Prognostics in Battery Health Management

Kai Goebel[1], Bhaskar Saha[2], Abhinav Saxena[3], Jose R. Celaya[3], and Jon P. Christophersen[4]

[1]NASA Ames Research Center, Moffett Field, CA 94035
[2]Mission Critical Technologies, NASA Ames Research Center, Moffett Field, CA 94035
[3]Research Institute for Advanced Computer Science, NASA Ames Research Center, Moffett Field, CA 94035
[4]Idaho National Laboratory, P.O. Box 1625, Idaho Falls, ID 83415

Prognostics and Health Management (PHM) has seen a resurgence recently with new service offerings in industry for guaranteed uptime and with military requirements asking for cost-containing condition-based maintenance (CBM) implementations. A chief component of PHM is prognostics, which is also its least mature element. Prognostics attempts to estimate remaining component life, given that an abnormal condition has been detected. Key to useful prognostics is not only an accurate remaining life estimate, but also an assessment of the estimate's confidence. The latter is often times expressed through a probability density function that envelopes the prediction, by allowing the computation of confidence bounds around it. It is the uncertainty estimate that poses particular challenges to the prediction since it must account for various sources stemming from measurements, state estimation, model inaccuracies, future load uncertainty, etc. In this article, we examine these issues using battery health management as a test case.

Batteries form a core component of many machines and are often times critical to the well being and functional capabilities of the overall system. Failure of a battery could lead to reduced performance, operational impairment and even catastrophic failure, especially in aerospace systems. A case in point is NASA's Mars Global Surveyor which stopped operating in November 2006. Preliminary investigations revealed that the spacecraft was commanded to go into a safe mode, after which the radiator for the batteries was oriented towards the sun. This increased the temperature of the batteries and they lost their charge capacity in short order. This scenario, although drastic, is not the only one of its kind in aerospace applications. An efficient method for battery monitoring would greatly improve the reliability of such systems.

The phrase "battery health monitoring" has a wide variety of connotations, ranging from intermittent manual measurements of voltage and electrolyte specific gravity to fully automated online supervision of various measured and estimated battery parameters. In the aerospace application domain, researchers have looked at the various failure modes of the battery subsystems. Different diagnostic methods have been evaluated, like discharge to a fixed cut-off voltage, open circuit voltage, voltage under load and electrochemical impedance spectrometry (EIS) [1] and combining conductance technology with other measured parameters like battery temperature/differential information and the amount of float charge [2]. Electric and hybrid vehicles have been another fertile area for battery health monitoring [3]. Dynamic models for the lithium ion batteries that take into consideration nonlinear equilibrium potentials, rate and temperature dependencies, thermal effects and transient power response have been built [4]. Sophisticated reasoning schemes have been applied to feature vectors with the goal of estimating state of charge (SOC), state of health (SOH) and state of life (SOL). Not withstanding the body of work done before, it still remains notoriously difficult to accurately predict the end-of-life of a battery from SOC and SOH estimates under environmental and load conditions different from the training data set. This is where advanced regression, classification and state estimation algorithms have an important role to play. We now describe the problem scenario and data collection scheme for battery health management used in our case study.

DATA

Data have been collected from second generation 18650-size lithium-ion cells (i.e., "Gen 2" cells) that were cycle-life tested at the Idaho National Laboratory under the Advanced Technology Development (ATD) Program. This program was initiated in 1998 by the U.S. Department of Energy's Office of Vehicle Technologies to find solutions to the barriers that limit the commercialization of high-power lithium-ion batteries for hybrid electric and plug-in hybrid electric vehicles. Towards that end, cells are aged under various conditions with the intent of addressing some of the key barriers such as poor low temperature performance, abuse tolerance, and accurate life prediction.

Life testing establishes behavior over time at various temperatures, states of charge and other stress conditions and includes both cycle-life and calendar-life testing. Reference performance tests are used to establish changes in the baseline performance and are performed periodically during life testing, as well as at the start and end of life testing.

