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# A new prognostics method for state of health estimation of lithium-ion batteries based on a mixture of Gaussian process models and particle filter

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ABSTRACT

State of health (SOH) estimation for batteries is a key component in the prognostics and health management (PHM) of battery driven systems. Due to the complicated operating conditions, it is necessary to implement the prognostics under uncertain situations. In this paper, a novel integrated approach based on a mixture of Gaussian process (MGP) model and particle filtering (PF) is presented for lithium-ion battery SOH estimation under uncertain conditions. Instead of directly assuming a certain state space model for capacity degradation, in this paper, the distribution of the degradation process is learnt from the inputs based on the available capacity monitoring data. To capture the time-varying degradation behavior, the proposed method fuses the training data from different battery conditions as the multiple inputs for the distribution learning using the MGP model. Then, a recursive updating of the distribution parameters is conducted. By exploiting the distribution information of the degradation model parameters, the PF can be implemented to predict the battery SOH. Experiments and comparison analysis are provided to demonstrate the efficiency of the proposed approach.



## 1. Introduction

Recently, with the advantages of high energy densities, longevity, and lightness, lithium-ion batteries have been playing a more important role in electronics system energy supplies, and therefore have begun to be widely used in military electronics, aerospace avionics, portable devices and other automotive vehicles [1,2]. However, battery deterioration and battery failure are common occurrences, which can lead to a reduction in systems performance, result in increased costs and catastrophic failure [3]. Therefore, prognostics and health management (PHM) for electronic device has received increased attention to determine the advent of systems failure and to mitigate system risk through the evaluation of system reliability in terms of the current life-cycle conditions [4,5].

Prognostics is the process used to predict the system's remaining useful life (RUL), which is defined as the period of time from the present health state to failure. Therefore, the estimation of the health state for batteries given the current system condition is the core of the battery PHM, from which maintenance decisions to efficiently mitigate risk can be made based on the actual battery condition. With an increasing demand for life-cycle cost reduction in battery-driven equipment and to provide useful prognostics information in the reliability monitoring for battery systems health management, indicators such as the state of life (SOL), the state-of-charge (SOC) and the state-of-health (SOH) are commonly used to describe the current health condition of lithium-ion batteries [6]. The SOL represents the remaining life of battery, which indicates at what time the battery will need to be replaced. The SOC is usually defined as the ratio of battery's remaining capacity to the maximum capacity. The estimation of the SOC is difficult as it depends on many factors such as varying environmental conditions and charge–discharge cycles. Unlike the SOC, the SOH is a subjective measure so there is no consensus on its definition. However, it can be viewed as an estimation which provides an indication of the performance for battery status in its current condition, rather than a measurement corresponding to a specific physical quality [7]. Commonly, the battery SOH estimation can be determined by calculating the ratio of the current impedance or capacity to its initial measurements. As considered in [23], the battery capacity percentages relative to its initial capacity are adopted for the SOH estimation in this study.

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There are many valuable prognostics methods for battery SOC/SOH estimation and RUL prediction [8–10]. Fuzzy logic with electrochemical impedance spectroscopy (EIS) measurements has been used to estimate the battery SOH [11,12]. Neural networks and artificial intelligent methods have also been commonly used to predict the batteries RUL [13]. Stochastic filtering approaches such as Kalman filtering [14], extended Kalman filtering [15,16], unscented filtering and Bayesian filtering [17–19] are other classical methods for battery SOH or SOC estimation. In general, stochastic filtering methods for prognostics are based on the state process or degradation model descriptions which can be used to capture the system failure mechanisms, and have shown good performance if the degradation model used accurately represents the actual system behavior. However, in many practical battery use settings there are uncertainties such as operating conditions, environmental conditions, and other inherent system uncertainties. Therefore, in practice, it is difficult to obtain accurate state process models or parameter descriptions, so the standard algorithm with filtering, which lacks of consideration for uncertainties may lead to poor reliability prediction. To address this issue, many approaches have been proposed such as a prognostics algorithm based on a relevance vector machine (RVM) and particle filtering for RUL prediction of lithium-ion battery, in which the RVM is used to learn nonlinear models from the experimental data [20,21]. He et al. used a Bayesian Monte Carlo method and the Dempster–Shafer theory (DST) to implement battery SOH prognostics and RUL estimation [22]. In their method, the degradation model parameters were treated as a dynamic process and the DST was used to initialize the capacity degradation model parameters from the training data sets of different batteries. Then, using the linear transition process model of parameters, the SOH estimation was obtained. Because of the uncertainties in the battery operations, the parameters used to describe the degradation model may be different under complex conditions. However, effective modeling for degradation model parameters under uncertainty has gained less attention in previous research. Recently, with the need to consider modeling flexibility and uncertainty representations, the use of Gaussian process regression (GPR) has been investigated for lithium-ion battery prognostics [23], where the degradation trends are learnt from battery data sets with the combination of Gaussian process functions. As an alternative to directly learning the degradation trends, learning for representing the parameters process of degradation model has not yet been fully investigated.

