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A state-space-based prognostics model for lithium-ion battery degradation

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ABSTRACT

This paper proposes to analyze the degradation of lithium-ion batteries with the sequentially observed discharging profiles. A general state-space model is developed in which the observation model is used to approximate the discharging profile of each cycle, the corresponding parameter vector is treated as the hidden state, and the state-transition model is used to track the evolution of the parameter vector as the battery ages. The EM and EKF algorithms are adopted to estimate and update the model parameters and states jointly. Based on this model, we construct prediction on the end of discharge times for unobserved cycles and the remaining useful cycles before the battery failure. The effectiveness of the proposed model is demonstrated using a real lithium-ion battery degradation data set.

1. Introduction

Lithium-ion (Li-ion) batteries have undergone rapid development since they were commercialized in 1991. Nowadays, due to their great advantages, they have been the most promising rechargeable batteries and applied as the main power sources in more and more fields, from the daily used mobile device industry, to the rising electric vehicle (EV) industry, even to the crucial marine and space system [17]. However, regardless of the type and design of Li-ion batteries, the degradation caused by aging occurs throughout life in every condition [1]. Two principle phenomena to identify the degradation are capacity fade and impedance raise. Capacity fade means that the maximal usable energy which can be stored in Li-ion batteries becomes less and less as the charge-discharge cycle increases. Impedance raise determines the reduction of the maximum of available power. As batteries degrade, they will be unable to supply sufficient energy or power for systems finally. This kind of functional failures announce the end of life for batteries [21].

In order to prevent Li-ion battery failures from occurring, and to optimize battery maintenance and replacement schedule, developing a Prognostics and Health Management (PHM) approach for Li-ion batteries, with emphasis on detecting underlying degradation and predicting remaining useful cycle (RUC), achieves more and more attention [21]. The common performance data for Li-ion batteries include voltage, current, impedance and capacity. Among them, both impedance and capacity have been widely used for degradation prognostics, because they are inherent battery properties and it is easy to identify and extract degradation features from their measurements. For example, Saha et al. [13] applied the proposed Bayesian learning framework on Li-ion battery prognostics based on internal impedance measurements. Zheng and Fang [22] developed a novel method using unscented Kalman filter (UKF) with relevance vector regression to predict the RUC. There are some other noted algorithms proposed for capacity or impedance degradation, such as artificial neutral network [9], relevance vector machine [18], and so on [5,20].

If given accurate impedance or capacity measurements, the above approaches are easily to implement and can present good prediction accuracy. The problem lies in that both impedance and capacity of Li-ion batteries cannot be measured simply and efficiently. In literature, the most widely used experimental technique for impedance measurement is electrochemical impedance spectroscopy (EIS) test [15]. This test is time-consuming and cost-ineffective to take regularly. It needs be conducted with bulk equipment and has strict requirements on experimental environment [20]. The battery capacity can be estimated by the Coulomb counting method which integrates discharging current from a fully charged state to a fully discharged state [21]. However, the capacity can only be obtained at the end of entire discharge process. Moreover, the measured capacity of each discharge cycle depends on the cut-off voltage greatly.

Different with impedance and capacity measurements, current and voltage can be easily obtained by the sensor technology in real applications. There have been some attempts to use the charging/discharging profiles for Li-ion battery degradation investigation. Some authors propose new capacity estimation methods based on the collected charging/discharging profiles. For example, Lu et al. [11] proposed using the four geometric features extracted from charging/

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discharging profiles to estimate battery capacity. Tao et al. [16] developed an approach named dynamic spatial time warping to recognize the similarities of current or voltage curves and further estimate battery capacity. These new capacity estimation methods can estimate the state of health (SoH), but cannot predict the RUC. Some authors try to extract features from charging/discharging profiles, and use these features as the health indicators to conduct the SoH estimation directly. For example, Widodo [19] introduced the sample entropy of discharging profiles into Li-ion battery degradation prognostics. Liu et al. [10] proposed a general framework for the health indicator extraction and optimization. However, to better utilize these extracted features, accurate capacity measurements should be used for model training or feature transformation before on-line application. Other authors rely on the equivalent circuit model (ECM) and derive circuit components from discharging profiles for the SoH estimations. For example, Jonghoon Kim once developed a framework for state of charge (SoC) and SoH joint estimation with the discharging profiles based on a designed ECM model [7,8]. Nevertheless, these ECM based methods can only provide the SoH estimation. The RUC prediction can not be achieved.

In this paper, we propose to develop a data-driven method for Li-ion battery degradation prognostics with the sequentially observed discharging profiles. On the one hand, we do not choose to extract features from the discharging profiles, because we think the discharging profile of a single cycle can be used to predict how long the battery can be used and what is the current releasable capacity given any cut-off voltage. These predictions are important for battery operation in a single cycle. One the other hand, we don't stop at the SoH estimation, but aim at the prediction of RUC. Based on the above considerations, a state-space-based prognostics model is adopted in this paper. In more detail, we build an observation model to depict the discharging profile of each cycle and use a state-transition model to track the evolution of the parameter vector in the observation model. With the orderly observed discharging profiles, we adopt the expectation maximization (EM) and extended Kalman filtering (EKF) algorithms to estimate the model parameters and states jointly. About the (unobserved) future cycles, we can predict the possible state-transition paths, simulate the sequence of discharging profiles and finally construct prognostics on end of discharging (EoD) time of each cycle and the RUC.

The remainder of this paper is organized as follows. Section 2 formulates a general state space model for Li-ion battery degradation. Section 3 introduces the model estimation and updating via EM and EKF algorithm. Section 4 presents the prognostics based on the well learned state-space model. Section 5 uses a real case study to demonstrate the effectiveness of the proposed model. Section 6 concludes the paper with discussions on future research directions.

