Remaining Useful Performance Analysis of Batteries

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Abstract— **A method for remaining useful performance (RUP) analysis for lithium-ion batteries is presented using Dempster-Shafer theory (DST) and Bayesian Monte Carlo (BMC). First, an empirical model is developed, which can provide a good fit to the battery fade data. Then, the parameters of the empirical model are initialized by combining sets of training data based on DST. When data become available through battery monitoring, the model parameters are updated by the BMC to manage the uncertainties in the degradation process. Once the model converges to the observed degradation process, it can be propagated to the acceptable performance threshold to predict the RUP of batteries. The proposed approach is validated using experimental data.**

Keywords-prognostics; lithium-ion batteries; Dempster-Shafer theory; Bayes updating; Monte Carlo; remaining useful performance.

I. INTRODUCTION

Energy storage has become one of the great challenges of the 21st century. Applications range from the powering of portable electronic devices, to maximizing power grid efficiency. Over the past two decades, lithium-ion batteries especially have become a chosen energy solution for many systems. This trend is due to the high energy density of lithium ion batteries which allows them to store the most electrical energy per unit volume as compared to lead-acid, nickel-cadmium, and nickel-metal-hydride cells [1]. This, along with their ability to be designed into various form factors allows them to fit the needs of a wide range of applications. With the wide application of lithium-ion batteries, there is an increasing interest in the reliability of lithium-ion batteries.

In real practice, the replacement of batteries usually takes place before the end of their actual life, depending on whether the battery can meet a specific performance requirement. The performance degradation of the battery can be characterized by the decrease in capacity during usage. When the battery's performance or its capacity is below a certain criterion, e.g. 80% of the rated capacity, it is considered as unreliable and should be replaced. In many applications, such as aerospace systems, electric vehicles and uninterruptible power supply (UPS) systems, the performance degradation of batteries could lead to loss of operation, downtime and even catastrophic system failure. These situations are often mitigated through stringent maintenance schedules which can be costly and may require the system to be taken out of operation on frequent intervals. Prognostics and health management (PHM) of batteries seeks to overcome these challenges by evaluating the amount of performance degradation a battery has undergone and estimating its remaining useful performance (RUP), which is defined as the number of recharge cycles prior to reaching its acceptable performance threshold (APT). With a PHM system in place, maintenance decisions can be made on a conditional basis and the system risks can be mitigated.

Battery prognostics come in two main approaches. The first is the physics of failure (PoF) based approach which uses first principle methods to model battery behavior. This approach was first demonstrated by Doyle and Newman [2] who mathematically described one-dimensional lithium transport through concentrated solution theory and porous electrode theory. This model predicted charge and discharge characteristics for new batteries but did not consider the effects of degradation mechanisms on performance. Ramadass et al [3] created a model incorporating increased film resistance, exchanging current density and overvoltage of parasitic reactions to predict capacity fade in lithium-ion batteries. These models provide good results and do not require training data. However, they tend to be computationally intensive and are not well suited for real time battery monitoring. The second approach to prognostics uses data driven methods. These techniques extract features from measurable parameters such as current, voltage, time, and impedance. The data are then used to derive information for prognostics [4]. Data driven methods avoid developing high-level physical models of the system under consideration so that they are less complex and costly to develop.

In this paper, a data-driven method for battery RUP prediction is presented. An empirical model is developed to capture the performance degradation of batteries. In order to make the model adapt to the real system response, a Bayesian Monte Carlo (BMC) approach is adopted to update the parameters of the degradation model based on continuous monitoring of capacity data for the battery. The performance of BMC improves as increased data becomes available to update the model. To reduce the convergent time of the model to the degradation trend, a Dempster-Shafer theory (DST) [5] based method is implemented to elicit the optimal initial model parameters from available training data sets. The proposed joint DST and BMC method is validated using real battery capacity data.

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II. Battery Degradation Model

The performance degradation of batteries can be characterized by the decrease in capacity during usage [6]. Capacity is the amount of charge a battery can hold in its fully charged state and is calculated as:

$$Q = \int_{t_{charged}}^{t_{discharged}} Idt \quad (1)$$

where Q is the capacity; I is the current drawn from the battery; t_c and t_d are the time at the fully charged state and discharged state respectively. As a battery undergoes degradation, the amount of charge it can hold will decrease. Once the capacity decreases to a certain threshold in which it no longer meets a specific performance criterion, the battery's performance is considered unacceptable and should be replaced. A threshold of 80% rated capacity has been identified in the literature [7].