In this paper, to consider the uncertainties in battery prognostics, a novel approach for lithium-ion battery SOH estimation is presented through an integration of MGP model learning and particle filtering. The proposed method consists of two phases; firstly, the MGP is used to learn the statistical properties of the degradation process model parameters using training data sets from uncertain battery conditions, which the GPR is exploited to initialize the distribution parameters for each component. Secondly, based on the parameter distribution information for the degradation process, particle filtering is exploited to obtain the battery SOH estimation. To avoid full data storage and excessive computational complexity, adaptive and recursively learning algorithms are investigated. Finally, experiments based on the NASA battery data sets are provided to demonstrate the performance of the new prognostics method. The contributions in this paper are twofold: (1) the prognostics algorithm for the lithium-ion battery SOH estimation is developed by combining the conditions from different batteries; (2) the proposed method implements particle filtering with distribution learning of the multimode process under uncertainty.

The remainder of this paper is organized as follows. In Section 2, the problems with the SOH estimation for lithium-ion battery prognostics under uncertainty are described. Then, an overview of Bayesian estimation and particle filtering are provided in Section 3. In Section 4, the prediction method which incorporates MGP learning and PF is developed. Experiments and analysis are given in Section 5 to demonstrate the performance of proposed prognostics algorithm. Finally, conclusions are drawn in Section 6.

## 2. Problem statement

Due to many complicated factors such as the battery operating environment, assembly technology, material properties, and initial conditions, the actual battery capacity degradation processes are different [24]. Therefore, battery prognostics are significantly affected by uncertainties. To track batteries capacity fading, the exponential model expressed by (1) is commonly used to represent the battery capacity degradation trends in many cases [25].

$$\text{Model I}: \quad Q = \alpha \cdot \exp(\beta \cdot l) + \eta \cdot \exp(\lambda \cdot l) \tag{1}$$

where $Q$ is the capacity of the battery and $l$ is the cycle number. The degradation model parameters are $\alpha$, $\beta$, $\eta$ and $\lambda$, where $\alpha$ and $\beta$ capture the internal impedance, and $\eta$ and $\lambda$ are related to the aging rate. Unfortunately, overfitting usually occurs because of the complex expression in model (1), and extrapolations of the model may result in poor performances. This is because the capacity degradation model is only an empirical approximation of the actual dynamic degradation, making it difficult to accurately model the parameter process in advance, meaning that modeling errors always occur. On the other hand, because of the uncertain environment and operational conditions, the degradation model parameters which characterize the battery conditions are random and usually have a non-linear transition. In addition, different degradation conditions can make large difference, which means that the dynamic degradation processes are difficult to model by using certain space state models. Further, there is no universally accepted best model for the degradation parameters [26]. Therefore, establishing an effective representation for the degradation process under uncertainties is the key to battery prognostics.

Most popular methods used to deal with batteries prognostics under uncertainty are based on data-driven and model-based methods [27,28]. Data-driven methods attempt to directly learn the battery degradation trends from the obtained measurement data. However, it is difficult to exploit the monitored data from different batteries in complex conditions and some regressors can be easily affected by the extreme data which usually appears near the self-recharge cycles as the battery capacity fades. Using offline learning, which takes advantage of the full historical monitoring data, the prognostics algorithm has a heavy computational burden [9]. Another methods assume a certain degradation parameters model, so classical filter methods can be exploited to predict the battery SOH, but the prediction performance can be affected by the gap between the assumed model and the actual degradation process. Although some hybrid approaches which incorporate patterns or models identification into the stochastic filter can make some improvements, the complicated and non-linear transition of the degradation process parameter under uncertainty which are very common in practice lack full consideration. To capture the time-varying degradation process effectively, a statistical description of the degradation process parameters through the exploitation of information from various battery conditions needs to be considered in the degradation process modeling. The battery SOH can then be estimated using non-linear filtering.

## 3. Bayesian estimation and particle filter

The particle filter is a Bayesian-based recursive estimator which is implemented through a sequential Monte-Carlo method with a resampling technique. In practice, many dynamic processes can