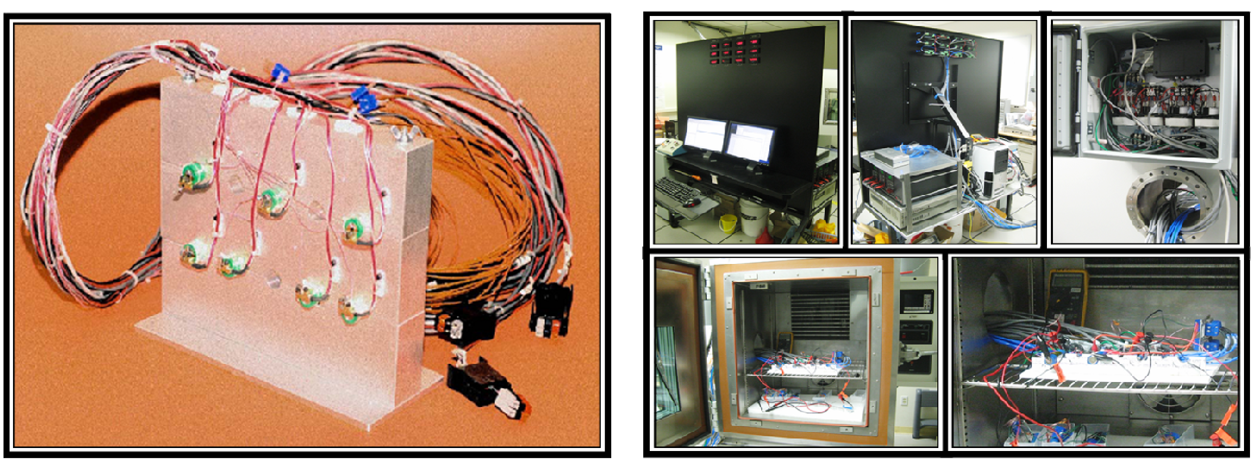
The Gen 2 cell testing involved exhaustive evaluation of baseline and variant cells, distributed amongst three national laboratories with a test matrix consisting of three states-of-charge (SOCs) (60, 80, and 100% SOC), four temperatures (25, 35, 45, and 55°C), and three life tests, namely calendar-life, cycle-life, and accelerated-life [5]. Completion of the tests took up to four years, depending on test and stopping criteria. The data used in this study were from cells that were cycle-life tested at 60% state-of-charge (SOC) and various temperatures (25^{o}C and 45^{o}C). Table 1 gives the chemical details of the cells under test.

Table 1 – Li-ion Cell (ATD Gen 2Cell Baseline) Chemistry

Positive Electrode	8 wt% PVDF binder 4 wt% SFG-6 graphite 4 wt% carbon black 84 wt% $LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$
Negative Electrode	8 wt% PVDF binder 92 wt% MAG-10 graphite
Electrolyte	1.2 M $LiPF_6$ in EC:EMC (3:7 wt%)
Separator	25 µm thick PE (Celgard)

As part of the reference performance test for these Gen 2 cells, electrical impedance spectroscopy (EIS) measurements were periodically taken to determine impedance changes in the electrode-electrolyte interface as a function of cell life. EIS measurements were initiated by discharging the cells from a fully-charged state to the specified open-circuit voltage (OCV) corresponding to the target SOC. Following an eight to twelve-hour rest at OCV, which allowed the cells to reach electrochemical equilibrium, the impedance was measured using a four-terminal connection over a frequency range of 10 kHz to 0.01 Hz, with a minimum of eight points per decade of frequency. This test was performed on all cells at 60% SOC.

All testing was performed with cells placed in environmental chambers to control ambient temperature. The chambers control the temperature to within ±3°C, as specified in the test plan [6]. Also, all Gen 2 cells were placed in thermal blocks to more uniformly control the cell temperature and minimize temperature transients (see Figure 1a). Thermocouples were also placed on each cell to monitor temperatures during life testing. Figure 1b shows a similar aging setup at the NASA Ames Research Center (ARC) which will be used to further investigate different prognostic methodologies.



(a) (b)

Figure 1 a – Thermal block with cells (INL); b – Prognostic testbed at NASA ARC

The cycle-life test consisted of constant power discharge and regeneration pulses with interspersed rest periods for a total duration of 72 seconds, and is repeated continuously while centered around 60% SOC. This profile assumes a full size battery pack and needs to be scaled to a cell-size level [5]. It has been demonstrated that battery capacity degradation can be characterized through changes in the internal parameters of the battery and these changes can be observed as shifts in EIS data plots. Figure 2 shows the shift in EIS data of a representative Gen 2 cell that was cycle-life aged at 25°C and 60% SOC.

