted from the basic measurements obtained during charge and the kNN regression technique is employed to learn the relationship between the capacity and the five charge-related characteristic features. Section 2.1 describes the five features. Section 2.2 discusses the use of the kNN regression to build a kernel regression model that approximates the non-linear relationship between the capacity and the features. In Section 2.3, PSO is adapted to finding the optimal combination of feature weights that are used in the kernel regression model.

2.1. Feature extraction

Typical voltage and current curves of a Li-ion battery cell during a charge cycle is shown in Fig. 1. The cell enters the charge stage after being discharged to a certain state of charge (SOC) level. A standard charge protocol comprises of two charge steps, the constant current (CC) charge step and the constant voltage (CV) charge step. During the CC charge step, the cell is charged at a predefined constant current until the cell terminal voltage reaches the charge cutoff voltage, V_{max}. Right after the CC charge step, the cell enters the CV charge step where the cell terminal voltage is held at V_{max} until a predefined time limit is reached. Accordingly, the total charge capacity can be divided into two parts, the CC charge capacity and the CV charge capacity. It is noted that the CV charge capacity typically accounts for only a very small portion (e.g., less than 5%) of the total charge capacity. We also note that, in practice, the Li-ion battery cell in an implanted medical device may not experience a complete charge (i.e., after the cell is full discharged). If the patient carrying the device charges the cell before its complete depletion, the cell will start charge at a partially discharged state.

Five features (see Fig. 1) that are representative of charge curves are chosen as the inputs to the kNN regression model. These five

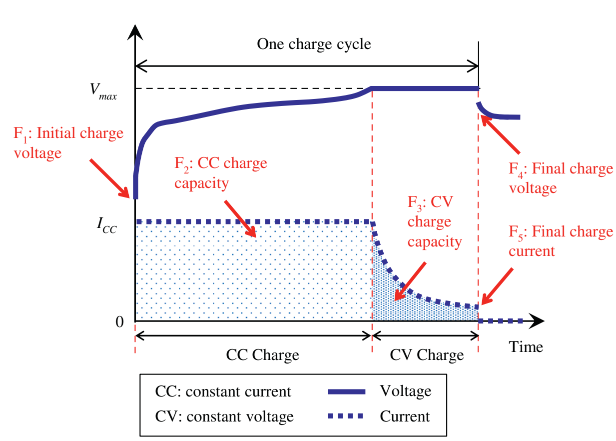

Fig. 1. Five charge-related features in an illustrative charge cycle.