Before Bayesian methods can be applied, a model for capacity fade with recharge cycles must be developed. The most important property of the model is that it should be robust, in order to account for the different variations of system responses.

Based on experimental data analysis, it was found that a regression model of the form:

$$Q = a \cdot \exp(b \cdot k) + c \cdot \exp(d \cdot k) \quad (2)$$

was able to provide a good fit to the capacity fade of lithium-ion batteries. Here, *a, b, c* and *d* are the model parameters, and *k* is the cycle number.

Fig. 1 shows the capacity fade trends with recharge cycles of four batteries from the same manufacturer as well as fitted curves based on Eq. (2). The APT is set to 80% rated capacity. From Fig.1, it can be seen that these trends can be well fitted by the model Eq. (2) with different model parameters. Thus as long as the parameters of this model are accurately estimated, the model is expected to provide good predictions of the battery's capacity at a given cycle number.

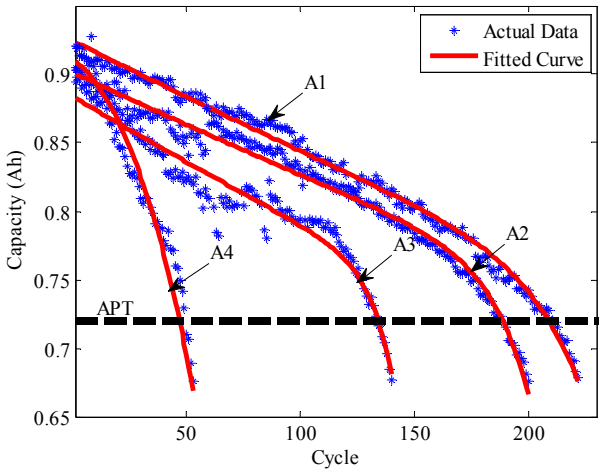

Figure 1. The regression results using model Eq. (2). APT stands for acceptable performance threshold.

III. Uncertainties in the Battery Prognostics

In Fig.1, the batteries show large differences in degradation trends, which is evident through the variations in the observed initial capacities and cycles to the acceptable performance threshold. These variations arise from uncertainties in the degradation process, which may result from several sources:

- Inherent system uncertainties: arise from differences in manufacturing assemblies and material properties.
- Operation environment uncertainties: the rate of capacity fade is highly dependent on test conditions such as the ambient temperature, discharge current rate, depth of discharge, and aging periods.
- Measurement uncertainties: arise from background noise of measurement devices and from system process noise.

Uncertainty management tools are needed for the prediction of the RUP of the batteries. The DST and BMC are adopted in this study to ensure that the proposed exponential model adapts to a specific battery system.

IV. Model Initializing Using Dempster-Shafer Theory

To demonstrate the proposed method, the data presented in Fig.1 was used, where the battery naming convention (A1, A2, A3, and A4) is used to represent each of the four batteries. The batteries labeled A1, A2, and A3 have been used as the training data and the data from A4 will be analyzed and predicted.

To provide accurate predictions from an early point in life, it is critical that these model parameters are well representative of the true physical response of the battery. A good combination of the initial parameters would shorten the convergence time of the model to the real system. Here, we used two methods to combine the parameters of the training data in order to get the "prior model" for the Bayesian updating. The first method of combination was to simply take the mean of each parameter from our three training data sets. The second method of combining parameters used the DST, which was proposed to combine evidence based on each data set's belief measurement [5]. It assumes that if two bodies of evidence agree they should be given a higher value of belief and hence weigh more when combining each piece of evidence together.

First, the Matlab curve fitting toolbox was used to fit the proposed model to each subset of data in the training set. These fits produced the parameters estimation with 95% confidence intervals shown in Table I.

Next, each of the parameters from their respective data sets, expressed through confidence intervals were compared in order to calculate the belief measure associated with each parameter. Initially, because we assume all sources to be equally creditable, the basic assignment, which assesses the likelihood of each set, was given an equal value:

$$m = \frac{1}{n} \quad (3)$$

where m is the assignment and n is the number of sets in the training set family. By using this as a starting point we can calculate the belief of each parameter using:

$$Bel(A_i) = \sum_{A_j \subseteq A_i} m(A_j) \tag{4}$$

Error! Reference source not found. gives a graphical representation of each parameter's confidence interval, where the yellow surface shows that $A_i \subseteq A_j$. For instance, in the top left figure, the parameter interval of a of the battery A2 is a subset of that of A3. As a result, the belief value of A3 for the parameter a is 0.333+0.333 = 0.666. This analysis provides the belief values shown in Table II for each of the parameters from the training data set family.