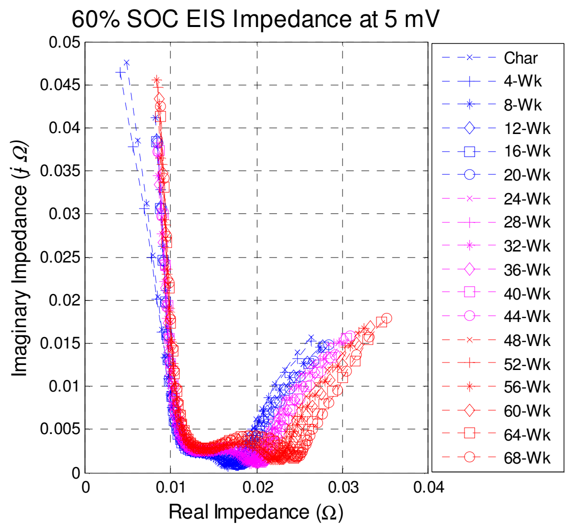


Figure 2 – Shift in EIS Data with Ageing

To describe these parameters the battery operation is expressed in the form of structural and functional models, which aid in the construction of the "physics of failure mechanisms" model. Features extracted from sensor data comprising of voltage, current, power, impedance, frequency and temperature readings, are used to estimate the internal parameters of the lumped parameter battery model shown in Figure 3. The parameters of interest are the double layer capacitance C_{DL}, the charge transfer resistance R_{CT}, the Warburg impedance R_W and the electrolyte resistance R_E. The values of these internal parameters change with various aging and fault processes like plate sulfation, passivation and corrosion.

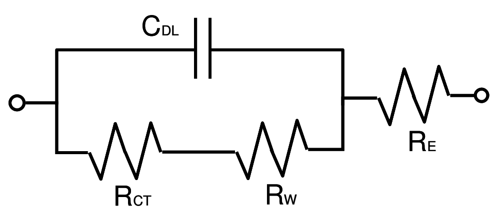


Figure 3 – Lumped Parameter Model of a Cell

Data Processing

The values of these internal parameters define the shape and position of EIS plots and hence can be extracted from these plots as diagnostic features. Figure 4 shows a zoomed in section of the data shown in Figure 2 with the battery internal model parameters identified. Since the Nyquist plot of a capacitance and resistance in parallel (C_{DL} and R_{CT} as shown in Figure 3) is expected to be a semicircle, we used data from the EIS curves in an automated fashion to fit semicircles to the middle portion of the graph. The fitting was performed in the least square sense as shown below:

$$\min\left\{\sum_i \left(Z_{i,\mathrm{Im}}^2 + \left(Z_{i,\mathrm{Re}} - c\right)^2 - r^2\right)^2\right\}, \tag{1}$$

where, $Z_{i,\mathrm{Im}}$ and $Z_{i,\mathrm{Re}}$ are the imaginary and real parts of impedance of data point i in the EIS plots of Figure 4. The center (on the x-axis) and the radius of the fitted semicircle are denoted by c and r respectively. The left intercept of the semicircles give the R_E values while the diameters of the semicircles give the R_{CT} values. Other internal parameters showed negligible change over the aging process and are hence ignored for further analysis.

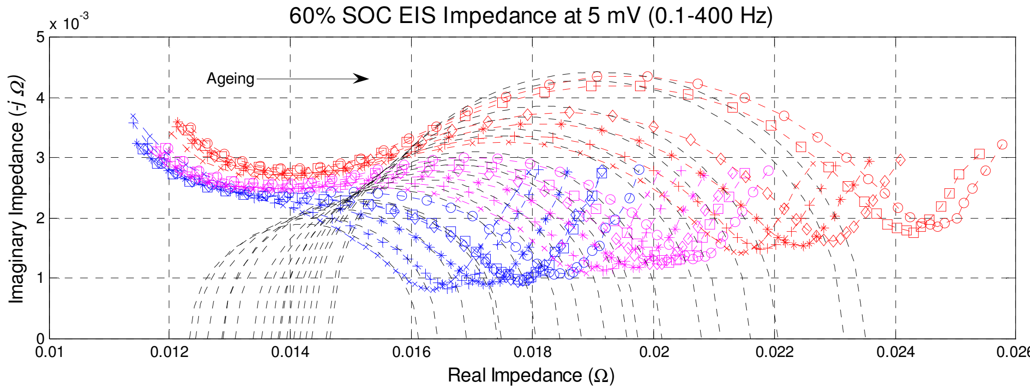


Figure 4 – Zoomed in EIS Plots with Internal Battery Model Parameter Identification

We noted that there was a very high degree of linear correlation between the C/1 capacity (capacity at nominal rated current of 1A) and the internal impedance parameter R_E+R_{CT} (Figure 5). We will show how this relationship can be exploited to estimate the current and future C/1 capacities.

