Real-time RUL prediction model of Lithium-ion battery based on Bayesian approach

Jihyun Park, Joonhyung Park

Datascience Team, Hyundai Mobis, Seoul, 06141, Korea
jihyun.park@mobis.co.kr
pjh2016@mobis.co.kr

ABSTRACT

Lithium-ion batteries are used in various fields such as electric vehicles and smart grids. Their lifespan gradually decreases from repeating charging and discharging continuously. Therefore, remaining useful life (RUL) prediction of battery is an important issue in terms of performance and safety. To make more accurate prediction, we propose a novel RUL prediction method based on Bayesian estimation with Markov chain Monte Carlo (MCMC). According to Bayesian updating, this method is effective to make a more accurate real-time RUL prediction. NASA battery data is applied for comparison of this method, as a result, the proposed method performs better prediction performance than other methods. The RUL prediction model of this study can provide a better decision for predictive maintenance.

1. INTRODUCTION

Lithium-ion batteries are used in various fields such as electric vehicles and smart grids(Hu et al. 2017). Accurate the operating time management of Lithium-ion battery is important to ensure the reliability and safety of battery systems. Lithium-ion battery is repeatedly charge and discharge, and their lifespan gradually decreases. As the number of charge and discharge cycles increases, the performance of Lithium-ion battery gradually deteriorates. Therefore, battery management system (BMS) is essential system for battery systems more reliable and safer(Wang, Miao, and Pecht 2013). Because of the complex degradation mechanisms, it is difficult to predict the battery lifetimes. Therefore, remaining useful life (RUL) estimation of battery has become hot issues in the Prognostics and health management (PHM) research(Waag, Fleischer, and Sauer 2014).

Many PHM researchers have carried out extensive efforts on the research of RUL prediction of Lithium-ion batteries. (Andre et al. 2013) developed a knowledge-based structured neural network(SNN). (Liu et al. 2014) introduced a novel fusion prognostic framework combined AR model and RPF algorithm. In (He et al. 2015)'s research, Gaussian process regression modeling approach was proposed to tackle accurate state of health estimation in lithium-ion batteries. (Zhang, Mu, and Sun 2018) proposed RUL prediction method based on the exponential model and particle filter.

This study is to propose a novel RUL prediction method of Lithium-ion battery. This method is useful to real-time RUL prediction by applying Bayesian estimation. This paper is organized as follows. Section 2 explains the data-driven RUL prediction method. Section 3 provides the empirical study in lithium-ion battery. Section 4 presents the conclusion.

2. DATA-DRIVEN RUL PREDICTION

This section describes the degradation model, fault prediction method based on Bayesian approach, and real-time RUL updating method.

2.1. Degradation Model

Degradation model is a mathematical expression of the deterioration process of the system. This study is assumed that the degradation model follows the Weibull survival function. The Weibull distribution is adaptable to many engineering systems such as battery(Kim, Park, and Ahn 2008). We use the property that the survival function of degradation system whose failure intensity follows the power law failure model is the Weibull survival function.

The degradation model of this study is used as survival function of two-parameters Weibull distribution in Eq. (1).

$$f(t) = e^{-\lambda t^{\beta}}, \tag{1}$$

where λ is scale parameter, β is shape parameter.

2.2. Bayesian approach to Fault Prediction

To estimate the parameters of the degradation model, this study uses the Bayesian approach. The Bayesian approach of this study is a method of inferring the posterior distribution from likelihood function of degradation model by using the likelihood principle. There are three reasons why fault prediction based on Bayesian approach is useful. First, it increases the fit for the degradation model. Second, using the Bayesian approach, it is easy to estimate the parameters of posterior distribution. Third, the Bayesian updating, a unique characteristic of Bayesian approach, has an advantage that it is easy to develop the data-driven predictive model(Andrieu et al. 2003).

Consider that the observation time is $\boldsymbol{x} = \{x_1, x_2, \cdots, x_i\}$, the observed value Y_i is presented as Eq.(2) and likelihood of Y is in Eq.(3).

$$Y_i | a, \lambda, \beta, c, \sigma^2 \sim N\left(a \cdot e^{-\lambda t^{\beta}} + c, \sigma^2\right), \tag{2}$$

$$L(a, \lambda, \beta, c, \sigma^2 | Y) = (2\pi\sigma^2)^{-\frac{n}{2}} exp\left\{-\frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(Y_i - a \cdot e^{-\lambda t^{\beta}} - c\right)^2\right\}, \tag{3}$$

where a is scale parameter of regression and c is constant coefficient.

According to the Bayesian theorem, the posterior distribution is

$$f(a, \lambda, \beta, c, \sigma^2 | Y) = \frac{L(a,\lambda,\beta,c,\sigma^2|Y)\pi(a,\lambda,\beta,c,\sigma^2)}{\int_a\int_\lambda\int_\beta\int_c\int_{\sigma^2} L(a,\lambda,\beta,c,\sigma^2|Y)\pi(a,\lambda,\beta,c,\sigma^2)\,da\,d\sigma^2\,dc\,d\beta\,d}, \tag{4}$$

where $\pi(a, \lambda, \beta, c, \sigma^2)$ is the joint prior distribution of a, λ, β, c and σ^2.

A non-parametric Bayesian estimation method should be used in non-linear problems such as Eq. (4). As non-parametric Bayesian estimation method, we use the MCMC(Markov chain Monte Carlo) to estimate unknown parameters. MCMC method provides an alternative way to simulate large enough samples from the complicated posterior distribution based on Markov chains(Andrieu et al. 2003). The Metropolis-Hastings(M-H) algorithm of MCMC method is performed.

