Prognostics of Lithium-Ion Batteries Using Model-Based and Data-Driven Methods

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Abstract—This paper presents an integrated approach to predict remaining useful life (RUL) of lithium-ion batteries using model-based and data-driven methods. An empirical model is adopted to emulate the battery degradation trend; real-time measurements are employed to update the model. In order to better deal with prognostics uncertainties arising from many sources in the prediction such as battery unit-to-unit variations, an online model update scheme is proposed in a particle filtering based framework. Filtered data within a moving window are used to adjust the model's parameter values in a real-time manner based on nonlinear least-squares optimization. The proposed approach is studied via experimental data, and the results are discussed.

Keywords—prognostics; lithium-ion batteries; remaining useful life; model-based; data-driven; model update

I. INTRODUCTION

Battery systems have been the most critical enabling technology among the available energy storage systems, which has seen a wide range of applications in transportation, consumer electronics, aerospace and defense sectors. Lithium-ion batteries possess advantageous features such as high energy density, lightness of weight, low self-discharge rate and long lifetime [1], which make them critical components in battery-powered systems to ensure the systems' normal operations with necessary power. Since the batteries are a core part of a battery-powered system, a battery failure can not only affect the system’s normal functionality and performance but would lead to increased system downtime but even result in catastrophic events. For example, a battery failure led to the Mars global surveyor loss in November 2006 [2]. Another battery failure resulted in a Beech A200 airliner crash during landing on April 8, 2000 [3].

These battery failures, however, could be prevented if a reliable predictor could be developed to accurately estimate the remaining useful life (RUL) of the battery. In the prognostics community, numerous RUL prediction algorithms have been proposed. In general, model-based and data-driven methods are dominant technologies in RUL prediction [4]. Model-based method uses domain expertise to build mathematical models; data-driven method uses historical data to build the models instead. However, there are few studies on RUL prediction in the battery community. Kozlowski [5] used a combination of model-based and data-driven method to obtain reasonable prediction results: an electrochemical model was related to the battery aging process; three different models – auto-regressive moving average (ARMA), neural networks and fuzzy logic were presented to make the RUL prediction. Burgess [6] used a Kalman filter in the latter phase of Lead-acid battery aging process to estimate the capacity degradation trend. Recently, several researchers made first attempts to tackle the prediction uncertainty in battery aging prognostics. Micea, Ungurean, Cârstoiu and Groza [7] used the curve fitting technique for the historical aging data to estimate in real time the battery aging process. Since particle filtering (PF) is able to describe a stochastic process and to present modeling uncertainties in the form of probability density function (PDF), it has been successfully employed in prognostics applications [8][9][10]. Also, model-based [8] and data-driven methods [9][10] can be easily implemented in the PF. For example, Orchard and Vachtsevanos [8] used Paris law to build the mathematical model of gear plate cracking; Chen, Zhang, Vachtsevanos and Orchard [9][10] used an adaptive neuro-fuzzy inference system to build various components’ failure models such as gear plate and bearings. In the battery community, Saha, Goebel, Poll and Christophersen [11] used the PF to give the probabilistic RUL results. A lumped parameter model of a cell was established to assist the construction of the battery aging model and its parameters were updated in conjunction with the model states. He, Williard, Osterman and Pecht [12] also used the PF to predict RUL. In their work, a regression model was used to estimate the battery aging dynamics and its parameters were updated online.

In this paper, we integrate the model-based and data-driven methods in the PF framework. An empirical battery aging model is given based on the domain expertise and regression analysis of experimental data. A robust model adaptation scheme is developed that uses Levenberg-Marquardt optimization method [13] to online adjust the model parameters’ values. The proposed method does not need to subtly adjust the initial parameters’ values in the parameter update model and it also can offer probabilistic prediction results in the form of PDF.