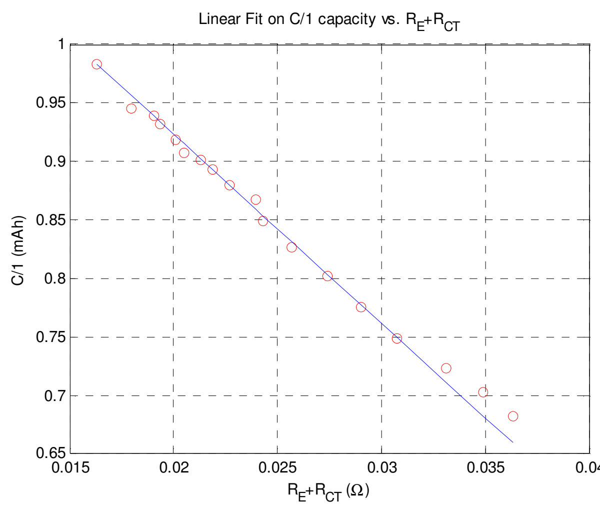


Figure 5 – Correlation between Capacity and Impedance Parameters

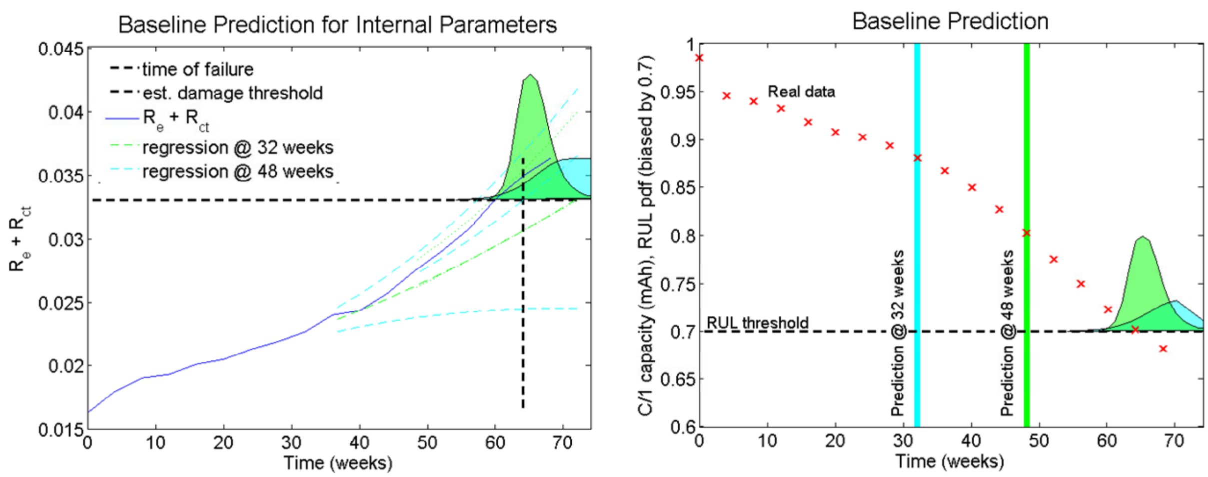
METHODS

The main objective of this study was to develop prognostics algorithms to predict remaining life of the batteries with high confidence. We also wanted to compare various prediction techniques for their strengths and weaknesses in addressing the issues of accuracy of predictions and uncertainty management against various trade-offs like complexity and computational burden, which may be crucial for some real-time applications. Starting with very simple statistical regression techniques, we applied more sophisticated probabilistic regression and advanced state estimation based hybrid algorithms to cover a wide range of algorithms. These techniques and corresponding results are presented next.

Statistics based Baseline Model

We first employed a simple data-driven routine to establish a baseline for battery health prediction performance and uncertainty assessment. We then employed more sophisticated models to improve on this baseline. Battery health is here directly tied to capacity. The battery is considered to be in a failed state when its capacity has faded by 30%. We constrained the problem by making available only information from batteries aged under specific environmental conditions to then predict the end-of-life of batteries operating under different environmental conditions (and therefore aging at different, unknown rates). EIS measurements were provided as health monitoring data to help with the state assessment. Performance assessment was done at specified intervals by measuring the accuracy of prediction. In addition, an uncertainty assessment was carried out to qualify the goodness of the prediction.

