Model-Based Prognostic Approach for Battery Variable Loading Conditions: Some Accuracy Improved

Madhav Mishra

SKF-University Technology Centre, Division of Operation and Maintenance Engineering,
Luleå University of Technology, Luleå, 971 87, Sweden

madhav.mishra@ltu.se

ABSTRACT

Prognostics and Health management (PHM) using a proper condition-based maintenance (CBM) deployment is a worldwide-accepted strategy and has grown very popular in many industries and academia over the past decades. PHM can provide a state assessment of the future health of systems or components, e.g. when a degraded state has been found. Using this technology, one can estimate how long it will take before the equipment will reach a failure threshold, in future operating conditions and future environmental conditions.
This paper deals with the improvement of prognostic accuracy for battery discharge prediction and compare with previous results done by the other researchers. In this paper, physical models and measurement data were used in the prognostic development in such a way that the degradation behaviour of the battery could be modelled and simulated in order to predict the end-of-discharge (EoD). A particle filter turned out to be the method of choice in performing the state assessment and predicting the future degradation.

Keywords: Prognostics, particle filter, Battery ,EoD

1. INTRODUCTION

The use of electrical powered systems and especially battery-powered ones has grown in popularity during the past decades resulting in a demand for increased battery life and performance. The progress in battery technology development has mainly been driven by the telecom industry and the cell-phone market but is now also boosted by other markets like battery-powered ground based and aerial vehicles. The global trends towards a fossil fuel free society is also adding to the investment rate in battery technology.

The Lithium ion (Li-ion) battery is a common type used in modern society daily life, e.g. consumer electronics, electric vehicles of all kinds, widely used in military electronics, and the important maritime and space systems, etc. Li-ion battery has many advantages, e.g. longer cycle-life, shorter recharge times, low self-discharge rate, and carrying high-power density, which provide them, is a promising energy storage device. However, all equipment deteriorates over time, as it operates under a certain voltage or load in the real environment, battery degrades similar to many other devices, its decrease in capacity with time and usage and eventually fails to give satisfactory performance.

Even though the battery performance in terms of large battery capacity is an important aspect, the ability to predict the end-of-discharge has grown in importance. Especially for unmanned battery powered vehicles like exploratory rovers, submarines, UAV’s (Unmanned Aerial Vehicle), etc. An important aspect of the mission success rate for these types of systems is the ability to maximize the usage of the system with respect to a given amount of battery charge without risking the mission.

These systems must be able to make the decision to return to base for recharging before the battery charge reaches the “point of no return”. The area of unmanned vehicle or robots includes a variety of different systems like automatic robotic hovers and lawn movers to unmanned space vehicles. Depending on the system and the severity of the consequences of a discharged battery, different efforts can be spent on predicting the end-of-discharge or the point, where the mission should be aborted or recalculated which is known as PHM Technology.

A major objective of Prognostic and health management (PHM) for lithium-ion batteries is to predict the Remaining Useful Life (RUL) based on observations during battery operation condition, which further provides a decision for replacement to mitigate system risks.

In order to estimate the remaining useful life (RUL) of a system, the damage state of the system is analyzed to predict the future degradation. An estimation of the end of life is carried out, adopting the approach devised by Daigle & Goebel (2011). The damage state of the system is estimated and its future degradation is predicted to determine the RUL of the system. Various studies have been published in the area of prognostic methods. There are two methods for estimation of the RUL: end-of-life prediction using a probability distribution function and deterministic RUL estimation when the output variable crosses a particular threshold. The first method was developed by Daigle & Goebel (2011) and involves model-based prognosis for estimation of the end of life (EOL).

The second method was developed by Saha et al. (2009a) and involves using a probability density function for determining the RUL. The degradation of isolated gate bipolar transistors was analysed and then prognosis was carried out by using particle filters

Orchard & Vachtsevanos (2009) applied particle filters to diagnosis and prognosis analyses of the plate of a planetary gearbox by considering fault degradation with the propagation of an axial crack. They concluded that deterministic models for damage progression provide better long-term predictions, although they are inadequate for the provision of proper confidence intervals. Since they implemented a physical model, the use of measured data might result in better confidence intervals. Saha et al. (2009b) compared different methods for RUL estimation. They concluded that there were advantages to be derived by combining machine-learning techniques, and specifically by combining a support vector machine and particle filters.

