

Designing Data-Driven Battery Prognostic Approaches for Variable Loading Profiles: Some Lessons Learned

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ABSTRACT

Among various approaches for implementing prognostic algorithms data-driven algorithms are popular in the industry due to their intuitive nature and relatively fast developmental cycle. However, no matter how easy it may seem, there are several pitfalls that one must watch out for while developing a data-driven prognostic algorithm. One such pitfall is the uncertainty inherent in the system. At each processing step uncertainties get compounded and can grow beyond control in predictions if not carefully managed during the various steps of the algorithms. This paper presents analysis from our preliminary development of data-driven algorithm for predicting end of discharge of Li-ion batteries using constant load experiment data and challenges faced when applying these algorithms to randomized variable loading profile as is the case in realistic applications. Lessons learned during the development phase are presented.

1. INTRODUCTION

The field of prognostics is steadily maturing as an important field under health management as newer algorithms are constantly being developed. Among the two main categories are data-driven and model-based algorithms with competing advantages and limitations (Schwabacher, 2005). This paper summarizes our experience from implementing a data-driven approach for a variable load discharge scenario for Lithium-ion (Li-ion) batteries using experimental data collected in controlled lab environment.

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An intuitive observation-based approach was initially implemented, which required considerable improvements as we learned about various shortcomings during the development process. In this paper we present our lessons learned from the exercise, as well as an analysis of various pitfalls that may be encountered in developing data-driven methods that may seem intuitive and relatively straightforward in the beginning but may not match up on expectations when actually implemented. The paper also presents a detailed description of our data-driven algorithm. Corresponding results are also compared with a model based algorithm using an empirical degradation model.

1.1. Motivation

The motivation for this work stems primarily from two sources. First, it is of growing interest to develop prognostic health management solutions for Li-ion batteries as the use of power storage technologies is gaining momentum in energy intensive industries. While several efforts have focused on relevant topics, an accurate way of estimating battery capacity during realistic load profiles with variable and/or random operational loading still deserves attention. This paper describes the results of our efforts towards developing a generic data-driven approach for developing prognostic algorithms for randomized variable loading scenarios. It is generally assumed that data-driven methods typically require large amounts of training data in the initial development phase, but wherever possible, allow a much rapid, easy to implement, and computationally inexpensive developments compared to model-based approaches. This however, comes at a cost of a significant data processing effort upfront and still does not guarantee a successful implementation. More often than not it calls for

re-evaluation of the initial hypothesis and may require significant changes adding to complexity as problems become more realistic. In this effort we exemplify a process where data-driven algorithms that were once perfected for constant loading profiles do not guarantee good performance when tried on variable loading case and requires rethinking of the strategy, which is in contrast to an empirical model-based approach where the original implementation still performs well. Contrary to our initial beliefs that for systems like Li-ion batteries, where the characteristics of charge-discharge processes show similar qualitative trends, data-driven methods can be adapted fairly quickly once a data processing methodology is in place, we found that there are significant challenges in developing a robust data-driven method.

The second source of motivation comes from our continuing efforts towards facilitating a standardized platform for comparison of various prognostic approaches. Assessing algorithmic performance and drawing comparisons against baselines is one of the enablers towards verification and validation. As the field of prognostics matures as a research area, it is important to create an infrastructure that facilitates verification and validation activities towards certification of prognostic health management systems. This has been somewhat difficult because until recently there were no standard methods to evaluate different algorithms in a comparable manner due to lack of benchmark datasets or performance metrics useful for prognostics. An extensive survey of health management applications and other related domains revealed that conventional metrics, borrowed ad hoc from diagnostic domains, had been reused, which did not serve as well (Saxena et al., 2008). Therefore, a set of prognostic performance metrics were developed with the perspective of using prognostic information in health management and decision making processes (Saxena, Celaya, Saha, Saha, & Goebel, 2010). However, this process could be further streamlined with the availability of benchmark run-to-failure datasets that can be used for prognostic algorithm development. With that intent several accelerated aging testbeds were designed and developed at NASA Ames Research Center and data were made available to the PHM research community to take advantage of through prognostics data repository (NASA, 2007). These datasets have been downloaded more than 20,000 times from all over the world and used for algorithm development in the last four years. One of the popular datasets (over 6000 downloads) includes Li-Ion battery aging data that contain a variety of operational conditions with several sensor measurement data collected in-situ (B. Saha & K. Goebel, 2011). Despite a large number of downloads we were unable to find more than just a few references reporting successful prognostic implementation on battery data (Orchard, Silva, & Tang, 2011; Orchard, Tang, & Vachtsevanos, 2011). In this paper we report results from a preliminary data-driven approach for a randomized variable

loading case. It is our hope that the community will take up the problem and find other ways that can then be compared with the ones reported here as initial baseline performance.