For the data-driven approach, one can glean, from the relationship between R_E+R_{CT} and the capacity C at baseline temperature (25ºC), the equivalent damage threshold in the R_E+R_{CT}, i.e., d_{th}=0.033. We also explored more sophisticated Robust linear regression techniques like robust MM regression and the robust-LTS (Least Trimmed sum of Squares) regression to extract this relationship. These methods are resistant to outliers and robust to deviations from a Gaussian distribution. The results obtained with the robust methods are similar to the one obtain from the simpler method discussed above and ratify the damage threshold d_{th}=0.033. Next, via extracted features from the EIS measurements, R_E+R_{CT} can be tracked at elevated temperatures (here 45 deg C). Ignoring the first two data points (which behave similar to what is considered as "wear-in" pattern in other domains), a second degree polynomial is used at the prediction points to extrapolate out to the damage threshold. Confidence bounds are projected to the damage threshold to show the uncertainty distribution around the prediction. Figure 6 illustrates that the prediction accuracy at prediction point t=32 weeks is rather poor. The prediction is late by 7.55 weeks and the associated uncertainty has extremely wide tails, particularly on the right side. In contrast, prediction accuracy performed at t=48 weeks is almost perfect, with an error of only 0.01 weeks (with the caveat that this is not likely a generalizable accomplishment). The resulting uncertainty distribution is much narrower, although it is still somewhat large on the right. Therefore, we establish that simpler methods can yield a fairly good estimate in situations like these. However, the confidence in these predictions is rather low and may not be favorable in critical applications.



(a) **(b)**

Figure 6 – Extrapolation to damage threshold and resulting uncertainty distribution; 6a: Regression on R_E+R_{CT}; 6b: Predictions shown superimposed to capacity

Probabilistic Regression Model

We then explored a Gaussian Process Regression (GPR) method to estimate the end-of-life. GPR is a probabilistic technique for nonlinear regression that computes posterior degradation estimates by constraining the prior distribution to fit the available training data [7]. It provides variance around its mean predictions to describe associated uncertainty in the predictions. We used GPR to regress the evolution of internal parameters (R_E+R_{CT}) of the battery with time at 45ºC. Relationship between these parameters and the battery capacity was again learned from experimental data at 25ºC. We found that GPR, being a probabilistic approach, fails to learn internal parameter evolution with only a few data points for learning when exposed to data up to only t =32 weeks. As shown in Figure 7a, the prediction at t = 32 weeks fails to follow the actual trend and hence leads to extremely late end-of-life predictions. However, with some more learning data up to t = 48 weeks it picks up the trend fairly well and corresponding end-of-life probability density function (pdf) is shown in Figure 7b. The end-of-life prediction at t = 48 weeks is 70 weeks with an error of +6 weeks of late prediction. These predictions got more accurate and precise as more data were made available for learning. Therefore, we conclude that although more sophisticated approaches like GPR are helpful in characterizing the uncertainty in the predictions, they need sufficient statistical data to properly learn the nonlinear dynamics of the process.

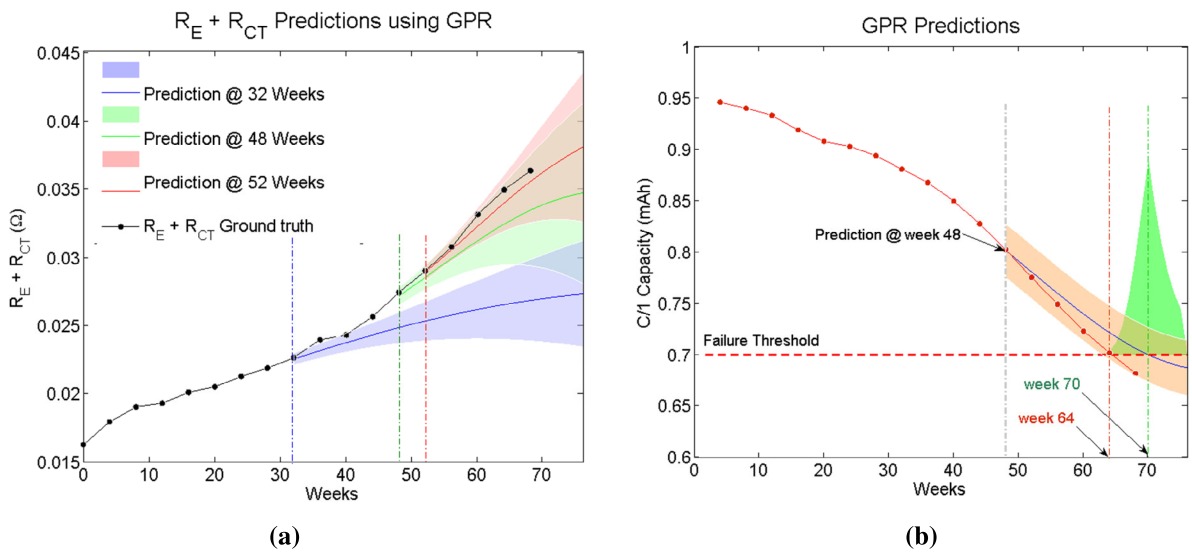


Figure 7 a – Predictions improve significantly as more training data is available; b – End-of-life predictions for battery capacity using GPR at week 48