The basic assignments can be calculated from the belief values using:

$$m(A_i) = \sum_{all\ A_j \subseteq A_i} (-1)^{|A_i - A_j|} Bel(A_j) \tag{5}$$

TABLE I. FITTED PARAMETERS FROM EACH SET OF TRAINING DATA, INCLUDING THE BOUNDS FOR THE 95% CONFIDENCE INTERVALS

Battery ID	Parameter	Low	Mean	High
A1	*a*	-0.00166	-0.001042	-0.000424
	b	0.02068	0.02268	0.02467
	c	0.9079	0.919	0.9301
	d	-0.00121	-0.001035	-0.00086
A2	*a*	-0.000002007	-9.86E-07	3.442E-8
	b	0.05283	0.05752	0.06221
	c	0.8931	0.8983	0.9035
	d	-0.0009007	-0.000834	-0.000767
A3	*a*	-0.00003788	-1.53E-05	7.272E-06
	b	0.05398	0.06296	0.07193
	c	0.8631	0.8757	0.8883
	d	-0.001188	-0.00094	-0.000692

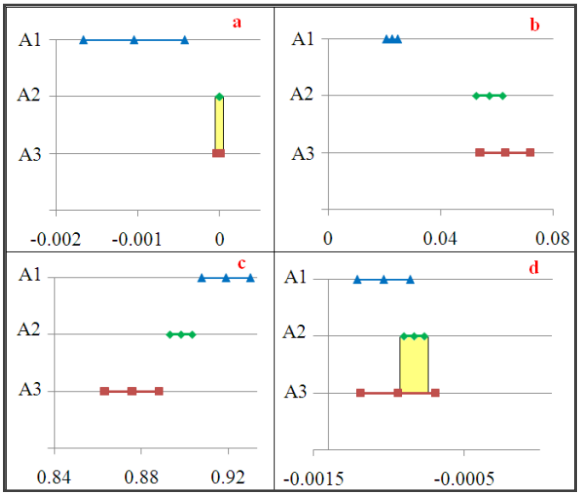

Figure 2. Comparison of parameter values expressed as intervals in order to calculate the belief value of each measurement.

TABLE II. BELIEF VALUES FOR EACH PARAMETER

	a	*b*	*c*	*d*
A1	0.333	0.333	0.333	0.333
A2	0.333	0.333	0.333	0.333
A3	0.666	0.333	0.333	0.666

When computing the cardinality of each parameter set, the Lebesgue measure must be used because each interval is considered uncountable. However, because the intervals are so small, and the sizes of the intervals are relatively similar, the difference in cardinalities between A_i and A_j can be considered zero. Therefore, the assignment conversion for this special case can be approximated by:

$$m(A_i) \approx \sum_{all\ A_j \subseteq A_i} Bel(A_j) \tag{6}$$

which means $m(A_i)$ can be approximated by the sum of all the belief values of subsets of the set A_i. Using this to convert the belief values as shown in Table II back to the basic assignment, and then normalizing these assignments we end up with the values for m shown in Table III. We can now combine each parameter using the weighted arithmetic mean:

$$CP = \sum_{i=1}^{3} m_i \, h_{A_i} \tag{7}$$

where h_{A_i} is the estimated parameters from training data, CP is the combined parameter from the initial model, and m_i are the basic assignments or the weight factors. This gives us the following combined parameter values: a= -0.00022; b= 0.04772; c= 0.897667; d= -0.00094.

TABLE III. BASIC ASSIGNMENTS FOR EACH PARAMETER VALUE

	a	*b*	*c*	*d*
A1	0.2	0.333	0.333	0.2
A2	0.2	0.333	0.333	0.2
A3	0.6	0.333	0.333	0.6

V. MODEL UPDATING VIA BAYESIAN MONTE CARLO

To model the uncertainty as discussed above, we assume that the parameters: a, b, c, and d, and the error of the model Eq.(2) are subject to Gaussian distribution:

$$\begin{cases} a_k = a_{k-1} + \omega_a & \omega_a \sim \mathcal{N}(0, \sigma_a) \\ b_k = b_{k-1} + \omega_b & \omega_b \sim \mathcal{N}(0, \sigma_b) \\ c_k = c_{k-1} + \omega_c & \omega_c \sim \mathcal{N}(0, \sigma_c) \\ d_k = d_{k-1} + \omega_d & \omega_d \sim \mathcal{N}(0, \sigma_d) \end{cases} \tag{8}$$

$$Q_k = a_k \exp(b_k \cdot k) + c_k \exp(d_k \cdot k) + v \quad v \sim \mathcal{N}(0, \sigma_v) \tag{9}$$

where Q_k is the measured value of the capacity at cycle k, and $\mathcal{N}(0, \sigma)$ is Gaussian noise with zero mean and standard deviation σ.