The remainder of this paper is given as follows: the next section presents the RUL prediction algorithm: capacity fade model, online model update, capacity estimation and RUL
prediction are illustrated in sequel. Section III discusses the experimental results and performance comparison with another popular prediction method. Section IV draws the conclusions.

II. RUL Prediction Algorithm

A. Capacity Fade Model

Exponential models could be potentially used to describe the battery capacity degradation, since some studies showed that the increase of battery internal impedance can be modeled via exponential functions and the impedance increase is closely related to the capacity fade [14][15]. Also, through the regression analysis of experimental data of different batteries’ aging, a sum of exponential functions can fit these aging trends well. Therefore, the degradation model is given below [12]:

\[ Q(t) = a \cdot \exp(b \cdot t) + c \cdot \exp(d \cdot t) \] (1)

where \( Q \) is the battery capacity, \( a, b, c, d \) are the parameters of the function, \( t \) is the cycle number.

If take the derivative of (1) with respect to \( t \), the aging model can be rewritten as

\[ Q(t + \Delta t) = Q(t) + \Delta t \cdot (a \cdot b \cdot \exp(b \cdot t) + c \cdot d \cdot \exp(d \cdot t)) \] (2)

Considering unit step size, (2) can be modified as

\[ Q(t + 1) = Q(t) + a \cdot b \cdot \exp(b \cdot t) + c \cdot d \cdot \exp(d \cdot t) + \delta \] (3)

A process noise \( \delta \) can be added

\[ Q(t + 1) = Q(t) + a \cdot b \cdot \exp(b \cdot t) + c \cdot d \cdot \exp(d \cdot t) + \delta \] (4)

where \( \delta \) is a random variable that follows a certain distribution such as Gaussian.

B. Capacity Fade Model Update

Prediction uncertainty mainly arises from the modeling (4) inaccuracy, since the model parameters’ values will change due to battery unit-to-unit variation, operational and environmental changes. Here, a time window is used to store \( m \) previous filtered capacity values. These capacity values are then employed to estimate the optimal model parameters. The objective function is given below:

\[ E(\theta) = \sum_{i=t-m+1}^{t} (Q(\theta, i) - \tilde{Q}_i)^2 \] (5)

where \( \theta = [a \ b \ c \ d]^T \), \( \tilde{Q}_i \) is the filtered capacity value in the \( i^{th} \) cycle, \( t \) is the current cycle, \( m \) is the time window size.

Using Levenberg–Marquardt optimization method [13], the parameter update equation is given by

\[ \theta(t + 1) = \theta(t) - (J^T J + \lambda I)^{-1} J^T r \] (6)

where \( J \) is the Jacobian matrix whose \( i^{th} \) row equals \( \frac{\partial Q(\theta, i)}{\partial \theta} \), \( r \) is a residual vector whose \( i^{th} \) row is \( Q(\theta, i) - \tilde{Q}_i \), \( \lambda \) is a damping factor.

C. Capacity Estimation

PF is used to estimate the capacity \( Q \) and its posterior PDF \( P(Q_k | y_{0:k}) \). Using the capacity degradation model (4), the prior PDF of the capacity for the next cycle is given by

\[ P(Q_k | y_{0:k-1}) = \int P(Q_k | Q_{k-1}) P(Q_{k-1} | y_{0:k-1}) d Q_{k-1} \] (7)

The capacity posterior PDF can be calculated by Bayes’ rule:

\[ P(Q_k | y_{0:k}) = \frac{P(y_k | Q_k) P(Q_k | y_{0:k-1})}{P(y_k | y_{0:k-1})} \] (8)

where the likelihood function \( P(y_k | Q_k) \) is defined by the measurement model:

\[ y_k = Q_k + v_k \] (9)

where \( v_k \) is a measurement noise.