Particle Filter Model

The behavior of the previous methods indicates that the regression techniques fail to learn non-linear trends in the absence of full-range training data. For such situations one must be able to track trends as they change and modify predictions to conform to established degradation models. With this goal in mind, we then examined the state of the art in prediction technology, i.e., particle filters. Particles filters not only use the information available from the process measurements but also incorporate any models available for the process. In this application, we combine them with relevance vector machines (RVMs). The process is broken down into an offline and an online part. During offline analysis, regression (specifically, relevance vector machine regression) is performed to find representative ageing curves. Exponential growth models, as shown in equation 2, are then fitted on these curves to identify the relevant decay parameters like C and λ:

$$\theta = C\exp(-\lambda t), \tag{2}$$

where, θ is a internal battery model parameter like R_{CT} or R_E. The overall model development scheme is depicted in the flowchart of Figure 8.

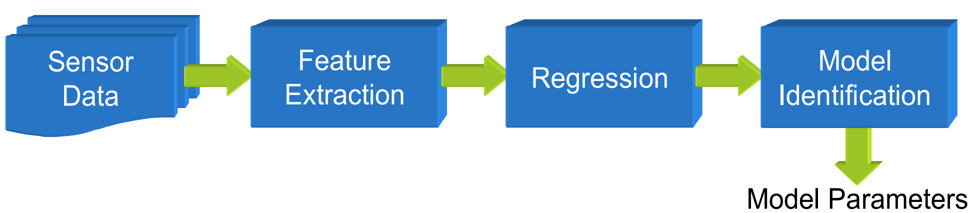


Figure 8 – Schematic of Decay Model Development

Particle Filters Background

Bayesian techniques provide a general rigorous framework for dynamic state estimation problems. The core idea is to construct a pdf of the state based on all available information. For a linear system with Gaussian noise, the method reduces to the Kalman filter. The state space pdf remains Gaussian at every iteration and the filter equations propagate and update the mean and covariance of the distribution. For nonlinear systems or non-Gaussian noise, there is no general analytic (closed form) solution for the state space pdf. The most popular solution to the recursive nonlinear state estimation problem is the extended Kalman filter (EKF). In that approach the estimation problem is linearized about the predicted state so that the Kalman filter can be applied. The desired pdf is approximated by a

Gaussian, which may have significant deviation from the true distribution causing the filter to diverge.

In contrast, for the *Particle Filter* (PF) approach [8], the pdf is approximated by a set of particles (points) representing sampled values from the unknown state space, and a set of associated weights denoting discrete probability masses. The particles are generated and recursively updated from a nonlinear process model that describes the evolution in time of the system under analysis, a measurement model, a set of available measurements and an *a priori* estimate of the state pdf. In other words, PF is a technique for implementing a recursive Bayesian filter using Monte Carlo (MC) simulations, and as such is known as a sequential MC (SMC) method.

Implementation

The state and measurement equations that describe the battery model are given below:

$$\begin{aligned}&\mathbf{z}_0 = \mathbf{C}\ ;\ \mathbf{\Lambda}_0 = \mathbf{\Lambda}\\&\mathbf{z}_k = \mathbf{z}_{k-1}.\exp(-\mathbf{\Lambda}_k)+ \boldsymbol{\omega}_k\\&\mathbf{\Lambda}_k = \mathbf{\Lambda}_{k-1} + \boldsymbol{\nu}_k\\&\mathbf{x}_k = [\mathbf{z}_k\ ;\ \mathbf{\Lambda}_k]\\&\mathbf{y}_k = \mathbf{z}_k + \boldsymbol{\upsilon}_k\end{aligned} \tag{3}$$

where, the vector comprises of R_E and R_{CT}, and matrices $\mathbf{C}$ and $\mathbf{\Lambda}$ contain their decay parameters C and λ values respectively. The $\mathbf{z}$ and $\mathbf{\Lambda}$ vectors are combined to form the state vector $\mathbf{x}$. The measurement vector $\mathbf{y}$ comprises of the battery parameters inferred from measured data. The values of the $\mathbf{C}$ and $\mathbf{\Lambda}$ vectors (for both R_E and R_{CT}) learnt from RVM regression are used to initialize the particle filter. The noise samples $\boldsymbol{\omega}$, $\boldsymbol{\nu}$ and $\boldsymbol{\upsilon}$ are picked from zero mean Gaussian distributions whose standard deviations are derived from the given training data, thus accommodating for the sources of uncertainty in feature extraction, regression modeling and measurement. System importance resampling of the particles is carried out in each iteration so as to reduce the degeneracy of particle weights. This helps in maintaining track of the state vector even under the presence of disruptive effects like unmodeled operational conditions (in our case, high temperatures).

