2015-01-2584

Determining remaining useful life for Li-ion batteries

Andrew Dickerson[1], Ravi Rajamani[1], Mike Boost[2], John Jackson[2]
[1]Meggitt USA, [2]Securaplane Technologies Inc.

Abstract

A high fidelity system for estimating the remaining useful life (RUL) for Li-ion batteries for aerospace applications is presented. The system employs particle filtering coupled with outlier detection to predict RUL. Calculations of RUL are based on autonomous measurements of the battery state-of-health by onboard electronics. Predictions for RUL are fed into a maintenance advisor which allows operators to more effectively plan battery removal. The RUL algorithm has been exercised under stressful conditions to assert robustness.

Introduction

Lightweight, high capacity, rechargeable batteries, primarily based on compounds of lithium, are ubiquitous in every day applications, replacing mature technologies such as NiCd (Nickel Cadmium) and NiMH (Nickel Metal Hydride) [1]. The aerospace industry is also undergoing the transformation to lithium based batteries, in a push for less weight and size. Aerospace batteries are required to deliver power reliably, have a multi-year life span, have a consistent output over their lifetime, and be certifiably safe.

While most lithium based aircraft batteries require more support through advanced electronics than do NiCd and SLA (sealed lead acid) equivalents, lithium chemistries are still of considerably greater energy density than traditional technologies. The integrated electronics handle many functions including charging, battery energy control, built-in testing, disconnects, and monitoring. Although these functions provide operational benefits, another electronic capability that is directed specifically towards maintenance and logistics optimization, is the prognostic health management (PHM) function. Securaplane, a Meggitt company, has been a leading supplier of SLA systems to airframers for decades, and is now developing and supplying advanced Li-Ion battery systems ([2][3]). Among many advanced features, these systems have integrated battery PHM capabilities as well. These comprise of a combination of algorithms with active electronics which autonomously calculate state of health (SOH), a measure of capacity in amp-hours as a percentage of rated capacity, the state of charge (SOC), and now, remaining useful life (RUL). The system, utilizing integration of data collection, processing, storage and reporting integrates high density energy storage and battery chemistry management into a single embedded package.

By additionally integrating the ability to send monitored data to the aircraft data systems, which can then be off-boarded for immediate processing, these battery systems enable redundant and sophisticated processing for both remaining useful life (RUL) predictions as well as near real-time stress level assessments.

The traditional method for maintaining batteries is primarily schedule-based, i.e. given certain hours of operation the batteries are pulled from service and tested to ensure sufficient capacity to support emergency electrical loading situations. In addition, the aircraft systems have a charge estimation system that indicates to the crew an indirect representation of the battery capacity in the form of pack voltage.

While capacity testing has been used as a method for RUL it is essentially crude and not fine enough, consequently leading to either more maintenance than required as precautionary practice or more gate delays due to insufficient battery capacity when least desired. A true, high fidelity RUL determination, autonomously communicating to the maintenance system has not been available. Such a feature would allow unscheduled removals to become scheduled removals. Further, maintenance removals would significantly diminish.

Another key element of battery PHM is the estimation of battery state of charge (SOC) which was discussed in a recent paper [4]. Along with the RUL estimator presented here, these will form a more comprehensive PHM suite for Securaplane battery systems.

In this paper, a method for calculating a robust RUL using system parameters already available within the Securaplane lithium battery system design combined with advanced algorithmic filters is presented.

Particle Filters

Battery health monitoring has been a subject of interest for more than a decade [5], and since its inception much work has been done to predict a battery's SOC, SOH, and RUL [6][7] . Investigators have used data-driven [8] and analytical models to predict RUL, but few, if any have proven them to be easily implemented for online use. Any chosen method to predict RUL under live battery operation should incorporate an aging model, because batteries lose capacity even when not in use, but be augmentable by measurements to account for effects of usage. The prediction method should also be robust to measurement noise, since measurements contain error, and easily handle non-linearity.

A number of algorithmic methods were considered, but a trade study by the authors indicated particle filters (PF) to be a superior selection in making RUL prediction in batteries. This is primarily due to simplicity of the methodology and its robustness. The trade study considered other algorithms including the extended Kalman filter, the unscented Kalman filter, autoregressive integrated moving average estimate, artificial neural networks, and polynomial regression. We considered the algorithms' strength in such categories as long-term and short-term stability, computational expense, robustness to non-Gaussian models, the ability to make "global" approximations, and the incorporation of an aging model.