PF is used to estimate the posterior capacity PDF by a set of random samples (or particles) with associated weights, as shown below

\[ P(Q_k | y_{0:k}) \approx \sum_{i=1}^{N} w_k^i \delta(Q_k - Q_k^i) \] (10)

where \( N \) is the total number of particles, \( \{Q_k^i, i = 1, 2, ..., N\} \) is a set of particles drawn from \( P(Q_k | y_{0:k}) \) with associated weights \( \{w_k^i, i = 1, 2, ..., N\} \) at cycle \( k \), and \( \delta(*) \) is the Dirac delta function.

Since \( P(Q_k | y_{0:k}) \) is usually unknown, importance sampling principle is used to sample \( Q_k^i \) from an importance density \( q(Q_k | y_{0:k}) \), and the corresponding weights can be updated:

\[ w_k^i \propto w_{k-1}^i \frac{P(y_k | Q_k^i) P(Q_k | Q_{k-1})}{q(Q_k^i | Q_{k-1}, y_{0:k})} \] (11)

If simply choose \( q(Q_k | Q_{k-1}, y_{0:k}) = P(Q_k | Q_{k-1}) \), yields

\[ w_k^i \propto w_{k-1}^i P(y_k | Q_k^i) \] (12)

Then, the capacity estimate can be calculated by

\[ \overline{Q}_k = \sum_{i=1}^{N} w_k^i Q_k^i \] (13)

D. RUL Prediction

The RUL prediction is started via the particles and associated weights obtained above. Capacity prediction results at the next cycle \( k+1 \) for each particle can be calculated via the capacity degradation model, as shown below:
where \(a, b, c, d\) are adjusted at each cycle via the online model update scheme and maintained invariable during the prediction. To predict the capacity value at the cycle \(k+2\), we use

\[
Q^k_{k+1} = Q^k_k + a_k \cdot b_k \cdot \exp(k_k \cdot k) + c_k \cdot d_k \cdot \exp(d_k \cdot k) \tag{14}
\]

Similar predictions are performed recursively until the predicted capacity values of all particles reach the threshold, as given by

\[
Q^k_{k+RUL_k} \geq 0.8Q_{rated} \tag{16}
\]

The PDF of RUL at the cycle \(k\) can be approximated by:

\[
P(RUL_k|\theta_0:k) \approx \sum_{i=1}^N w_k^i \delta(RUL_k - RUL_k^i) \tag{17}
\]

The expectation of RUL can be calculated by:

\[
\overline{RUL}_k = \sum_{i=1}^N w_k^i RUL_k^i \tag{18}
\]

III. EXPERIMENTAL RESULTS

Four different battery aging trends were employed: A1 and A2 were chosen from the type A batteries; B1 and B2 were chosen from the type B batteries. Type A has a rated capacity of 0.9Ah; type B has a rated capacity of 1.1Ah. The battery capacity was estimated via Coulomb counting method. The details of the experimental setup can be found in [12].

Fig. 1 shows the testing data A1, A2, B1, B2 and the aging trend called “Initial” whose initial parameters’ values were obtained from Dempster-Shafer theory. The initial parameters’ values are: \(a = -0.00022; b = 0.04772; c = 0.89767; d = -0.00094\), the same values as adopted in [12] to make a fair comparison. As we can see, the initial aging trend is different from all of the testing data and the four sets of testing data show the various aging characteristics.

For comparison purposes, the random walk models were used to adjust the model parameters in the PF [11] [12]. The parameter update equation can be expressed by

\[
\theta(t+1) = \theta(t) + w \tag{19}
\]

where \(w\) is a vector follows normal distribution \(0, \Sigma_w\), \(\theta = \{a, b, c, d\}\). Here, we call it random walk particle filtering (RWPF).