The initial values of a, b, c, and d are defined by the weighted sum of the model parameters obtained from the

training data based on DST. For convenience, we denote that $X_k = [a_k, b_k, c_k, d_k]$ as the parameter vector at cycle k. The goal of this study is to estimate the probability distribution of the parameters given a series of capacity measurements: $Q_{0,k} = [Q_0, Q_1, \dots, Q_k]$, namely $P(X_k|Q_{0:k})$. Within a Bayesian framework, the posterior distribution $P(X_k|Q_{0:k})$ can be recursively computed by two steps: prediction and update [8, 9]. Given the probability distribution $P(X_{k-1}|Q_{0:k-1})$ at cycle k-1, the prediction stage involves using the model (8) to obtain the prior probability distribution of X_k via the Chapman-Kolmogorov equation:

$$P(X_k|Q_{0:k-1}) = \int P\big(X_k\big|X_{k-1,}Q_{0:k-1}\big)P(X_{k-1}|Q_{0:k-1})\,dX_{k-1} = \int P\big(X_k\big|X_{k-1,}\big)P(X_{k-1}|Q_{0:k-1})\,dX_{k-1} \quad (10)$$

At cycle k, a new observation Q_k is obtained and used to update the prior distribution via Bayes rule [5], so as to obtain the required posterior distribution of X_{k-1}:

$$P(X_k|Q_{0:k}) = \frac{P(X_k|Q_{0:k-1})P(Q_k|X_k)}{P(Q_k|Q_{0:k-1})} \quad (11)$$

where the normalizing constant is

$$P(Q_k|Q_{0:k-1}) = \int P\big(Q_k\big|Q_{0:k-1,}\big)P(Q_k|X_k)\,dX_k \quad (12)$$

There recurrence relation (10) and (11) form the basis for the exact Bayesian solution [10]. However, it is hard to analytically evaluate these distributions, since they require the evaluation of complex high-dimensional integrals.

An alternative approach is to adopt Monte Carlo sampling [10-12]. In all generality, the posterior probability $P(X_k|Q_{0:k})$ can be written as:

$$P(X_k|Q_{0:k}) = \int P\big(\xi_k\big|Q_{0:k,}\big)\delta(\xi_k - X_k\ )dX_k \quad (13)$$

Assuming that the true posterior probability $P(X_k|Q_{0:k})$ is known and can be sampled, an estimation of it is given by:

$$P(X_k|Q_{0:k}) \approx \sum_{i=1}^{N_s} \omega_k^i\, \delta(X_k - X_k^i) \quad (14)$$

where $X_k^i, i = 1,2,3, \dots, N$ is a set of independent random samples drawn from $P(X_k|Q_{0:k})$, and ω_k^i is the Bayesian importance weight associated with each sample X_k^i. In practice, we do not know $P(X_k|Q_{0:k})$. To overcome this problem, one may resort to importance sampling, i.e. to sample X_k^i from an arbitrarily chosen distribution $\pi(X_k^i|Q_{0:k})$ called importance function [12]. Then the estimate of ω_k^i can be obtained by:

$$\omega_k^i = \frac{P\big(Q_{0:k}\big|X_k^i\big)P(X_k^i)}{\pi(X_k^i|Q_{0:k})} \quad (15)$$

A recursive formula for updating the weights can be obtained as [12]:

$$\omega_k^i = \omega_{k-1}^i \frac{P\big(Q_k\big|X_k^i\big)P\big(X_k^i\big|X_{k-1}^i\big)}{\pi\big(X_k^i\big|X_{k,}^i Q_{0:k}\big)} \quad (16)$$

The weight ω_k^i should be normalized after each updating. If we choose the importance function as:

$$\pi(X_k^i\big|X_k^i,\ Q_{0:k}\big) = P\big(X_k^i\big|X_{k-1}^i\big) \quad (17)$$

then the non-normalized weight updating rule become:

$$\omega_k^i = \omega_{k-1}^i P\big(Q_k\big|X_k^i\big) \quad (18)$$

As the number of Monte Carlo sampling $N \to \infty$, the approximation Eq.(14) approaches the true posterior density $P(X_k|Q_{0:k})$.