A PF is a Monte Carlo simulation that implements a recursive Bayesian filter. It uses random distributions of particles to sample a range over which a measurement may occur. In order to predict forward, a posterior density function is represented by a set of random particles with associated weights. Particles are progressed according to a state space model, which can be nonlinear. The initial state and noise distributions can take any form required. Particle weights at each time step are assigned by comparison to measurements, with higher weights implying more contribution to the estimate. Only heavily weighted particles, above a certain threshold, are progressed forward.

By adjusting the spread uniformity and noise in the redistribution of particles, the filter reacts more or less readily to measurement data at the next time step. The Securaplane filter is tuned such that the mean value of all the particles is used for the filter's prediction value at each step. In the absence of measurement data, the filter predicts future values by propagating weighted particles forward in time. Consequently, extrapolation is used to find a battery's end-of-life (EOL) date. Without prediction correction via measurements, the prognostic predictions progress almost linearly. A generic PF technique for prediction is shown in Figure 1, which is quite generic based on particle filter literature.

Practical Application

For battery systems, an assumption of future usage is required to increase accuracy of the RUL estimate. Securaplane lithium batteries collect significant amounts of data throughout the operating life of the battery. Such data is processed through and introduced to the RUL algorithm as means for influence including weighting for recent usage parameters. Consequently, future usage is estimated to align with past usage and adjusts the PF extrapolation.

Other variables that affect the RUL are added to the algorithm including the natural aging of the lithium battery cells independent of use and cell service history.

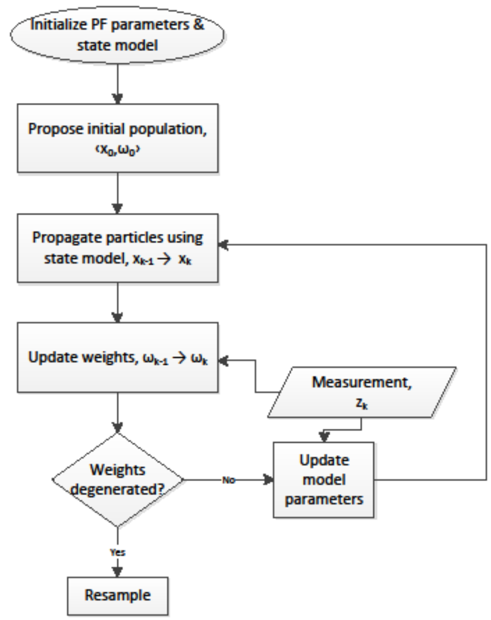

Figure 1. General operation of a particle filter

The novel aspect of this work is that it combines the development of a unique RUL estimator with a maintenance advisor for battery systems called the Li-ion Maintenance Advisor (LiMA). This principle uses a periodic measurement of state of health to develop the RUL estimate. The inputs and outputs of the LiMA are shown in Figure 2. Once the RUL estimate is available, the LiMA uses the estimate, along with a conservative estimate of future operating conditions, to develop an advisory. This is an estimate that takes into consideration both the calculated RUL as well as approved maintenance practice to ensure that the battery can be safely dispatched for flight, or removed for maintenance. Details of the overall system will be presented in a future paper.

Figure 2: The Li-ion maintenance advisor (LiMA)

A new RUL prediction can be made upon each new entry of SOH. SOH is calculated at a dynamic frequency per a specific algorithm, using real-time impedance measurements, within Securaplane lithium batteries. Upon the completion of an SOH measurement, the RUL algorithm automatically begins execution using the updated SOH dataset.

Outlier Removal

As with any interpolation or extrapolation algorithm a certain amount of error in SOH measurements will exist. However, with the non-linear nature of battery aging and the sensitivity to certain variables such as temperature, either non-convergence or boundary extrapolation results may occur. Consequently, rare, erroneous SOH calculations generated by the SOH algorithm need to be mitigated within the immediate and downstream algorithms. To remove inaccurate influence on the RUL's particle filters, prediction, an outlier filter is used at strategic times during within the RUL algorithm. The outlier filter uses a moving window to sort out potential inaccurate data points. Exclusion bounds are a function of the local median and data scatter and are dynamically calculated. Figure 3 shows an example of outlier identification. Data points determined as outliers are eliminated from the data set used within the PF. Consequently the accuracy of the data set processed within the RUL particle filter algorithm is significantly amplified.