2. METHOD

2.1. Particle-filter approach

For this work, data took on battery that had been discharged under a randomized sequence of loads between 1A and 4A levels (Saha et al., 2009). Particle filtering utilizes Bayesian estimators (Arulampalam et al, 2002) by means of Monte Carlo simulation. The technique uses a number of hypothetical states of the studied system, also known as particles, takes samples of the unknown states and attaches different weights to them. These weights represent probability masses estimated using Bayesian recursions (Candy et al., 2011). The advantage of particle filters over Kalman filters is that the former provide a sufficient amount of samples to yield an optimal estimate (Khodadadi et al., 2010)

3. RESULTS

The results were evaluated based on the alpha-lambda prognostic metric, as described in Saxena et al., (2008). Figure 1 shows the experimental observation versus the observation filtered using the particle filter. The current in the battery is acted as an input to the model, and correspondingly its predicted values must be assumed. If the future inputs are not known, then some assumption must be made based on experience. We assume that the future inputs are known exactly and there is no process noise, i.e. there is a constant current of 2.25 A, which is the average current during the experiment. At each prediction step, we assume that there is a future current with a distribution between load 1A and 4A during the remainder of the discharge

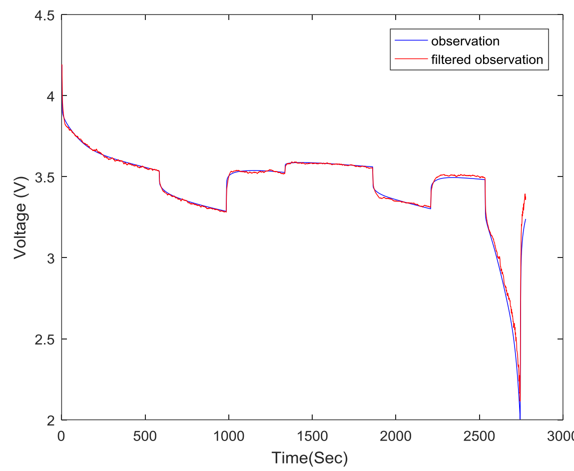

Figure 1. Estimation result.

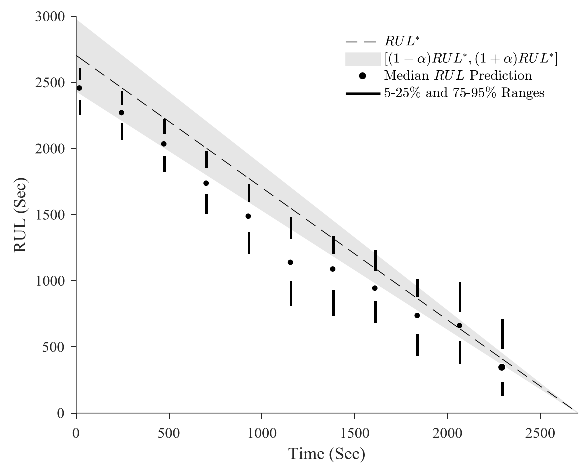

Figure 2: Alpha-lambda metric plot for the prediction algorithm

Figure 2 shows the RUL prediction versus time. The predictions are shown against the true RUL along an accuracy matrix or cone defined by alpha=0.1 and the predictions were made as shown in Table 1. Which can already detect some improvement compared with the previous result as mentioned in the Table 1

Table 1. Results for validation, Column describing previous error refers to Saxena et al. (2012), battery 62, cycle 2. Time in Sec.

t_p Prediction time	$True_{RUL}$	RUL	Error	Previous Error
20	2684	2486	198	-700
247	2457	2259	198	-57
475	2229	2040	189	46
703	2001	1782	219	67
930	1774	1470	204	21
1157	1547	1187	360	8
1385	1319	1091	228	89
1612	1092	925	167	89
1840	864	803	61	132
2068	636	640	-4	183
2296	408	385	23	173

4. CONCLUSION

This paper presented some improvement result based on work done before and learned from implementing a model-based prediction approach for variable loading condition as mentioned by Saxena et al. (2012). In summary, estimated results and predictions are quite accurate, within 10% of the true RUL until 2600 s. As shown in Table 1, the result of the prediction algorithm presented in this paper is more stable than the result of previous attempts performed by Saxena et al. (2012), Furthermore, the RUL prediction in the presented algorithm converges towards the true RUL when time elapses, in contrast to the previous work, see Table 1.

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BIOGRAPHY

Madhav Mishra is a PhD researcher at the Division of Operation and Maintenance Engineering within the framework of the SKF-University of Technology Centre (UTC), Luleå University of Technology, Luleå, Sweden. His research focus on prognostics and health management to improve the RUL prognosis of an asset by developing hybrid models. He obtained a Master's degree in Control Systems Engineering with a specialization in Mechatronics from the Netherlands, and he later worked at PHILIPS Semiconductors/NXP in Nijmegen in the Netherlands as a Senior Design Engineer Mechatronics where he was involved in the design and development of a high-speed rotating machine. He is currently a visiting researcher at PCoE at the NASA Ames Research Center, California, USA.