1.2. Paper Organization

The rest of the paper is divided into several sections. Section 2 presents a brief background of various efforts related to prediction of battery life and battery discharge. Application domain is described in Section 3, which explains the nature of experiments conducted, lays out the problem of variable loading, and presents some observations. Section 4 starts by describing the overall approach taken and presents details of feature extraction, learning procedure, and prediction algorithms. Section 4 concludes with a brief discussion of underlying learning algorithms that are used in our prediction framework. Section 5 presents the results and discussions, followed by conclusions in Section 6. More details on the results are included in appendix for reader's reference.

2. BACKGROUND

Predicting the End-of-Discharge (EoD) times for batteries has been investigated in the recent years to predict the time when (a predefined) cut-off threshold voltage is reached and the power source is no longer available to continue the task (Bhaskar Saha & Kai Goebel, 2011). Depending on the application type and availability of data, there are many other approaches that focus on state-of-charge (SOC) estimation, current/voltage estimation, capacity and state-of-health (SOH) estimation. SOC estimation is by far the most popular approach where charge counting or current integration is used in different ways to estimate battery capacity. This approach suffers from various inaccuracies resulting under realistic usage environments (Meissner & Richter, 2003). Use of extensive lookup tables relating open-circuit voltage (OCV) to SOC is popular in the electronics industry, which requires extensive testing and data collection to build such mappings (Lee, Kim, & Lee, 2007). For safety critical applications it is important to determine when the system will lose power, and hence use of voltage threshold for time to end of charge prediction is preferred. This implicitly assumes a direct relationship between available voltage and available charge from the battery. An example of one such application is described in (Bhaskar Saha & Kai Goebel, 2011) where EoD time is predicted for an e-UAV (electric unmanned air vehicle). It is also illustrated how variable the loading can be during extreme maneuvers and a time to EoD prediction must account for expected future loads and environmental conditions. An EoD time prediction application using an empirical model based Bayesian approach is discussed in (Saha, Goebel, Poll, & Christophersen, 2009). Among data-driven approaches, in (Rufus, Lee, & Thakker, 2008) a virtual sensor is described based on a data-driven approach but primarily for SOH estimation and RUL prediction based

on usage patterns and environmental factors such as operational temperature. A statistical approach to battery life prediction that builds parametric models of the battery from collected data is described in (Jaworski, 1999). Another data-driven effort extracts and tracks changes in the internal impedances from voltage characteristics obtained from battery cycling data (Luo, Lv, Wang, & Liu, 2011). All changes are attributed to battery aging only, thereby not considering load and temperature as influencing factors. Recent years have seen a growing interest in the use of and machine learning techniques, e.g., Hamming network (Lee, Kim, Lee, & Cho, 2011), and stochastic filtering techniques e.g., unscented filter (Santhanagopalan & White, 2010) and extended Kalman filter (Hu, Youn, & Chung, 2012) to estimate the state of charge and/or degradation parameter (e.g., state of capacity) of a Li-ion battery cell under a randomly varying loading condition. Most of these data-driven approaches are shown to work on similar data to what they were trained on. This requires availability of operational data from real environment, which is not always the case. In this work we take an alternative approach by using data-driven models that are developed from a set of controlled experiments. We investigate whether it is possible to extract relevant features from current and voltage measurements collected during battery usage (discharge cycles) under controlled experiments in various fixed loading conditions to learn data-driven models that would then allow us to predict EoD for a variable loading scenario. Furthermore, estimated capacity values are not used in making the predictions, since it is generally very difficult and inaccurate to obtain battery capacities during operation.

3. APPLICATION DOMAIN

The methods developed in this work are based on aging data for 18650 Li-ion batteries available from prognostics data repository hosted by NASA Ames (B. Saha & K. Goebel, 2011). The data used for algorithm development and testing is generated in a battery testbed described in (Saha & Goebel, 2009). This testbed allows charging and discharging of batteries and collecting relevant information to estimate the state of the battery. In-situ measurement of battery current, voltage and temperature are available and these are used for development (training) of data-driven algorithms. Several charge/discharge cycles are typically applied to a set of batteries. These batteries were charged to 4.2 volts using an initial constant current (CC) profile of 1.5A until 4.2V is reached, followed by a constant voltage (CV) mode until current drops to 10mA. Since the main objective of these algorithms is to estimate EoD, a subset of batteries is discharged at constant current during discharge cycles; with current levels of 1A, 2A and 4A between different batteries. Figure 1 shows representative discharge profiles for the training cases discharged at three different constant current values.

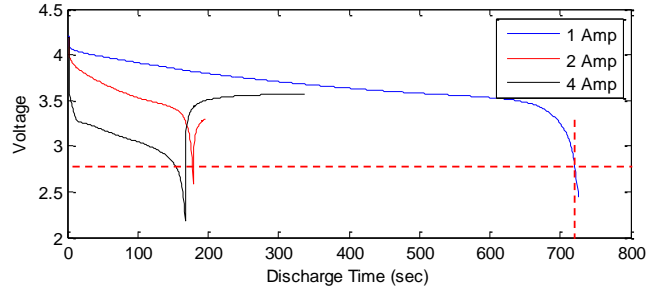


Figure 1. Constant load discharge profiles at 1, 2 and 4 A currents.