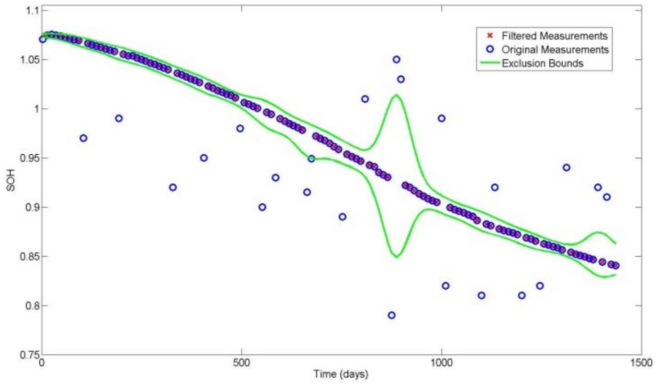

Figure 3. Noisy data filtered by outlier filter.

Robust Design

The random nature of consecutive runs of a PF creates some variation within output predictions. Robustness in prediction is garnered through an added algorithm that effectively reduces the weight of outlying RUL predictions which balances confidence with computation time.

When successive RUL values are gathered by iteration, a supplementary outlier filter is used to further refine the RUL, converging on a final value for submittal to the crew or maintenance computer.

Maintenance Directives

The maintenance advice the LiMA provides may be used to pre-order parts or schedule service, thereby reducing the cost and severity of maintenance actions taken. For example, if the RUL can be tracked, the operator of the aircraft can order a replacement battery well in advance and still be assured that a part will be available to dispatch the aircraft. A spare does not have to be stocked in inventory in anticipation of a failure, nor does it have to be rushed to repair due to an unscheduled removal. This "just-in-time" practice can lead to substantial savings in the MRO supply chain.

Additionally, RUL calculations are automatically used to warn the operator when the most recently predicted RUL drops below a certain threshold.

Algorithm Test Results

The Securaplane RUL algorithm was tested by displaying its predictive response to a variety of data sets, both normal and under stressed situations including sudden cell short circuit failure. SOH data was gathered on actual cells during repetitive cycling within field conditions but artificially adjusted and normalized to mimic usage by an operator. Figure 4 represents one application specific usage under higher stress than typical.

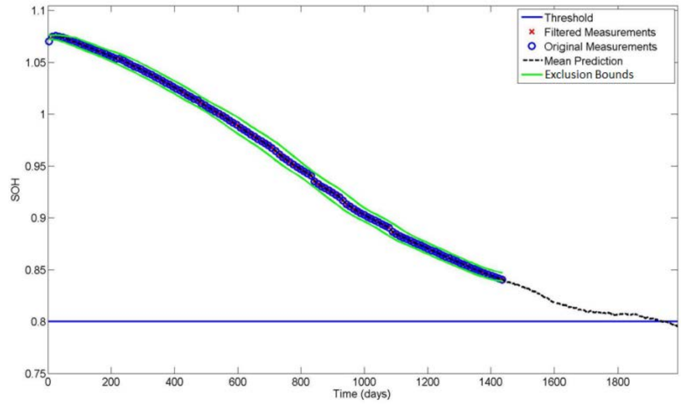

Figure 4. SOH data that may be typical throughout the lifespan of a battery. The prediction shown by the black curve represents just one run of the PF.

The first RUL stress test assumes that the operator used the Securaplane lithium battery in a manner such that the battery system was unable to calculate the SOH for months. This is actually extremely remote conditions yet useful for RUL algorithm "pressure test". Figure 5 shows the PF spans gaps in data and adequately responds to any available data by correcting its slope.

