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Interacting multiple model particle filter for prognostics of lithium-ion batteries

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ABSTRACT

We propose a new data-driven prognostic method based on the interacting multiple model particle filter (IMMPF) for determining the remaining useful life (RUL) of lithium-ion (Li-ion) batteries and the probability distribution function (PDF) of the associated uncertainty. The method applies the IMMPF to different state equations. Modeling the battery capacity degradation is very important for predicting the RUL of Li-ion batteries. In this study, improvements are made on various Li-ion battery capacity models (i.e., polynomial, exponential, and Verhulst models). Further, three different one-step state transition equations are developed, and the IMMPF method is applied to estimate the RUL of Li-ion batteries with the use of the three improved models. The PDF of the predicted RUL is obtained by combining the PDFs obtained with each individual model. We conduct four case studies to validate the proposed method. The results are as follows: (1) the three improved models require fewer parameters than the original models, (2) the proposed prognostic method shows stable and high prediction accuracy, and (3) the proposed method narrows the uncertainty PDF of the predicted RUL of Li-ion batteries.

1. Introduction

Lithium-ion (Li-ion) batteries have become prevalent in various devices ranging from tiny Bluetooth headsets and cell phones to laptops and tablet computers. These batteries efficiently cater to the energy needs of these devices. When compared with other types of batteries, Li-ion batteries have exceptionally high energy densities, long lifetimes, and stable electrochemical properties. Further, Li-ion batteries can store electrical energy with slow energy loss when not in use, and they do not exhibit a memory effect [1].

Meanwhile, the development of hybrid electric vehicles (HEVs) and military unmanned aerial vehicles (UAVs) has attracted increasing attention. Both these automotive technologies rely on Li-ion batteries [2], and in this context, the failure of Li-ion batteries can lead to operation loss, downtime, and even catastrophic system failure. Currently, batteries are considered to be an unreliable power source because they tend to exhibit an exponential decay of capacity after passing the point of failure. In this regard, the remaining useful life (RUL) of a battery is defined as the time interval from the time of observation to the time of battery failure [2]. From the perspective of practical application, detecting the performance degradation, successfully predicting the end of life (EOL) or remaining useful life (RUL) of Li-ion batteries, and ultimately preventing fatal failure is imperative [3]. With particular regard to Li-ion batteries, the RUL of a Li-ion battery is defined as the time interval from the moment of consideration to the end of the battery's useful life [4].

Prognostics and health management (PHM) is a discipline that encompasses many technologies and methods to accurately assess the lifetimes of products in order to ensure and maintain normal operation of systems and equipment [5]. PHM for batteries has garnered considerable attention in studies on various performance metrics [6–9]. Traditionally, prognostics can be implemented via either physics-based or data-driven approaches. Model-based approaches [10] typically involve building mathematical functions to describe the physics and failure modes of a system and thus incorporate a physical understanding of the system into estimating the RUL. The empirical model forms an integral part of model-based approaches. Models in the model-based approaches are constructed from empirical models, analytical models, physical models, and so on. However, accurate analytical models are usually difficult to develop for complex dynamic systems, particularly ones that operate in noisy and uncertain environments [11]. With regard to batteries, the construction of an accurate analytical model relies on knowledge of a battery's life cycle loading conditions, material properties, and failure mechanism, and the process tends to be computationally complex. On the other hand, data-driven approaches [12] are not based on accurate modeling of the physics of a system; instead, they mine hidden information through various data analysis methods. With regard to batteries, the main advantage of data-driven approaches is that they do not require extensive knowledge on battery chemistry

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and failure mechanisms. Prognostic data are derived from measurable parameters such as voltage, current, and temperature.

Some data-driven approaches for predicting the RUL of Li-ion batteries include auto-regressive moving average (ARMA) [13,14], neural network (NN) [11,15], fuzzy logic [16], support vector machine (SVM) [17], relevance vector machine (RVM) [18–20], and other intelligent computation methods [21,22,25–28]. The ARMA relies more on historical data and is a type of linear model prediction method. It is more suitable for point estimation and not multi-step prediction. The ARMA has low accuracy for long-term prediction. NNs offer the advantages of a strong fault tolerance, strong memory function, adaptability, and self-learning. However, they are more suitable for point estimation and afford low precision with multi-step forecasting. The NN approach has a strong dependency on the historical data. Training parameters will not have generalization capability once new data are acquired, which can cause predictions to diverge. Fuzzy logic has certain features that are similar to those of the NN method. Fuzzy logic methods allow a certain level of uncertainty and ambiguity in processing incomplete and noisy data, and they require appropriate design of the membership functions. Meanwhile, the SVM can be directly used with small samples and high-dimensional data for nonlinear performance degradation data classification and prediction. However, it has low multi-step prediction accuracy. The RVM has not only the advantages of SVM but also the ability to describe the prediction uncertainty. Its disadvantages include a high level of computational complexity, large operational storage resources, and poor online operation in real-time. Here, we remark that intelligent computation approaches are practical forecasting methods that make the derivation of a physical model unnecessary.

