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Bayesian hierarchical model-based prognostics for lithium-ion batteries

Madhav Mishra[a,b,*], Jesper Martinsson[c], Matti Rantatalo[b], Kai Goebel[d]

[a] SKF-University Technology Centre, Luleå University of Technology, 971 87, Luleå, Sweden
[b] Division of Operation and Maintenance Engineering, Luleå University of Technology, 971 87, Luleå Sweden
[c] Division of Mathematical Science, Luleå University of Technology, 971 87, Luleå Sweden
[d] NASA Ames Research Center, Intelligent Systems Division, Moffett Field, CA 94035, USA

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A B S T R A C T

To optimise operation and maintenance, knowledge of the ability to perform the required functions is vital. The ability is governed by the usage of the system (operational issues) and availability aspects like reliability of different components. This paper proposes a Bayesian hierarchical model (BHM)-based prognostics approach applied to Li-ion batteries, where the goal is to analyse and predict the discharge behaviour of such batteries with variable load profiles and variable amounts of available discharge data. The BHM approach enables inferences for both individual batteries and groups of batteries. Estimates of the hierarchical model parameters and the individual battery parameters are presented, and dependencies on load cycles are inferred. A BHM approach where the operational and reliability aspects end of life (EoD) and end of life (EoL) is studied where its shown that predictions of EoD can be made accurately with a variable amount of battery data. Without access to measurements, e.g. predicting a new battery, the predictions are based only on the prior distributions describing the similarity within the group of batteries and their dependency on the load cycle. A discharge cycle dependency can also be identified in the result giving the opportunity to predict the battery reliability.

1. Introduction

The use of electrically powered systems and especially battery powered systems has grown in substantially in recent decades, resulting in demands for increased battery performance. Battery technology development was initially driven by the telecom industry and the cell phone market, but it is now being boosted by other markets such as the markets for battery-powered ground-based and aerial vehicles. Global trends towards a fossil-fuel-free society is also increasing investment in battery technology.

Lithium-ion (Li-ion) batteries are a commonly used battery type e.g., in consumer electronics, electric vehicles of all types, military electronics, and maritime and space systems. Li-ion batteries have many advantages over other battery restriction, e.g., longer cycle lives, shorter recharge times, low self-discharge rates, and high power densities. However, battery capacity decreases with time and usage, eventually failing to provide satisfactory performance.

Battery performance metrics, such as capacity or state of charge represent important information and the ability to predict the end of discharge (EoD) has grown in importance, especially for unmanned battery-powered vehicles such as exploratory rovers, submarines, and UAVs (Unmanned Aerial Vehicles). An important operational aspect for these types of systems is the ability to maximize the usage of the system considering the available battery charge without jeopardizing a mission. For example, most such systems must be able to return to base before the battery discharge reaches a threshold limit beyond which the return trip would be jeopardized.

There are many types of unmanned vehicle and robots, which include a variety of different systems, from automatic robotic hovering vehicles and lawn mowers to unmanned space vehicles. Depending on the system and the severity of the consequences of a discharged battery, different methods can be used for predicting the EoD or the point whereby the mission should be aborted or recalculated. For example, for space missions, such as Mars-based rovers a hypothetical that operate from a home base, it is essential to understand the discharge behaviour of batteries due to the remote operational locations of such missions. The Mars rover needs to collect samples from different locations on Mars. For every collected sample, a certain amount of battery charge is consumed. To complete the mission along a planned route, the rover needs to predict the available remaining charge that will be consumed for each observation point and whether it should travel to certain observation points or return to the origin home base. A lack of this ability could result in catastrophic consequences.

* Corresponding author at: Division of Operation and Maintenance Engineering, SKF-University Technology Centre, Luleå University of Technology, Luleå 97187, Sweden.
E-mail address: madhav.mishra@ltu.se (M. Mishra).

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It is evident that the probability of mission failure can be reduced by improving the prognostic capability for determining the remaining battery charge. In these cases, it may not be appropriate to consider standard battery prediction methods used in the consumer electronics industry, which are often based on lookup tables alone; such tables may be dependent on the battery use times. Therefore, it is important to implement a prognostic and health management (PHM) technology for critical systems to successfully predict and manage the lifetime of batteries, monitor their health state in real time, evaluate the performance and predict the remaining useful life (RUL). PHM technology for real-world industrial systems is relatively immature compared to diagnosis technology. It is not always easy to predict the EoD because this depends on the utilized physical degradation models and run-to-failure data, which are not always available.

The output voltage of a battery gradually decreases with use. If the voltage level of the battery is below a predefined threshold, it cannot drive a load and the battery needs to be recharged. This threshold voltage can be used as the EoD condition. Due to certain physical phenomena, a battery degrades with repeated charging-discharging cycles, and the degradation depends on the operating conditions. The discharging characteristics also range because inherent electro-chemical reactions also change. The decrease in the capacity of a battery over time is manifested in an increase in the internal impedance. For the above-mentioned reasons, it is important to understand the behaviour of the battery and to predict the remaining useful life (here, the EoD) so that one can make the necessary decisions for mitigating relevant risks. The main objective concerning the lithium-ion batteries in this study is to measure the battery discharge and predict the EoD considering the operating conditions. There exists various types of methods that can predict battery discharge. The most common prognosis methods are physics-based approaches, which use mathematical formulations based on physical phenomena or principals, and data-driven approaches [1–3].

