Microelectronics Reliability 78 (2017) 212–219

Contents lists available at ScienceDirect

Microelectronics Reliability

journal homepage: www.elsevier.com/locate/microrel

Battery remaining useful life prediction at different discharge rates

Dong Wang, Fangfang Yang *, Yang Zhao, Kwok-Leung Tsui

Department of Systems Engineering and Engineering Management, City University of Hong Kong, Hong Kong, China

ARTICLE INFO

Article history:
Received 6 October 2016
Received in revised form 24 August 2017
Accepted 6 September 2017
Available online xxxx

Keywords:
Remaining useful life
Lithium-ion batteries
Particle filter
Prognostics and health management
Different discharge rates

ABSTRACT

Lithium-ion batteries are widely used in hybrid electric vehicles, consumer electronics, etc. As of today, given a room temperature, many battery prognostic methods working at a constant discharge rate have been proposed to predict battery remaining useful life (RUL). However, different discharge rates (DDRs) affect both usable battery capacity and battery degradation rate. Consequently, it is necessary to take DDRs into consideration when a battery prognostic method is designed. In this paper, we propose a discharge-rate-dependent battery prognostic method that is able to track usable battery capacity affected by DDRs in the process of battery degradation and to predict RUL at DDRs. An experiment was designed to collect accelerated battery life testing data at DDRs, which are used to investigate how DDRs influence usable battery capacity, to design a discharge-rate-dependent state space model and to validate the effectiveness of the proposed battery prognostic method. Results show that the proposed battery prognostic method can work at DDRs and achieve high RUL prediction accuracies at DDRs.

1. Introduction

Lithium-ion batteries are widely used in hybrid electric vehicles, consumer electronics, etc. Considering several significant battery capacity degradation factors [1], including storage voltage, environment temperature, discharge rate, depth of discharge, etc., one needs to take these factors into consideration in battery prognostics and health management [2], especially battery remaining useful life (RUL) prediction. Here, battery RUL can be regarded as how many charge/discharge cycles are left before battery capacity fails to provide reliable power for electric systems and products [3].

As of today, many battery prognostic methods have been proposed to predict battery RUL at a constant discharge rate. Among these battery prognostic methods, particle filter (PF) based battery prognostic methods [4–9] have attracted lots of attention because PF provides a way to solve numerical integration required in non-linear state space models. Moreover, PF based methods have been demonstrated to be effective in diagnostics and prognostics of other critical components, such as bearing [10], gear [11], carrier plate [12], gas turbine [13], aluminum electrolytic capacitors [14], fatigue crack [15,16], etc. For PF based battery prognostics, Saha et al. [17] proposed to combine relevance vector machine and PF so as to predict battery RUL at a constant discharge rate. In their further comparison study [18], they experimentally demonstrated that the PF based prognostic method has higher RUL prediction accuracies than autoregressive integrated moving average and extended Kalman filter based prognostic methods. Following the work done by Saha et al., He et al. [19] used a bi-exponential function as an empirical battery degradation model so as to fit battery degradation data at a constant discharge rate and they experimentally found that the bi-exponential function has good ability to fit the battery degradation data. Based on the empirical battery degradation model, they built a state space model at a constant discharge rate and used PF to posteriorly estimate parameters distributions for battery RUL prediction at a constant discharge rate. To better fit local battery degradation behavior, Xing et al. [20] combined an exponential function and a polynomial function with an order of 2 to form an ensemble empirical battery degradation model and they experimentally demonstrated that the new empirical battery degradation model is able to predict battery RUL at a constant discharge rate better than the bi-exponential function based prognostic method. Since then on, many other researchers have tried to improve battery RUL prediction accuracies at a constant discharge rate by enhancing the performance of PF, including its particle diversity [21,22], model adaptation [23] and its importance function [24–26].

Even though the aforementioned battery prognostic methods had good RUL prediction accuracies at a constant discharge rate, these prognostic methods did not consider the influence of discharge rate on battery degradation. Actually, given a room temperature, discharge rate is one of the most significant factors to influence battery capacity degradation [27]. Normally, the higher a discharge rate, the faster a capacity degradation rate. Moreover, discharge rate affects usable capacity. The higher a discharge rate, the smaller a usable capacity. And, when a discharge rate is changed from a high rate to a low rate, most 'lost' capacity caused by the high rate is revoked [28]. This is the reason why we use

* Corresponding author.
E-mail addresses: dongwang4-c@my.cityu.edu.hk (D. Wang), fangfyang2-c@my.cityu.edu.hk (F. Yang), yangzhao9-c@my.cityu.edu.hk (Y. Zhao), kltsui@cityu.edu.hk (K.-L. Tsui).

http://dx.doi.org/10.1016/j.microrel.2017.09.009
0026-2714/

usable capacity instead of capacity in this paper to distinguish capacity influenced by different discharge rates (DDRs). Consequently, it is necessary to take DDRs into consideration when a battery prognostic method is designed.