Batteries are considered fully discharged (100% depth of discharge) when they have reached 2.7V. The higher the discharge current, the less time it takes for the battery to discharge. The increased voltage drop off rate towards the end of the discharge cycle is typical for this type of batteries. This is very relevant to the algorithm development since it presents a challenge in implementing typical regression-based data-driven methods when dealing with the steep non-linearity towards the end of the discharge cycle.

While discharge profiles under fixed load conditions were used for algorithm training, variable loading cases (to represent realistic profiles) were generated for algorithm validation. In the variable load discharge profile, the current is varied randomly between 1A and 4A levels. The variable load case provides additional challenges to the EoD time estimation algorithm. It can be observed from Figure 2 that each time the load changes from one discrete value to another, there is a transient in the battery voltage value. In addition, the time of steep drop in the voltage towards the end of discharge is uncertain as it changes every time the load current changes and not just with the state of voltage of the battery.

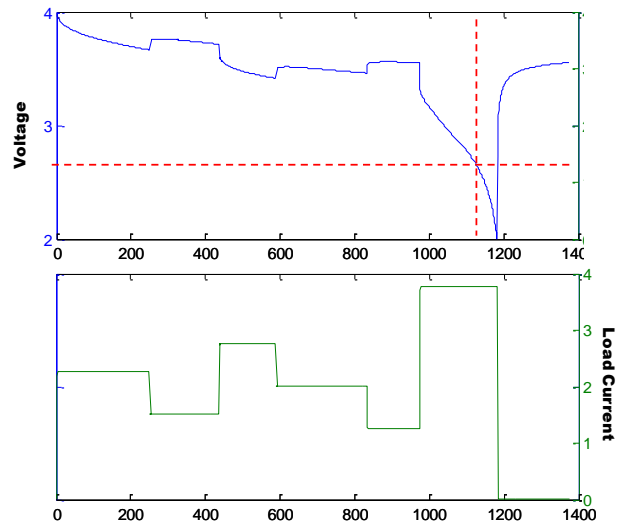


Figure 2. Variable load discharge profile between load current levels of 1A and 4A.

Battery performance degradation due to operational usage also affects EoD time estimation for a particular usage cycle. For instance, Figure 3 shows several discharge profiles for a battery used under constant discharge loading. It can be observed that the amount of time it takes for the battery to discharge to the 2.7V threshold is reduced considerably for latter cycles during the battery life. In addition, the rate of voltage decay in the pseudo-linear region also changes with battery age. Finally, the knee point, signaling the beginning of the exponential voltage decay region towards the end of discharge cycle, also changes in location and it becomes more difficult to identify due to reduced curvature as battery ages. These changes in voltage profile characteristics form the basis of feature extraction as described in the next section.

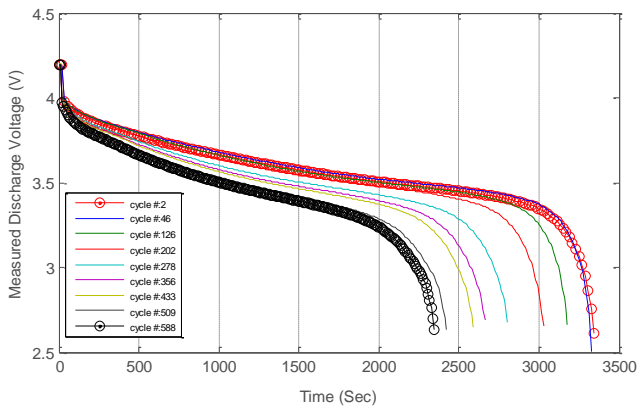


Figure 3. Constant load discharge profiles from different stages of battery life from a single battery.

4. PROGNOSTIC APPROACH

In this section, we present our approach to predict the end of discharge (EoD) time of the battery, denoted as t_{EOD} . This is the time at which the battery voltage reduces to 2.7V. The aim here is to predict the t_{EOD} for different discharge runs of the battery, given (i) an incomplete discharge cycle data until current time, and (ii) the complete (randomly changing) future operating loading. It should be noted that for this phase of algorithm development we assume a perfect knowledge of future load profile for the current discharge event. Furthermore, no partial charge and discharge events are included in these scenarios, therefore a charge cycle initiates only after the battery is fully discharged. These assumptions will be relaxed in the next phase of development as we learn more about these batteries first in these simplistic scenarios.