VI. Remaining Useful performance analysis

Using the BMC approach, we can update the parameter vector at each cycle. In the updating procedure, N_s samples are used to approximate the posterior probability density function (PDF). Each sample represents a candidate model vector $X_k^j, j = 1,2, \dots, N_s$, so the prediction of Q would have N_s possible trajectories with the corresponding importance weights ω_k^j. Then, the h-th step ahead prediction of each trajectory at cycle k can be calculated by:

$$Q_{k+h}^i = a_k^i\, exp\big[b_k^i \cdot (k+h)\big] + c_k^i\, exp\big[d_k^i \cdot (k+h)\big] \quad (19)$$

The estimated PDF of the capacity prediction can be obtained by:

$$P(Q_{k+h}|Q_{0:k}) \approx \sum_{i=1}^{N_s} \omega_k^i\, \delta(Q_{k+h} - Q_{k+h}^i) \quad (20)$$

Since the APT is defined as 80% of the rated capacity, the RUP estimation L_k^i of the i-th trajectory at cycle k can be obtained by solving the following equation:

$$0.8Q_{rated} = a_k^i \exp\big[b_k^i \cdot (k + L_k^i)\big] + c_k^i \exp\big[d_k^i \cdot (k + L_k^i)\big] \quad (21)$$

Then, the PDF of the RUP at cycle k can be approximated by

$$P(L_k|Q_{0:k}) \approx \sum_{i=1}^{N} \omega_k^i\, \delta(L_k - L_k^i) \quad (22)$$

VII. Prognosis Results

In the case study, the initial model was defined with DST, using A1, A2 and A3 as the training data. A4 is used as the testing sample to validate the proposed algorithm.

Fig. 3 shows prediction results after 18 cycles. The prediction error is 1 cycle away from the actual performance failure time. The yellow zone depicts the shape of the RUP PDF estimation at 18 cycles. Fig.4 presents the prediction result at 32 cycles. Since more data were available to update the model parameters, the accuracy of the prediction is improved and the RUP PDF is narrower than that obtained at 18 cycles, which means the precision of the prediction is improved.

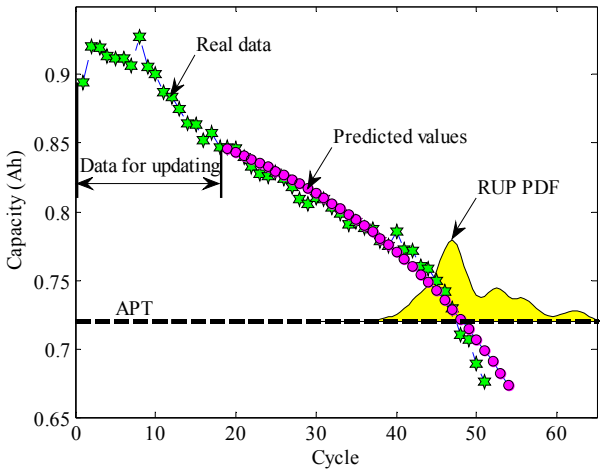

Figure 3. Prediction result at 18 cycles for the battery A4. The initial model is obtained based on Dempster-Shafer theory. The prediction error is 1 cycle.

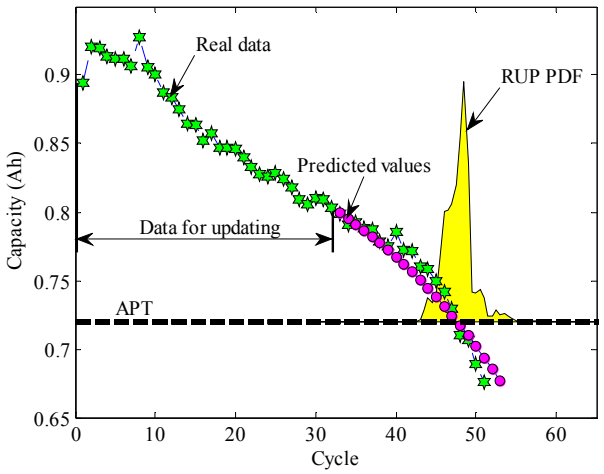

Figure 4. Prediction result at 32 cycles for the battery A4. The initial model is obtained based on Dempster-Shafer theory. The proposed approach accurately predicted the performance failure time of the battery.