In this paper, a discharge-rate-dependent battery prognostic method is proposed. The main contributions of this paper are highlighted as follows. Firstly, an experiment was designed to collect four battery degradation data at DDRs. The design of the experiment aims to investigate how DDRs affect usable battery capacity. Even though only four battery degradation samples at DDRs are available for our analyses, it took one year to collect them and the collection of battery degradation at DDRs is time-consuming. Secondly, because DDRs influence the value of usable capacity, it is difficult to directly use some empirical battery degradation models working at a constant discharge rate, such as the exponential function [17,18,23,25], the bi-exponential function [19], the ensemble function [20], etc. to describe battery degradation at DDRs. It is necessary to develop a more general battery degradation model working at DDRs. In this paper, we take the exponential function as an example and extend it to a more general empirical battery degradation model working at DDRs by discovering the relationship between the amplitude and slope of the exponential function and DDRs. According to our preliminary analyses, the exponential function is good enough in this paper to describe a battery degradation curve at a specific discharge rate. If one parameter has a linear relationship with discharge rate, only four hidden states are required in the state space modeling of battery degradation at the DDRs, which can be efficiently and posteriorly updated by using PF. Thirdly, based on the more general empirical battery degradation model, a discharge-rate-dependent state space model is proposed to track usable capacity degradation data at DDRs. More interestingly, given a constant discharge rate, the discharge-rate-dependent state space model can be reduced to the state space model used in [17,18,23,25]. Fourthly, we illustrate how to use PF to posteriorly estimate the parameter distributions of the discharge-rate-dependent state space model. Once the parameter distributions of the discharge-rate-dependent state space model are determined, we are able to predict battery RUL at DDRs by extrapolating the established state space model to a discharge-dependent soft failure threshold. Here, the discharge-rate-dependent soft failure threshold is taken as 80% of initial usable capacity values at DDRs. The main reason why we are interested in predicting RUL at DDRs is that we are concerned about how many charge/discharge cycles are left if the current discharge rate is changed to another concerned discharge rate. Battery RUL prediction at DDRs is able to suggest users when they are not allowed to use a higher discharge rate instead of the current discharge rate. According to our literature review, this new idea related to battery RUL prediction at DDRs is new and seldom reported.

The rest of this paper is outlined as follows. An experiment was designed in Section 2 to collect usable capacity degradation data at DDRs. In Section 3, to mathematically describe usable capacity degradation data at DDRs and predict battery RUL at DDRs, the discharge-rate-dependent battery prognostic method is proposed. In Section 4, the effectiveness of the proposed prognostic method is experimentally validated. Conclusions are drawn in the last section.

2. Design of an experiment for collection of usable lithium-ion battery capacity degradation data at DDRs

Before the discharge-rate-dependent battery prognostic method is detailed in Section 3, an experiment was designed to collect lithium-ion battery degradation data at DDRs. In the experiment, four cylindrical BAK 18650 battery samples and their specifications are tabulated in Table 1. The room temperature was kept at an environment temperature of 25 °C. The battery test bench, composed of an Arbin BT2000 tester for loading and sampling the batteries, a host computer with an Arbin MITS Pro Software for on-line experiment control and data recording, and a computer with Matlab R2012b Software for preliminary data analysis, is shown in Fig. 1(a). A profile comprising a sequence of repetitive 0.5C, 1C, 3C, and 5C constant current discharge regimes was implemented to collect usable capacity degradation data in the course of four-cycle rotation aging. The four batteries were recharged with a schedule recommended by manufacturer, which comprised a 1C constant current charging step followed by a constant voltage charging step until a cutoff current of C/100 was reached. Fig. 1(b) shows the measured current and voltage profile in a four-cycle rotation interval. In the Arbin testing system, the discharge and charge currents were respectively represented by negative and positive values. The accumulated usable discharge capacity was calculated by integrating the current over time.

Table 1
The specifications of the four battery samples used in the experiment.

Cathode	$LiFePO_4$
Anode	Graphite
Rated capacity	1 Ah
Upper/lower cut-off voltage	3.6 V/2 V
End-of-charge current	0.01C
Max continuous discharge current	10C

To show the rated capability of a lithium-ion battery, the relationship between the discharge curve and the accumulated usable capacity is plotted in Fig. 1(c). Clearly, the maximum releasable capacity at 5C is only 0.92 Ah, which is less than those at the lower discharge rates, especially 0.5C. Thus, the deliverable usable capacity is reduced if the battery is discharged at a very high rate. The usable capacity degradation data of one of the four batteries are plotted in Fig. 2(a), where the peculiar increasing usable capacity data at some initial four-cycle rotations have been artificially removed for the sake of RUL prediction because these usable capacity are not sufficiently useful in describing usable capacity degradation. It was observed that the DDRs have significant impacts on usable capacity degradation data. The higher a discharge rate, the smaller usable capacity. Additionally, when a battery was discharged at a high rate of 5C, it is observed that its associated usable capacity is more fluctuated. This phenomenon is explained by a high battery surface temperature with a high variation at a discharge rate of 5C. By attaching a thermocouple to the surface of a battery with a sampling rate of 1 s, we plot the averages of the battery surface temperatures in every discharging process in Fig. 2(b), in which it is observed that the higher a discharge rate, the higher a battery surface temperature.

3. The proposed discharge-rate-dependent prognostic method for battery RUL prediction at DDRs

In this section, we propose a discharge-rate-dependent prognostic method which is able to track usable capacity degradation data at DDRs and to predict battery RUL at DDRs. In the proposed discharge-rate-dependent prognostic method, one of the most important key steps is to construct a discharge-rate-dependent state space model so as to describe usable capacity degradation data at the DDRs including 0.5C, 1C, 3C and 5C as shown in Fig. 2(a). Here, batteries 1 to 3 are used to provide the historical batteries data and battery 4 is used to provide the testing degradation data. Using the historical degradation data at the DDRs have the following three purposes. Firstly, because a physical battery degradation model is seldom reported, it is necessary to use the historical battery degradation data at the DDRs to establish an empirical battery degradation model. Secondly, it is necessary to extend the empirical battery degradation model to a more general empirical battery degradation model working at the DDRs. Thirdly, based on the more general empirical battery degradation model, a discharge-rate-dependent state space model is constructed. Moreover, its parameters are initialized by the historical battery degradation data.

To achieve the first purpose, a discharge-rate-dependent soft failure threshold $x_{\text{threshold}} = 1.093 - 0.01665 \times D$ is firstly defined. Here, D is the discharge rate. The discharge-rate-dependent soft failure threshold