4.1. Feature Extraction and Training

Recall that even though our eventual goal was to predict the t_{EOD} for battery discharge cycles under random loading conditions, we train our prognostic approach using battery discharge cycle data collected under constant loading

conditions of 1A, 2A, and 4A. As a first step, training data were prepared by carrying out *denoising* of the constant loading cycle data. Some incomplete and corrupted runs were also removed from the training data. Once the denoised battery discharge cycles are obtained, we observe that the voltage versus time plots (see Figure 4) for different discharge cycles have the same trend, and each voltage discharge plot consists of three different and distinct regions. The first two regions can be approximated by linear trends followed by a third region with a sharp drop-off curve. The first pseudo-linear region is due to instant drop in voltage due to internal battery impedance on application of load current. For simplicity, this impedance is approximated by an aggregated internal resistance, which is estimated as the ratio of the observed voltage drop and the applied load current. It is understood that as battery degrades the internal resistance of the battery increases, and hence an estimate of this internal resistance can be used as a proxy for battery SOH. This estimate of internal resistance is used in creating the maps of how the load and SOH affect voltage profiles.

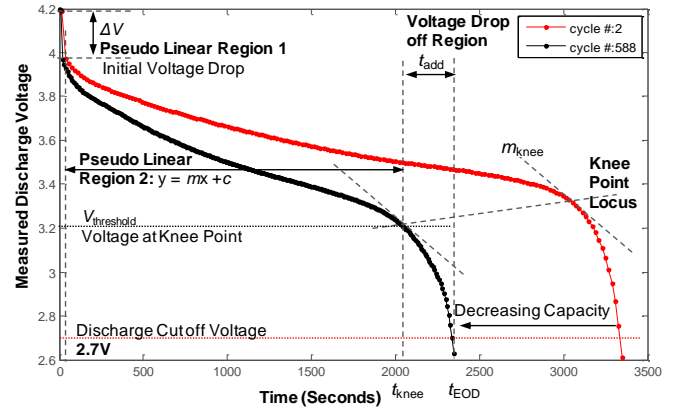


Figure 4. Illustration of features extracted from training data.

The second pseudo-linear region spans majority of the discharge profile where voltage available across battery terminals goes down proportionally as battery charge is depleted. It can be observed from Figure 3 that as the battery ages the slope of this pseudo-linear region changes and the corresponding voltage drop is higher for a given amount of discharge time. Furthermore, this slope is also affected by the load current level. Hence, a mapping (f_1) is created that relates this slope (m) to changes in battery health (SOH_{est}) and load current (I_{meas}). This second pseudo-linear region is followed by a sharp drop-off in the voltage. We term this point as the knee point, and denote t_{knee} , the knee point time to be the time at which the discharge curve enters into steep voltage drop region. For this work, we simplified t_{knee} to be the time at which the discharge curve has a predetermined slope value, m_{knee} . It was observed that, generally, at t_{knee} , the battery has consumed approximately 90% of its available charge. The identification of t_{knee} is crucial in prediction t_{EOD} , since it is

used in determining the slope of the second pseudo-linear region.

Given the trend of the voltage discharge plots, over the set of all denoised battery discharge cycles under different constant loading conditions, the following features are extracted in order to compute the t_{EOD} :

1. The battery SOH, which is approximated by internal resistance, R_{meas} and is estimated by computing the ratio of voltage drop and the change in load current, $R_{meas} = \frac{\Delta V}{\Delta I}$, as observed in the first pseudo-linear region of the voltage discharge plot (see Figure 4). ΔI is the change in current when the battery is loaded and ΔV is the corresponding voltage drop in battery terminal voltage. R_{meas} is also used in proportionally adjusting the voltage level whenever load is switched from one value to another.
2. The slope, m , of the second pseudo-linear region of the voltage discharge plot.
3. The knee point time, t_{knee} , beyond which a battery is observed to retain only about 10% of its total capacity for a given SOH. This feature is based on empirical observation and is found to be consistent across all cycles at all SOH. For computational purposes this point is identified by the time at which a corresponding threshold voltage V_{th} is reached.
4. t_{add} , the additional time taken corresponding to remaining 10% capacity discharge, which needs to be added to t_{knee} in predicting t_{EOD} ; therefore, $t_{EOD} = t_{knee} + t_{add}$. This allows us not to model the non-linear behavior explicitly and just adjusting the estimates by additive offsets computed from the mapping f_3 .

It is observed that each of the above features depends on the state of health of the battery and the load level. R_{meas} characterizes the internal impedance of the battery and represents battery age. Hence, we use R_{meas} as an approximation for SOH. It is assumed that SOH does not change within a given discharge cycle. Hence, given the load, I_{meas} , and $SOH_{est} \approx R_{meas}$, we learn the following three multidimensional mappings:

$$V_{th} = f_1(I_{meas}, SOH_{est})$$

$$m = f_2(I_{meas}, SOH_{est})$$

$$t_{add} = f_3(I_{meas}, SOH_{est})$$

These mappings can be implemented using several different techniques. In this work, we focus learning these mappings using the least-squared polynomial regression, and artificial neural network. Once these mappings are learned, the t_{EOD} can be predicted by using the future load profile information.

4.2. Architecture

The data-driven prognostic approach adopted in this paper is presented in Figure 5. The first step to this approach is the estimation of the SOH of the battery. In our approach, we estimate SOH_{est} by estimating the R_{meas} of the battery using voltage and current measurements, V_{meas} and I_{meas} , respectively, at the start of the discharge cycle. SOH_{est} and the future operating loading profile of the battery are then fed into three mappings, which estimate V_{th} , m , and t_{add} , which are then used for predicting the t_{EOD} .