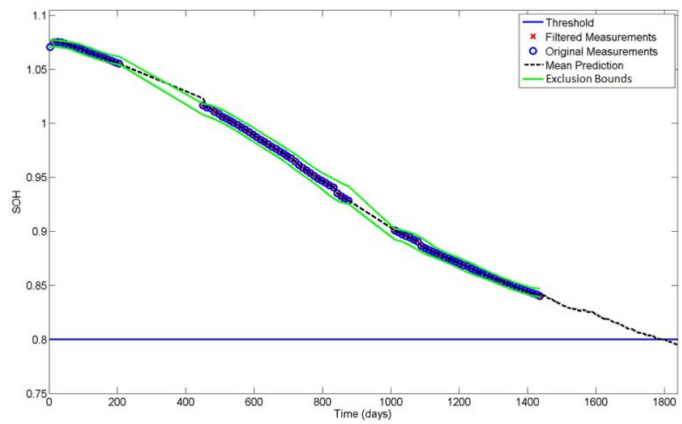

Figure 5. Test for large gaps in SOH measurements.

A fast slope change in SOH data was simulated next. Figure 6 shows an environment where a sudden SOH change resulting in a steep change in environmental conditions, such as a battery suddenly transferred from a cooler environment to an extreme desert environment operation. The slope of the predictions does not appear to change, but the algorithm adjusts to new conditions, reporting decreased RUL. Notice how the outlier exclusion bands in Figure 6 widen upon the sudden slope change in SOH.

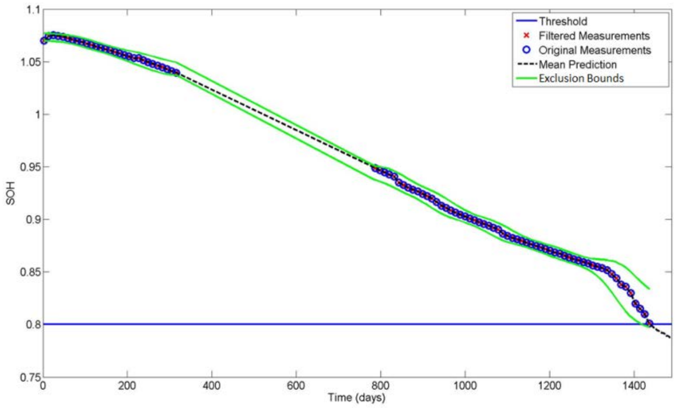

Figure 6. Test for quick decline in SOH near EOL.

As with any battery system a cell can fail due to dendrites or factory assembly parasites. Figure 7 simulates a sudden short circuit failure of a cell within an eight cell battery string system. This failure causes a step change in SOH. The outlier filter categorizes the tails of the data surrounding the jump as outliers yet quickly corrects for the RUL calculations. This is not ideal, however adjusting the limits of the outlier filter would diminish the filter's potential to detect outliers in other scenarios.

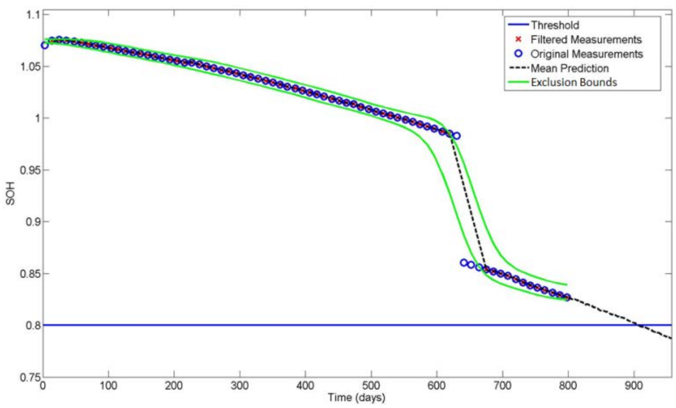

Figure 7. Test for cell module failure.

Throughout the life of the battery, RUL predictions will change as SOH measurements hone in on EOL. Expectedly, additional measurement information better guides the prediction, but it is instructive to test the variance of predictions to the most reliable prediction for RUL, namely the prediction furthest along in life. Using truncated forms of the data set presented in Figure 4, we simulate RUL measurements taken throughout a battery's life. For example, using SOH measurements up to day 204, the RUL algorithm predicts the EOL to take place on day 1240. On day 1000, the EOL is predicted to be day 1547. Figure 8 plots the normalized useful life predictions $E = (UL_{\text{final}} - UL)/UL_{\text{final}}$, taken about every 200 days, indicating the variance of each prediction to the last prediction. The last prediction calculated was done on day 1436, which gave a total useful life UL_{final} = 1648 days. This equates to a RUL = 1648 – 1436 = 212 days. Generally, one would expect E to decrease toward EOL, however some variance of slope in E is seen due to the non-linearity of the data in Figure 4.