2. A state-space model for Li-ion battery degradation

As presented in last section, we propose to take full use of the observed discharging profiles (current and voltage) for Li-ion battery degradation prognostics. In this section, we start with the simplest battery operation case in which the battery is discharged in a steady mode, i.e., loading current, ambient temperature, depth of discharge, and etc. are held constant. In this way, we focus on extracting the degradation pattern from the voltage profiles of different cycles.

As shown in Fig. 1(b), the output voltage in each cycle drops as the discharge proceeds. This drop is mainly caused by the existence of internal impedance and the motion of active lithium ions between the battery electrodes along with electro-chemical reactions. This means the path of voltage drop is not random. For a specific type of Li-ion batteries, the voltage profiles would always present a similar decline trend during discharging processes. Therefore, we can use the same parametric family to characterize all of the observed voltages profiles.

Here, we denote $U_i(t)$ as the measured voltage at time t in the i^{th} discharging cycle. The discharging profile can be expressed by the observation model

$$U_i(t) = h(t; \boldsymbol{\theta}_i) + \nu_i(t), \quad t \geq 0, \tag{1}$$

where $h(t; \boldsymbol{\theta}_i)$ is the profile characterizing function with parameter vector $\boldsymbol{\theta}_i$, and $\nu_i(t)$ is the measurement error which is assumed to be independent and identically distributed with $\nu_i(t) \sim N(0, \sigma^2)$ at any time point t. For any cycle, once $\boldsymbol{\theta}_i$ is known, the output voltage at any time t can be estimated, and the entire discharging profile can be depicted easily. Moreover, given a cut-off voltage ζ_i, both EoD time T_i and releasable capacity Q_i can be figured out.

As the charge-discharge cycle increases, the internal impedance will increase, and the amount of active lithium ions and other electrode materials will decrease. These changes make the voltage profiles of different cycles present variation. In another word, this variation can be used to identify the battery degradation. Based on the observation model, the transition of $\{\boldsymbol{\theta}_i, i = 1, 2, \ldots\}$ decides the variation of their discharging profiles and further stands for the battery degradation. Thus, we treat the parameter vectors $\{\boldsymbol{\theta}_i, i = 1, 2, \ldots\}$ of different cycles as a series of hidden states in battery degradation process. The state transition model can be expressed as

$$\boldsymbol{\theta}_i = f_i(\boldsymbol{\theta}_{i-1}) + \boldsymbol{\omega}_i, \tag{2}$$

where $f_i(\cdot)$ is the state-transition function, and $\boldsymbol{\omega}_i$ is the transition noise which is assumed to be zero mean multivariate Gaussian noise with covariance $\boldsymbol{Q}_i$. Considering that the battery is operated in a steady mode, we assume the state transition function $f_i(\cdot)$ and covariance $\boldsymbol{Q}_i$ are the same for different i. For simplicity, we use the simplest linear function

$$f(\boldsymbol{\theta}_{i-1}) = \boldsymbol{B}\boldsymbol{\theta}_{i-1} + \boldsymbol{b} \tag{3}$$

to clarify the following prognostics approach and parameter estimation procedure.

Combining the observation model (1) and state-transition model (2), a general state-space model for Li-ion battery degradation is established. Different with conventional state-space models, the outputs are not simple value-type observations (e.g. impedance and capacity) ([4,12]) but curve-type (voltage profiles). With this state space model, we can use the observed voltages profiles to estimate their hidden state $\boldsymbol{\theta}$, predict state evolution trajectory for future cycles, depict the future discharging profiles and construct RUC prognostics on a Li-ion battery.

Remark**.** The above model is built under the steady mode without considering the effects of impacting factors like temperature and discharging current, which can influence not only the discharging profiles but also the degradation of Li-ion batteries. To incorporate the effects caused by these impacting factors, we can treat them as known inputs $\boldsymbol{u}_i$ to our state-space model. Then the model can be written as

$$\boldsymbol{\theta}_i = f_i(\boldsymbol{\theta}_{i-1}, \boldsymbol{u}_i) + \boldsymbol{\omega}_i,\ U_i(t) = h(t; \boldsymbol{\theta}_i, \boldsymbol{u}_i) + \nu_i(t). \tag{4}$$

As a consequence, the function $f_i(\cdot)$ and $h(\cdot)$ could be more complex, and the corresponding prognostics and inference could be more difficult.

3. Model estimation and updating

In last section, we built a general state-space model which is summarized as following,

$$\boldsymbol{\theta}_i = \boldsymbol{B}\boldsymbol{\theta}_{i-1} + \boldsymbol{b} + \boldsymbol{\omega}_i \boldsymbol{U}_i = \boldsymbol{h}(\boldsymbol{\theta}_i) + \boldsymbol{\nu}_i, \tag{5}$$

where $\boldsymbol{U}_i = [U_i(t_{i1}), \ldots, U_i(t_{im_i})]$ is the observed voltage profile, $\boldsymbol{h}(\boldsymbol{\theta}_i) = [h(t_{i1}; \boldsymbol{\theta}_i), \ldots, h(t_{im_i}; \boldsymbol{\theta}_i)]$ is the approximation of profile, $\boldsymbol{\theta}_\mathrm{i}$ is the hidden degradation state, $\boldsymbol{\omega}_i$ and $\boldsymbol{\nu}_i$ are the process and observation noises which are both assumed to be zero mean multivariate Gaussian noises with covariance $\boldsymbol{Q}$ and $\sigma^2\boldsymbol{I}$ respectively.

Suppose we have observed the first k discharging voltage profiles.