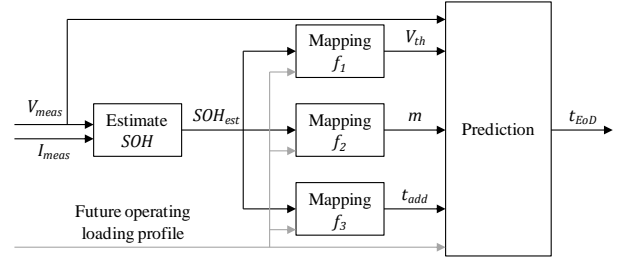


Figure 5. Data-driven prognostics architecture.

4.3. Prediction

Recall that although mappings are created using constant load profile data to learn various relationships, the algorithm performance is evaluated using data from random loading profiles. Given discharge cycle data until current time, i.e., the time stamped current and voltage measurements recorded from the battery, and the knowledge of expected (randomly changing) loading profile in future, our goal is to make correct prediction for t_{EOD} . Since, the training data do not contain the information about transients that arise during load switching, an adaptation parameter α is incorporated into the prediction scheme, which gets adapted based on observed data and is used to adjust the values obtained from the mappings. This allows us not having to update the entire mappings that were built offline in training phase but still incorporate the differences that are seen in run-time data due to various factors not considered in the learning step. Algorithm 1 describes our steps for predicting the t_{EOD} for a discharge cycle.

The algorithm takes as inputs the vector of n prediction time-points, \mathbf{t}_p , the vector of n time-intervals, \mathbf{t}_{future} , and a vector of n future current loading values, \mathbf{I}_{future} , each element of which corresponds to the current loading time-intervals in \mathbf{t}_{future} . First, we initialize α , our slope adjustment multiplier. Then, we compute SOH_{est} as explained above. Next, for each discharge cycle, we assess m for the given I_{meas} and SOH_{est} from the mapping f_1 and extrapolate from the battery voltage measured at prediction time, t_p , to the end of the current load level segment, i.e., until the next load level is switched. The threshold voltage V_{th} is also computed. If at the end of the loading cycle,

$V \leq V_{th}$, determine the time t at which $V = V_{th}$, compute t_{add} based on I_{meas} and SOH_{est} , and determine $t_{EoD} = t + t_{add}$, and stop. Otherwise, from the last segment, determine the real slope, m_{meas} and adapt the slope adjustment multiplier α to be used for the next load segment, and the loop is repeated until either all future load segments are included in the prediction or a knee point is reached and a final EoD prediction is made.

Algorithm 1: Prediction

Input:

1. $\mathbf{t}_p = [t_{p1}, t_{p2}, \dots, t_{pm}]$
2. $\mathbf{I}_{future} = [I_1, I_2, \dots, I_n]$
3. $\mathbf{t}_{ifuture} =$
 $[[t_{I1start}, t_{I1end}], [t_{I2start}, t_{I2end}], \dots, [t_{Instart}, t_{Inend}]]$
4. SOH_{est}

initialize α
for $i = 1:m$
 $t_p \leftarrow \mathbf{t}_p(i)$
 $k \leftarrow \inf\{j \in [1, n]: t_p \in \mathbf{t}_{ifuture}(j)\}$
 $m \leftarrow f_2(\mathbf{I}_{future}(k), SOH_{est})$
 $m \leftarrow m \times \alpha$
 $V \leftarrow m \times (\mathbf{t}_{ifuture}(k, 2) - t_p) + V_{meas}(t_p)$
 $V_{th} \leftarrow f_1(\mathbf{I}_{future}(k), SOH_{est})$
if $V \leq V_{th}$
 $t \leftarrow$ time at which $V = V_{th}$
 $t_{add} \leftarrow f_3(\mathbf{I}_{future}(k), SOH_{est})$
 $t_{EoD} \leftarrow t + t_{add}$
break
else

$$\text{compute } m_{meas} = \frac{V_{meas}(t_p(k)) - V_{meas}(t_p(k-1))}{t_p(k) - t_p(k-1)}$$

$$\alpha \leftarrow \frac{m_{meas}}{m}$$
end
end

4.4. Learning Algorithms

In order to assess the contribution of data-driven learning step in our prognostic framework we selected two regression algorithms continuing from previous benchmarking efforts (Goebel, Saha, & Saxena, 2008; Saha, Goebel, & Christophersen, 2008). One of them is of very low complexity based on linear polynomial regression and the other represents a more sophisticated approach, i.e. an artificial neural network (ANN). Finally, to compare the performance a particle filter based algorithm is used, which uses empirical models and measurement data to predict battery EoD. These algorithms are briefly described next.

4.4.1. Polynomial Regression

For the purpose of generating the three mappings a simple linear polynomial mapping based on least-squared regression was employed to compare with other regression approaches such as ANNs. As can be seen from the three learned mappings in Figure 6, there is significant of noise in data, which makes it difficult to learn clear relationships, especially in cases where one-to-many relationship exists between the input combinations and the output.