The system description model developed in the offline process is fed into the online process where the particle filtering prognosis framework is triggered by a diagnostic routine. The algorithm incorporates the model parameter as an additional component of the state vector and thus, performs parameter identification in parallel with state estimation. Predicted values of the internal battery model parameters are used to calculate expected charge capacities of the battery. The current capacity estimate is used to compute the SOC while the future predictions are compared against end-of-life thresholds to derive RUL estimates. Figure 9 shows a simplified schematic of the process described above.

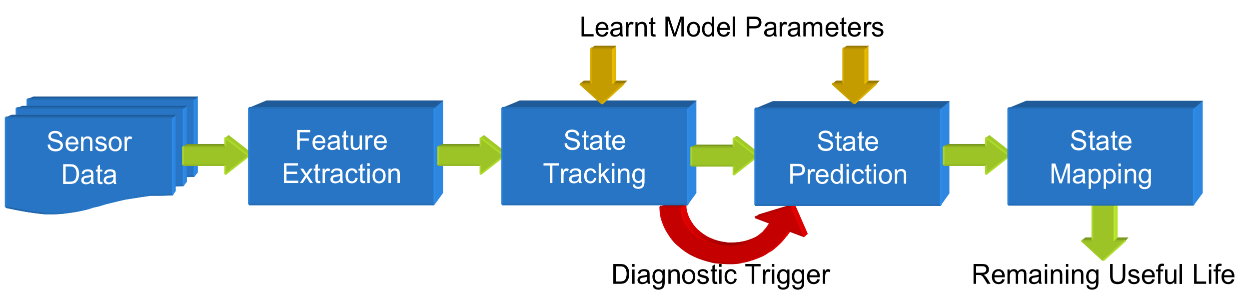


Figure 9 – Particle Filter Framework

For the test data, the estimated λ value for the R_{CT} growth model (equation 2) is considerably larger than of the training data (collected at 25°C), i.e., λ_{test} = 0.1123 compared to λ_{train} = 0.0125. Remaining-useful-life (RUL) is derived by extrapolating out the capacity estimates into the future (Figure 10) until predicted capacity hits a certain predetermined end-of-life threshold. The weight vector of the PF algorithm is used to calculate the RUL distribution.

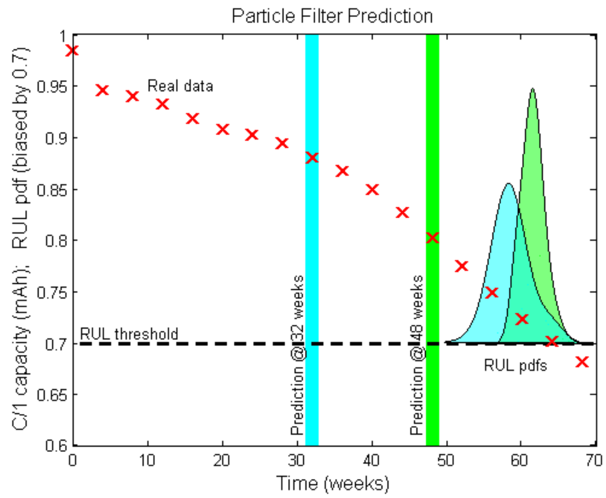


Figure 10 – Particle Filter Prediction

The particle filter approach yields RUL error of 5.8545 weeks early at 32nd week and an error of 2.59 weeks early for predictions made at 48th week. In comparison to other approaches discussed earlier, PF results better accuracy. More importantly, early predictions are considered more favorable than late predictions to avoid any unanticipated failures. The results also show that the RUL pdf improves in both accuracy (closeness of the mean to the actual RUL) and precision (narrowness of the pdf, indicating higher confidence in the mean value) as more measurements are included. This indicates that Bayesian statistical approaches are well suited to handle various sources of uncertainties since they define probability distributions over both parameters and variables and integrate out the nuisance terms.