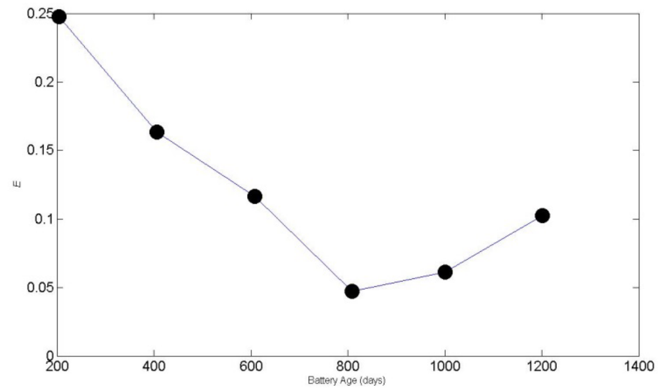

Figure 8. Normalized useful life predictions throughout a battery's life.

Conclusions

Recent studies have shown particle filters to be a good choice for live, online predictions of a lithium battery's remaining useful life. However, a particle filter by itself results in lower fidelity and occasionally undesirable RUL extrapolations. Coupling the particle filter with other specialty filters and extrapolation modifiers results in excellent fidelity and robustness properties for the algorithm. Predictions of remaining useful life even under stressful fringe conditions are accounted for. This allows operators to more adequately prepare for battery service, leading to savings in the MRO supply chain and gate delay penalties.

Future Work

RUL information is integrated into the LiMA in a heuristic way to calculate what action to take at the next service stop. The details of this directive algorithm are still under development and will be shared in a subsequent paper.

Additional heuristic rules are associated with the RUL calculation, particularly during the infancy of the battery system when SOH actually rises during the first few cycles, but these too are not germane to this paper and will be presented at a later time.

References

[1] Economist. "In search of the perfect battery." The Encyclopedia of Battery and Energy Technologies (Woodbank Communications) 386 (2008).

[2] Boost, M., "Securaplane Rechargeable Lithium Battery Systems," SAE Technical Paper 2014-01-2216, 2014, doi:10.4271/2014-01-2216.

[3] Boost, M., "Rechargeable Lithium White Paper 1.0," Available on the securaplane.com website.

[4] Boost, M., Hamblin, K., Jackson, J., Korenblit, Y., Rajamani, R., Stevens, T., & Stewart, J, "Practical PHM for Medium to Large Aerospace Grade Li-Ion Battery Systems," Proc. European Conf. of the PHM Society 2014: Nantes, France, July 2014.

[5] Arulampalam, M. S., Maskell, S., Gordon, N. &. "A tutorial on particle filters for online nonlinear/non-gaussian Bayesian tracking." Signal Processing, IEEE Transactions on Signal Processing, 2002: 50, 174-188.
[6] Saha, B., Goebel, K., Poll, S. & Christophersen, J. "Prognostics methods for battery health monitoring using a Bayesian framework." Instrumentation and Measurement, IEEE Transactions on Signal Processing, 2009: 58:2, 291-296.
[7] Saha, B., Quach, C. C. & Goebel, K. F. "Exploring the model design space for battery health management." Proceedings of the Annual Conference of the Prognostics and Health Management Society. 2011.
[8] Saxena, A., Celaya, J. R., Roychoudhury, I., Saha, S., Saha, B. & Goebel, K. "Designing data-driven battery prognostic approaches for variable loading profiles: Some lessons learned." European Conference of Prognostics and Health Management Society, 2012.
[9] An, D., Choi, J.-H. & Kim, N. H. "A tutorial for model-based prognostics algorithms based on MATLAB code." Proceedings of the Annual Conference of the Prognostics and Health Management Society, 2012

Acknowledgments

The authors thank Achyuta Ramayya, Joe Stewart, and Blaise Guélat for great discussions during the course of writing and revising this paper.

Definitions/Abbreviations

ATP	Acceptance test procedure
EOL	End of life
LiMA	Li-ion Maintenance Advisor
MRO	Maintenance, repair, and operations
RUL	Remaining useful life
SOC	State of charge
SOH	State of health
UL	Useful life