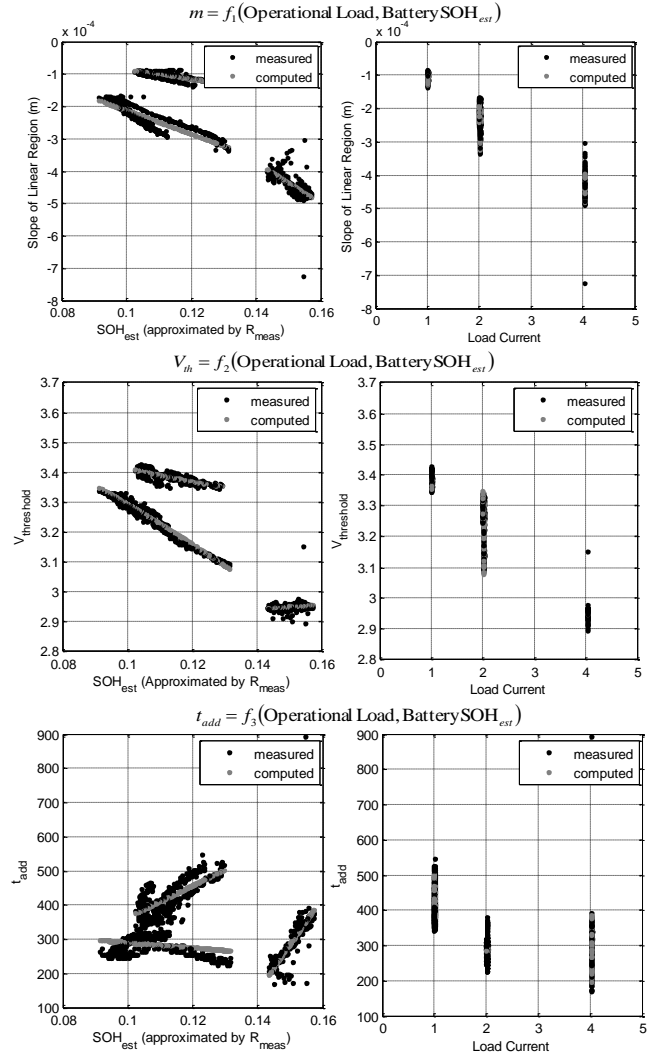


Figure 6. The three mappings based on polynomial regression. Gray cross markers show quality of fit (computed data) using test (measured) data.

Since no obvious reason was available for such behavior, first order polynomials (linear models) were fit to data based on empirical observations. The quality of fit, also shown in Figure 6, supports this choice. Once these mappings were built they were used to compute features for input combinations present in test data. It must be noted that for learning phase the input space has only three discrete values available for I_{meas} . Since the load in the test scenario is a

continuous variable, a linear interpolation was used to arrive at feature value for test loads spanning between the training loads of 1A, 2A, and 4A.

4.4.2. Artificial Neural Network Based Regression

An alternative approach to constructing the mappings f_1 , f_2 and f_3 was implemented based on artificial neural networks. The fitting of these functions provides several complications for the training on the neural network due to the nature of the training data. The neural network structure was therefore selected to obtain the simplest mapping, as close as possible to a plane. This is done to avoid over fitting which is a challenge imposed by the data. The data was normalized for the training of all the mappings in order to improve the performance of the neural network training. This normalization consisted of subtracting the sample mean and dividing the data by the sample standard deviation. The standard Levenberg-Marquardt algorithm was used for the optimization during the training process. Simple network structures with single hidden layer with two neurons for mapping f_1 , and a single hidden layer with one neuron was used for f_2 and f_3 .

4.4.3. Benchmark Algorithm – Particle Filters

As part of our previous work, we have developed particle filter-based prognostic approaches for battery health management (Orchard, Tang, Saha, Goebel, & Vachtsevanos, 2010; Saha & Goebel, 2009; Bhaskar Saha & Kai Goebel, 2011) on the same data sets as used in this work. We use the results obtained from this approach as our comparison standard, with the hope that our data-driven methods can perform as well as a Particle Filter-based approach. A particle filter (PF) (Arulampalam, Maskell, Gordon, & Clapp, 2002; Gordon, Salmond, & Smith, 1993) is a sequential Monte Carlo method that approximates the state probability density function (PDF) using a weighted set of samples, called *particles*. The value of each particle describes a possible system state, and its weight denotes the likelihood of the observed measurements given this particle's value. As more observations are obtained, the value of each particle in the next time step is *predicted* by stochastically moving each particle to a new state using a non-linear process model describing 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. Then, the weight of each particle is *updated* to reflect the likelihood of that observation given the particle's new state. For prognostics, the PF is used to only predict the future values of particles based on future operating loading profiles, and not update them for future operating loading profiles, since future measurements are not available. In this work, a detailed discharge model of the cells, as described in (Bhaskar Saha & Kai Goebel, 2011), is used as the process model for the PF. The model parameters include double layer capacitance, the charge transfer resistance, the

Warburg impedance, and the electrolyte resistance. The model was developed by analyzing the way the impedance parameters change with charge depletion during the discharge cycle.