The factor of uncertainty can be one of the main challenges in predicting the battery health [29]. Difficulties are posed by the uncertainties associated with predicting the RUL of Li-ion batteries, including operational and environmental factors, unit-to-unit variation, measurement noise, modeling inconsistencies, and degraded sensor fidelity [30]. Therefore, the management of the uncertainty of the battery health also influences the RUL prediction [31].

A method involving the use of a particle filter (PF) is typically used to determine the RUL uncertainty of a Li-ion battery. A PF is suitable for solving nonlinear, non-Gaussian, and time-varying parameters for system prediction, and there is no need for model training [32]. Many researchers have improved on the PF method [14,21,22,27,28,] or the state function [13,14,19,31,32,33] to reduce the RUL uncertainty. Many studies have demonstrated that the PF approach is a comparatively good RUL prediction method. The PF framework uses a learning model, statistical estimates of noise, and anticipated operational conditions to provide estimates of the RUL in the form of a probability density function. Predicting the RUL of Li-ion batteries requires estimating the nonlinear state of the capacity of the Li-ion battery via the use of offline battery-capacity data. PF is suitable for estimating the nonlinear system states, and it can significantly contribute to RUL prediction for Li-ion batteries.

As regards PF-based methods, Liu et al. proposed a regularized auxiliary PF approach for system state estimation and battery life prediction [25]. This approach was intended as a more reliable engineering tool for system state estimation and forecasting. In this method, empirical density regularization is implemented in the auxiliary PF, and samples are drawn from a continuous distribution to

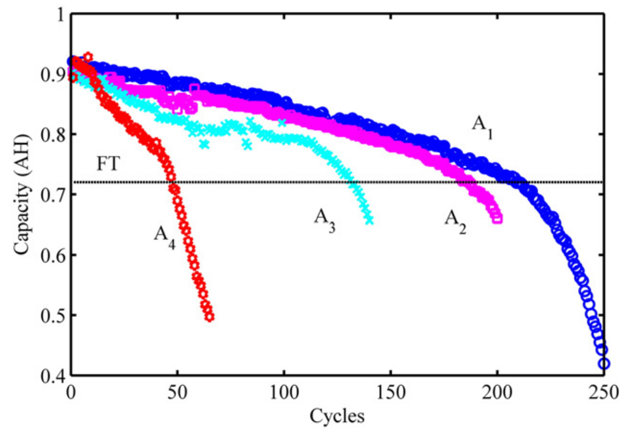

Fig. 1. Capacity degradation trends of four different batteries during full cycle (FT = failure threshold).

diversify the particles. However, this empirical model requires the impedance to be measured, which is expensive and time-consuming. Miao et al. presented an improved PF algorithm to predict the battery RUL: the unscented particle filter (UPF). The UPF can predict the actual RUL with an error margin of less than 5% [26]. However, the battery degradation model is obtained empirically. This model is an exponential model and requires the initialization of four parameters. The selection and initialization of the model parameters are important for predicting the RUL. In this regard, Xing et al. developed a model to predict the RUL of Li-ion batteries that combines an empirical exponential model and polynomial regression model [31]. Further, Saha et al. proposed an empirical model based on a PF framework to predict the RUL of Li-ion batteries [21]. The basis for their model is linked to the internal processes of Li-ion batteries, and the model was validated by using experimental data. The experimental data of these internal processes are difficult to obtain owing to the complicated internal structure of the battery. He et al. proposed a method for estimating the RUL of Li-ion batteries based on the Dempster–Shafer theory (DST) and Bayesian Monte Carlo (BMC) method [22]. In this method, an empirical model consisting of two exponential functions is used to model the battery capacity degradation trends. The initial model parameters are obtained with the DST. The BMC is used to update the model parameters. The initial parameters differ depending on the experiments from which they are obtained. Determining the initial values of model parameters through many experimental results is impractical, and therefore, there is uncertainty in the predicted results.

The various capacity degradation models incorporated in the above methods use algorithms that are adapted to specific data sources, battery types, internal battery structures, etc. There are three types of typical capacity degradation models based on the data-driven approach: the polynomial [31], exponential [28], and Verhulst models [33]. The polynomial model yields the best fit in the linear stage of capacity degradation, whereas the exponential model yields the best fit in the nonlinear stage of capacity degradation. The polynomial and exponential models are both empirical models. The Verhulst model was inspired by a biological forecasting

Table 1
Properties of the experimental battery pack.

Properties of the battery	A1	A2	A3	A4
Rated capacity	0.9 A·h	0.9 A·h	0.9 A·h	0.9 A·h
Ambient temperature	[25–30 °C]	[25–30 °C]	[25–30 °C]	[25–30 °C]
Constant charging current	0.45A	0.45A	0.45A	0.45A
Constant discharging current	0.45A	0.45A	0.45A	0.45A
FT	0.72 A·h	0.72 A·h	0.72 A·h	0.72 A·h
Experimental full cycles	250	200	140	65

Table 2
Goodness of fit of models 1 and 2.

No. of battery	RSS		R^2_{adj}	
	Model 1	Model 2	Model 1	Model 2
A1	0.1895	0.007644	0.9279	0.9971
A2	0.01643	0.005586	0.9737	0.991
A3	0.04184	0.01714	0.8813	0.951
A4	0.02162	0.009709	0.9752	0.9887