Data-driven methods are independent of physical/expert knowledge and can be developed based on statistical models that describe the degradation behaviour of the batteries. Data-driven methods can be classified into two categories. Methods of the first category measure the internal impedance of the battery using electro-chemical impedance spectroscopy (EIS) methods. Various methods are based on EIS methods [4] and non-linear filtering methods [5,6]. Non-linear filtering methods depend on modelling the battery degradation. The main disadvantage of EIS is that such methods are time intensive and cost inefficient. Xing et al. [7] noted that methods of this category require measurements in conditioned environments because they are sensitive to noise. Methods of the second category measure the capacity of each cycle of the battery. Various types of methods can be found in the literature; for example, He et al. [8] proposed an empirical exponential model to fit capacity fading curves. An empirical second-order polynomial regression model and a least square estimation were introduced by Micea et al. [9] to predict the battery degradation behaviour. Similarly, Xing et al. [7] proposed an ensemble model that fuses exponential and polynomial regression models using a Bayesian particle filter approach.

Numerous publications have addressed [3,5,10–14] physics-based prognostic approach. The main challenge in this category is that the measured capacity is dependent upon the threshold voltage and that this threshold voltage further relies on the available capacities in different cycles, which makes any comparison difficult. Another problem is that the degradation of the battery also depends on external factors such as the temperature, discharging rate, and depth of discharge [12].

Selecting an appropriate prognostic algorithm for a particular application is crucial to the ultimate success of a prognostic programme [15] and Zhang et al. [16] presents and explained a new method to estimate and predict the RUL for degrading systems with recovery. For generating probabilistic results, Bayesian approaches represent promising techniques for the EoD estimation of batteries. A hierarchical model that depends on Bayesian approaches combining both discharging and degrading processes to predict EoD was proposed by Xu et al. [12]. The Bayesian framework provides probability distributions that provide advantages over point value estimates such as quantifying the risk of failure and addressing uncertainties [17]. For example, for prognostics using a neural network, the neural network is not typically established in a probabilistic framework [18] and instead estimates the EoD as a single time point.

For battery EoD prognostics, the main reasons for applying Bayesian hierarchical analysis are that the Bayesian hierarchical structure [19,20] can account for individual and group-level variations when estimating group-level regression coefficients [20] and it can obtain reasonable estimates for battery parameters with small sample sizes [21]. The variations in the different hierarchical levels can be expressed and analysed for different cases such as different battery batches, load cases, and temperatures. This variation is difficult to represent using other prediction approaches [20]. The hierarchy means that we use the measured data of several batteries under different conditions to estimate informative prior distributions [19]The prior distributions will capture similarities of the behaviours within the group of batteries and under similar conditions [20]. These distributions will assist to make better inference (e.g. prognostics and parameter estimates) and are especially helpful in difficult situations, such as prognostics for new batteries without access to any measurements or for batteries where measurements are either sparse, noisy or partly missing [20,21].

This paper presents a Bayesian Hierarchical Model (BHM)-based EoD prognostic for Li-ion batteries. Two batteries with 16 discharge events each were used together with a simplified battery circuit model of the battery. The approach is demonstrated by examining detailed discharge voltage profiles during different discharging cycles with variable load profiles. The effects of the available measurement data are also investigated. To demonstrate the BHM approach and group-level dependencies we need more than one battery and more than one discharge cycle. Access to more batteries and load cycles is always desirable, as more details regarding the prior distributions would emerge.

This paper is organized as follows. Section 2 describe Data and Battery Model. Section 3 proposes a prognostic approach using a BHM. The results are presented in Section 4. Section 5 discusses the proposed approach based on the results with future research directions, and Section 6 concludes the paper.

2. Data and battery model

2.1. Data description

We present a case study of a Li-ion battery to demonstrate the performance of our proposed BHM for battery prognosis. The proposed method has been verified using data from the NASA prognostics data repository [22]. The batteries were discharged under different loads (I) between 1 A and 4 A. The data used for the algorithm development and testing were generated using the battery testbed described in [4]. This testbed allows for the charging and discharging of batteries and collecting relevant information to estimate the state of the battery [2]. Fig. 1 represents the combination of the discharging cycles of two Li-ion batteries of the same type with total sixteen discharging cycles used in the study. Fig. 1 shows the distribution of the discharging cycles to demonstrate their discharging behaviour over time.

2.2. Description of the model

The main focus of this paper is to investigate the properties Bayesian hierarchical structure in prognostics and not to develop new battery models. To emphasize the hierarchical structure and reduce the increased complexity associated with a large number of battery parameters, we choose the simplified battery circuit model shown in Fig. 2 to model the battery discharge. It is a simplified version of the model presented in Sankararaman et al. [23]. This relatively simple battery model is sufficient to capture the major dynamics behavior of the battery, but