5. RESULTS AND DISCUSSIONS

Algorithms described above were tested on data collected from two batteries that were discharged under randomized sequence of loads between 1A and 4A levels. For this paper we present results from two discharge cycles from each of the batteries chosen from an early stage of life (second and fourth discharge cycles). The results obtained from all four cases were similar in characteristics, and only one set is presented below for conciseness. The rest of the three sets are included in the appendix for reference. Results are evaluated based on alpha-lambda prognostic metric as described in (Saxena et al., 2010).

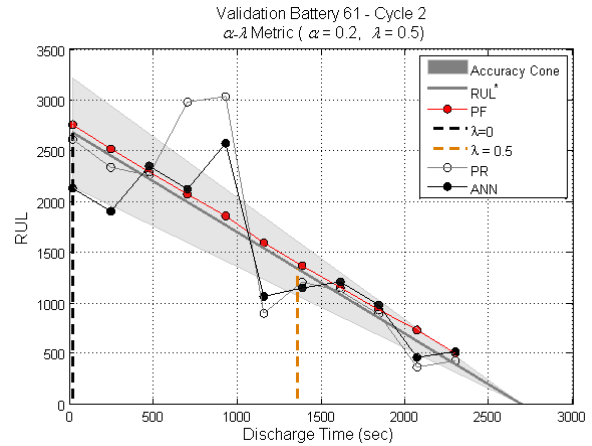


Figure 7. Alpha-Lambda metric plot for comparing algorithmic performance.

Table 1. Prediction results comparing data-driven prediction approach based on two different learning algorithms and an empirical model based prediction.

t_p	RUL*	Particle Filter		ANN Regression		Polynomial Regression	
		RUL	Error	RUL	Error	RUL	Error
20	2673	2750	77	2126	-547	2606	-67
247	2446	2511	65	1899	-547	2330	-116
475	2218	2287	69	2344	126	2253	35
703	1990	2067	77	2116	126	2972	982
930	1763	1853	90	2568	805	3026	1263
1157	1536	1589	53	1063	-473	897	-639
1385	1308	1365	57	1147	-161	1204	-104
1612	1081	1151	70	1207	126	1116	35
1840	853	993	80	979	126	888	35
2068	625	735	110	464	-161	369	-256
2296	397	505	108	523	126	432	35

It can be observed from Figure 7 (and numerical data provided in Table 1) that the data-driven method based on two different mappings performs in similar fashion, but the performance is not as good as the model based approach. Furthermore, given the nature of the data (see Figure 6) the method based on ANN mapping performs poorer. It can be explained based on the fact that it has a harder time learning simple relationship compared to polynomial regression. On further analysis several potential issues were identified that may have contributed to the poor performance of this data-driven approach:

- As evident from Figure 6, feature data from the measurements are noisy and in the absence of suitable denoising scheme learning meaningful relationships may be difficult. Especially in the case of randomized loading profiles the effect of noise may be non-linear that may not be captured by interpolating observations from three constant loading scenarios
- Constant loading scenarios lack the information about the effects of transients that are bound to be present in variable loading case during the times when load is switched from one level to another. Such information is crucial for accurate predictions
- Features extraction involves linearization of several non-linear regions and hence the performance is sensitive to choices made such as definition of the knee point, definition of slope m , etc. These choices are purely observation based and require a more thorough sensitivity analysis, which requires considerable effort as part of data-driven solution.
- Quality of mapping learned from data lies at the heart of data-driven prediction approach; however there is no direct provision of updating the mapping as new data comes in. This translates into a problem especially for a situation where training data are significantly different than test data and are missing some important knowledge.

6. CONCLUSIONS

This paper presented the results and lessons learned from implementing a data-driven prediction approach for variable loading scenario based on data acquired from controlled lab environment for constant loading scenarios. It was observed that such methods may not always lead to good performance when applied to realistic datasets. While the performance obtained in this effort is not generalized to all data-driven methods by any means, the lessons learned are presented for the research community to avoid potential pitfalls that one may run into. This effort also establishes a preliminary baseline for performance on the battery aging datasets available from NASA's prognostic dataset repository, which will help other approaches in comparative evaluation and successive improvements in performance.