DISCUSSION

We consider batteries representative of complex systems whose internal state variables are either inaccessible to sensors or hard to measure under operational conditions. The work presented here exemplifies how more detailed model information and more sophisticated prediction techniques can improve both the accuracy as well as the residual uncertainty of the prediction. The more dramatic performance improvement between various prediction techniques is in their ability to learn complex non-linear degradation behavior from the training data and discarding any external noise disturbances. An algorithm that manages these sources of uncertainty well can yield higher confidence in predictions, expressed by narrower uncertainty bounds. We observed that the particle filter approach results in RUL distributions narrower by several σs (if approximated as Gaussian) as compared to other regression methods. On the other hand it requires a more complex implementation and computational overhead over these methods. This illustrates the basic tradeoff between modeling and algorithm development effort and prediction accuracy and precision. For situations like battery health management where the rate of capacity degradation is rather slow, one can rely on simple regression methods that tend to perform well as more data is accumulated and still predict far enough in advance to avoid any catastrophic failures. Techniques like GPR or even the baseline approach can offer a suitable platform in such situations by managing the uncertainty fairly well with much simpler implementations. Other situations, on the other hand, may allow much smaller prediction horizons and hence require precise techniques like PFs.

In this study we conclude that there are several methods one could employ for battery health management applications. Based on end user requirements and available resources a choice can be made between simple or more elegant techniques. Particle Filter based approach emerges as winner when accuracy and precision are considered more important than other requirements.

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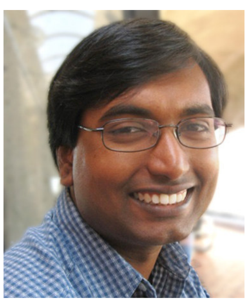
BIOGRAPHIES

Kai Goebel *Goebel is a senior scientist at NASA Ames Research Center where he leads the Prognostics Center of Excellence (prognostics.arc.nasa.gov). Prior to that, he worked at General Electric's Global Research Center in Niskayuna, NY from 1997 to 2006 as a senior research scientist. He has carried out applied research in the areas of artificial intelligence, soft computing, and information fusion. His research interest lies in advancing these techniques for real time monitoring, diagnostics, and prognostics. He has fielded numerous applications for aircraft engines, transportation systems, medical systems, and manufacturing systems. He holds half a dozen patents and has published more than 75 papers. He received the degree of Diplom-Ingenieur from the Technische Universität München, Germany in 1990. He received the M.S. and Ph.D. from the University of California at Berkeley in 1993 and 1996, respectively.*



Bhaskar Saha *is a Research Programmer with Mission Critical Technologies at the Prognostics Center of Excellence, NASA Ames Research Center. His research is focused on applying various classification, regression and state estimation techniques for predicting remaining useful life of systems and their components. He has also published a fair number of papers on these topics. Bhaskar completed his PhD from the School of Electrical and Computer Engineering at Georgia Institute of Technology in 2008. He received his MS from the same school and his B. Tech. (Bachelor of Technology) degree from the Department of Electrical Engineering, Indian Institute of Technology, Kharagpur.*

Abhinav Saxena *is a Staff Scientist with Research Institute for Advanced Computer Science at the Prognostics Center of Excellence, NASA Ames Research Center. His research focus lies in developing prognostic algorithms for engineering systems. He is a PhD in Electrical and Computer Engineering from Georgia Institute of Technology, Atlanta. He earned his B.Tech in 2001 from Indian Institute of Technology (IIT) Delhi, and Masters Degree in 2003 from Georgia Tech. Abhinav has been a GM manufacturing scholar and also a member of Eta Kappa Nu and Gamma Beta Phi engineering honor societies along with IEEE and ASME.*

Jose R. Celaya *is a visiting scientist with Research Institute for Advanced Computer Science at the Prognostics Center of Excellence, NASA Ames Research Center. He is a PhD candidate in Decision Science and Engineering Systems from Rensselaer Polytechnic Institute, from were he obtained a Master of Science degree in Electrical Engineering in 2003; and a B.S. in Cybernetics Engineering from CETYS University in 2001.*

Jon P. Christophersen *is a research engineer with the Energy Storage and Transportation Systems Department at the Idaho National Laboratory in Idaho Falls, ID. He has lead responsibility for all high power cell testing, analyses, and reporting under the Advanced Technology Development Program, as well as various FreedomCAR deliverables. This includes the investigation and successful implementation of novel testing profiles and procedures, developing new analysis techniques, developing and validating various life predictive modeling tools, and coordinating complex testing and analyses between various national laboratories. He has over 20 publications and numerous conference presentations related to energy storage. Mr. Christophersen .received a B.S. and M.S. in electrical engineering from the University of Idaho in Moscow, ID in 1999 and 2005, respectively.*