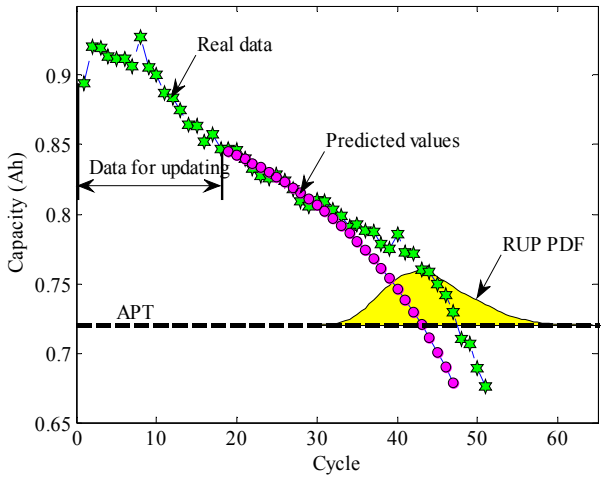

Figure 5. Prediction result at 18 cycles for the battery A4. The initial model is defined by the mean averaging method. The prediction error is 4 cycles.

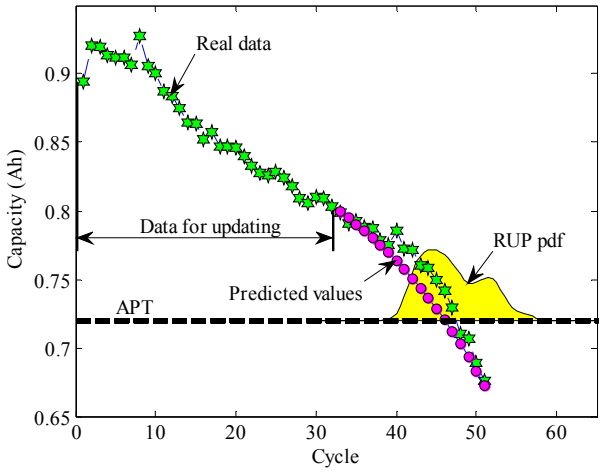

Figure 6. Prediction result at 32 cycles for the battery A4. The initial model is defined by the mean averaging approach. The prediction error is 1 cycle.

To demonstrate the effectiveness of DST in aggregating information from training data, we present the prognostic results where the initial model parameters are simply defined by the average of each parameter from the three training data sets. The prediction results at 18 cycles and 32 cycles are shown in Fig.5 and Fig.6, respectively. We can see that the prognostic error at Fig.5 and Fig.6 are 4 and 1 cycles respectively, which is greater than those using DST to define the initial model. Moreover, the RUP PDFs in both Fig.5 and 6 are wider than those in Fig.3 and Fig.4. Therefore, the uncertainty of prediction is higher when using the mean averaging approach for model initializing.

VIII. CONCLUSION

Prognostics and health management (PHM) can monitor the ongoing health of products, predict remaining useful performance (RUP) and provide warning to avoid catastrophic failure. This paper presents a new data driven PHM approach for Lithium-ion batteries. Uncertainties in the battery degradation are discussed and their effects on the prognostics are taken into account in this paper. Dempster-Shafer theory (DST) and Bayesian Monte Carlo (BMC) were used to reduce these uncertainties and to provide the RUP prediction for Lithium-ion batteries. The use of the DST for initialization of the degradation model parameters from training data was found to increase the accuracy of estimating RUP compared to simple averaging. In the case study, DST successfully elicited the initial model from the training data. BMC is then applied to update the initial model and estimate the RUP, based on the capacity measurement of the battery under testing. The BMC, although its main steps are similar to particle filter, is a regression method in essential. Different from the state space model in the particle filter, it directly use an exponential model to fit the capacity data under a Bayesian framework. The proposed method provides satisfactory prediction results in the case study. The use of the method is not limited in battery prognostics. It can be generalized to other prognostic

applications where a regression model is available. This work is an initial effort towards comprehensive PHM solution of lithium-ion batteries. It has limitations and needs improvement. For example, the effect of capacity gain during battery rest periods is not considered in this study. The models for the rest effect should be incorporated into the prognostic framework in the future work.

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