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NOMENCLATURE

m	slope of second linear segment of discharge profile
SOH_{est}	estimated state of health
I_{meas}	measured battery load current
R_{meas}	measured internal resistance of battery
V_{th}	threshold voltage at which end of life is reached
t_{EoD}	time till end of discharge
t_{add}	till till end of discharge from knee point
m_{meas}	real slope of second linear segment of discharge profile
α	slope adjustment multiplier
\mathbf{t}_p	vector of m prediction time-points
$\mathbf{t}_{ifuture}$	vector of n time-intervals
\mathbf{I}_{future}	vector of n future current loading values

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BIOGRAPHIES

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Kai Goebel received the degree of Diplom-Ingenieur from the Technische Universitt Mnchen, Germany in 1990. He received the M.S. and Ph.D. from the University of California at Berkeley in 1993 and 1996, respectively. Dr. Goebel is a senior scientist at NASA Ames Research Center where he leads the Diagnostics and Prognostics groups in the Intelligent Systems division. In addition, he directs the Prognostics Center of Excellence and he is the technical lead for Prognostics and Decision Making of NASAs System-wide Safety and Assurance Technologies Program. He worked at General Electrics Corporate 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 holds 15 patents and has published more than 200 papers in the area of systems health management.

APPENDIX

Table 2. Results for validation battery 61, cycle 4.

t_p	RUL*	Particle Filters		ANN Regression		Polynomial Regression	
		RUL	Error	RUL	Error	RUL	Error
20	2793	2763	-30	2297	-496	2615	-178
247	2566	2510	-56	2698	132	2714	148
475	2338	2286	-52	1946	-392	2736	398
703	2110	2008	-102	990	-1120	861	-1249
930	1883	1796	-87	944	-939	372	-1511
1157	1656	1553	-103	481	-1175	572	-1084
1385	1428	1325	-103	855	-573	871	-557
1612	1201	1114	-87	857	-344	813	-388
1840	973	887	-86	641	-332	531	-442
2068	745	660	-85	877	132	893	148
2296	517	432	-85	649	132	665	148

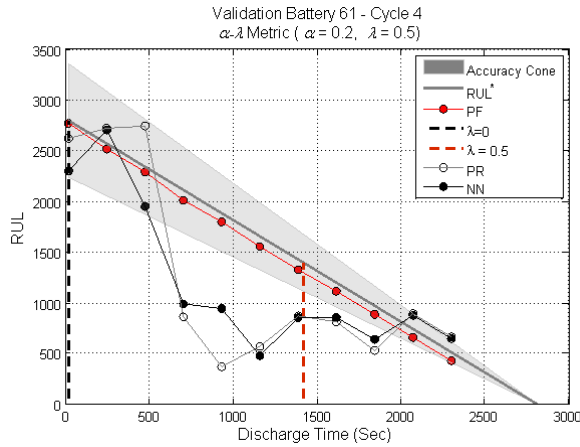


Table 3. Results for validation battery 62, cycle 2.

t_p	RUL*	Particle Filters		ANN Regression		Polynomial Regression	
		RUL	Error	RUL	Error	RUL	Error
20	2597	1897	-700	2876	279	2870	273
247	2370	2313	-57	1463	-907	1663	-707
475	2142	2188	46	938	-1204	1465	-677
703	1914	1981	67	777	-1137	1058	-856
930	1687	1708	21	812	-875	845	-842
1157	1460	1468	8	1066	-394	1060	-400
1385	1232	1321	89	838	-394	1505	273
1612	1005	1094	89	1003	-2	1278	273
1840	777	909	132	1046	269	1050	273
2068	549	732	183	686	137	817	268
2296	321	494	173	600	279	594	273

Validation Battery 62 - Cycle 2
 α - λ Metric ($\alpha = 0.2, \lambda = 0.5$)

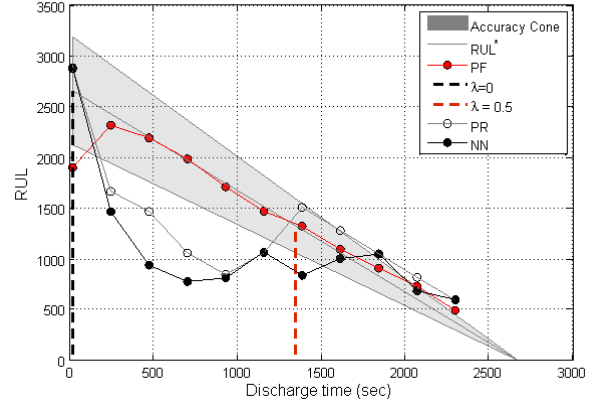


Table 4. Results for validation battery 62, cycle 4.

t_p	RUL*	Particle Filters		ANN Regression		Polynomial Regression	
		RUL	Error	RUL	Error	RUL	Error
20	2519	2386	-133	1897	-622	2546	27
247	2292	2358	66	1405	-887	1740	-552
475	2064	2168	104	1560	-504	1697	-367
703	1836	1582	-254	1843	7	1863	27
930	1609	1580	-29	1616	7	1636	27
1157	1382	1473	91	1115	-267	1165	-217
1385	1154	1269	115	881	-273	676	-478
1612	927	1030	103	934	7	954	27
1840	699	616	-83	706	7	726	27
2068	471	598	127	478	7	498	27
2296	243	357	114	0	-243	0	-243

Validation Battery 62 - Cycle 4
 α - λ Metric ($\alpha = 0.2, \lambda = 0.5$)