The RUL prediction errors for A1 using the proposed algorithm and the RWPF are shown in Fig. 2 and 3, respectively. The error is calculated by the predicted mean of the RUL PDF minus the actual RUL. Through comparison, the RWPF demonstrates better prediction accuracy. Fig. 4 and 5 show the prediction results at the 22\(^{nd}\) cycle using the proposed algorithm and the RWPF, respectively. Through the observation of the real data of A1, a rapidly decreasing capacity trend occurs before around 25\(^{th}\) cycle. The degradation model in the proposed algorithm can adapt itself to such kind of the battery aging dynamics, as shown in Fig. 4 (the estimated curve before the 22\(^{nd}\) cycle calculated by the updated model can approximate the real data well (the root mean square error (RMSE) is 0.0099)). This is the main reason that the predicted RUL is smaller than the actual RUL before the 25\(^{th}\) cycle since the prediction only depends on the previous degradation trend to predict future aging conditions. Although the RWPF demonstrates accurate prognostics results (Fig. 3), the updated degradation model actually cannot capture the battery historical aging dynamics (Fig. 5, the RMSE is 0.0301) and thus it may be hard to verify its correctness and reliability.

Fig. 6 shows the RUL error for the A2 battery data using the proposed prediction algorithm. Similar to the A1 testing data, the dynamical changes of the degradation trend of A2 lead to the predicted RUL errors. Fig. 7 shows the prognostics results at the 100\(^{th}\) cycles. We can see that the updated degradation model can accurately capture the historical aging trend up to the current prediction cycle (or the 100\(^{th}\) cycle). The RWPF cannot provide reasonable RUL results for this set of testing data. Fig. 8 shows the prediction results at the 100\(^{th}\) cycle. This result may be caused by the inappropriate values of the parameter’s variance \(\Sigma_w\) in the random walk model (19) for this testing data A2, although these values generate satisfying RUL prediction results for the testing data A1 (Fig. 3).

The RUL errors for the B1 and B2 battery data using the proposed prediction algorithm are shown in Fig. 9 and 10, respectively. The RWPF still cannot give reasonable prediction results: the weighted capacity prediction trends are gradually increased. From all of the testing results of the proposed predictor (Fig. 2,6,9,10), we can see that more accurate RUL estimates can be achieved in the latter phase of the prediction since more data are received to update the aging model that allows the model to capture the overall aging dynamics.

Figure 1. Battery aging trends. A1 and A2 are the aging trends of the type A batteries; B1 and B2 are the aging trends of the type B batteries; Initial is the aging trend using the initial model parameters obtained from Dempster-Shafer theory.
Figure 2. RUL error of A1 using the proposed prognostics algorithm.

Figure 3. RUL error of A1 using RWPF.

Figure 4. Prognostics results of A1 at the 22th cycle using the proposed prognostics algorithm. The update degradation model fits the historical aging curve well (the real data between the 1st and the 22th cycle).

Figure 5. Prognostics results of A1 at the 22th cycle using RWPF. The update degradation model cannot fit the historical aging curve well (the real data between the 1st and the 22th cycle).

Figure 6. RUL error of A2 using the proposed prognostics algorithm.

Figure 7. Prognostics results of A2 at the 100th cycle using the proposed prognostics algorithm. The update degradation model fits the historical aging curve well (the real data between the 1st and the 100th cycle).
IV. CONCLUSIONS

This paper presents a reliable predictor for the remaining useful life prognostics of lithium-ion batteries. A sum of exponential functions is used to represent the battery aging dynamics, based on the domain expertise that the internal impedance increase of batteries can be modeled via exponential functions and the regression analysis of experimental data that a sum of exponential functions can closely approximate multiple capacity fade trends. A moving time window is used to gather estimated capacity values, by which Levenberg–Marquardt optimization method is employed to optimally update the model parameters in real time. Particle filtering (PF) uses the self-adapted aging model to predict the remaining useful life (RUL) of battery in the form of probability density function (PDF).

To make a comparison, the commonly used random walk particle filtering (RWPF) is used to online update model parameters and to perform predictions. The experimental results show that the proposed predictor can provide reasonable and reliable RUL prediction results and more accurate RUL estimation can be obtained in the latter phase of the prediction as more aging data are received; and the RWPF cannot guarantee the prediction robustness for different battery aging dynamics.

REFERENCES