In the Bayesian approach, let us assume that the posterior distribution is $p(\theta | a, \lambda, \beta, c, \sigma^2)$ from which we wish to generate a sample of size m. Denote $\theta_{(j)}$ to be the vector of generated values in the j generation of the algorithm. The procedure of M-H algorithm follows as:

Procedure of M-H method

Step 1. Set $j = 1$

Step 2. Generates an initial value for $\theta_{(0)}$

Step 3. Repeat

- A. Set the proposal distribution $q(\theta^* | \theta)$
- B. Generates a proposal for θ^* from $q(\theta^* | \theta)$
- C. Evaluates the acceptance probability
  $$\rho(\theta, \theta^*) = min\left(1, \frac{p(\theta^*|a,\lambda,\beta,c,\sigma^2)q(\theta|\theta^*)}{p(\theta|a,\lambda,\beta,c,\sigma^2)q(\theta^*|\theta)}\right).$$
- D. Generates a u from the $uniform$ (0,1)
- E. If $u \leq \rho(\theta, \theta^*)$, accept the proposal and set $\theta = \theta^*$
- F. Conduct the next M-H step in $j = j + 1$

Step 4. Until $j = m$

2.3. Real-time RUL Updating

We aim to predict RUL of lithium-ion battery from degradation model. We can estimate the lifetime distribution from fault prediction based on Bayesian approach. The threshold causing the failure is expressed as y_{th}, and the estimated lifetime derived from degradation model. It is Eq. (5).

$$t_{i,j} = \left(\left(-\frac{1}{\lambda_{(j)}}\right) log_e\left(y_{th} - c_{(j)}\right)\right)^{\frac{1}{\beta_{(j)}}}. \tag{5}$$

The estimated lifetimes follow the form of a Normal distribution because sampled lifetime values are independent identically distribution. It is the principle of central limit theorem Therefore, the estimated lifetimes are $T_i = \{t_{i1}, \cdots, t_{im}\}$, it is presented as Eq. (6).

$$T_i = \boldsymbol{inf}\{x: f(x_i | a, \lambda, \beta, c, \sigma^2) > y_{\boldsymbol{th}}\}. \tag{6}$$

As more data are observed over time, the posterior distribution is updated through the Bayesian updating principle. It is shown in Eq. (7).

$$f_{t+1}(a, \lambda, \beta, c, \sigma^2 | Y) \propto L_t(a, \lambda, \beta, c, \sigma^2 | Y)\pi_t(a, \lambda, \beta, c, \sigma^2). \tag{7}$$

From this process, the real-time RUL estimating can be performed by repeatedly learning and prediction.

3. EMPIRICAL STUDY

3.1. Data Description

In this paper, we use battery data sets from the NASA Prognostics Center of Excellence Data Repository(Saha and Goebel 2007). The dataset of lithium-ion batteries is obtained in the process of charging, discharging, and measuring impedance. Charging proceeds in two steps. First step is in constant current (CC) mode, current is maintained at 1.5 A until the volage reaches to 4.2 V. The next step is in constant voltage (CV) mode, the voltage is held at 4.2 V until the battery current reaches 20 mA. Discharging proceeds in CC mode, holding the current at 2 A until the battery voltage drops from 4.2 V to 2.7 V. Finally, the battery impedance is measured using electrochemical impedance spectroscopy (EIS). The battery degradation experiment is that the three processes are repeated until 30% of the battery capacity is lost and reaches 1.38 Ah. It is shown in Figure 1.

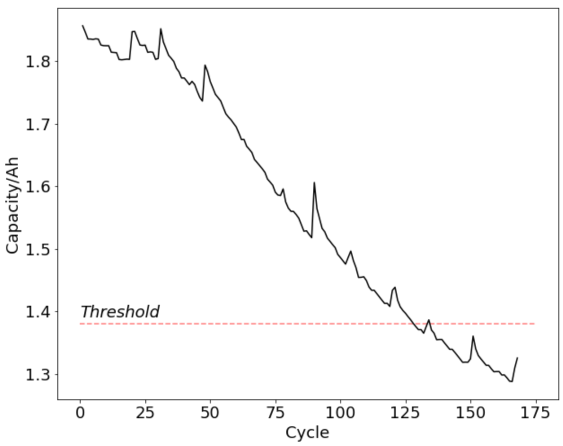

Figure 1. Battery dataset

3.2. Data-driven RUL Prediction

In the Bayesian approach, prior distributions are used to describe the uncertainty of the unknown parameters of model. Prior distributions of this study use flat prior or Normal distribution. In this study, the prior distributions are normal distribution. They are Eq. (8).

$$\begin{aligned} a &\sim Normal(\mu_a, s_a^2), \\ \lambda &\sim Normal(\mu_\lambda, s_\lambda^2), \\ \beta &\sim Normal(\mu_\beta, s_\beta^2), \\ c &\sim Normal(\mu_c, s_c^2), \end{aligned} \tag{8}$$

where λ >0 is scale parameter, β >0 is shape parameter.

The battery should be retired to ensure the safety and reliability of the battery performance in 80% of its initial capacity. In this study, staring point which means the current observation cycle is assumed to be the same for comparison with previous studies(Zhang, Mu, and Sun 2018; Liu et al. 2014). It is $T_{current} = 60, 80, 100$. Hierarchical Bayesian model is applied for searching the optimal initial values. Prior means of scale and shape parameter are flat priors. The number of MCMC simulations is 5,000 and acceptance rate is 0.9. When the starting point is 60, the final RUL prediction is shown in Figure 2.

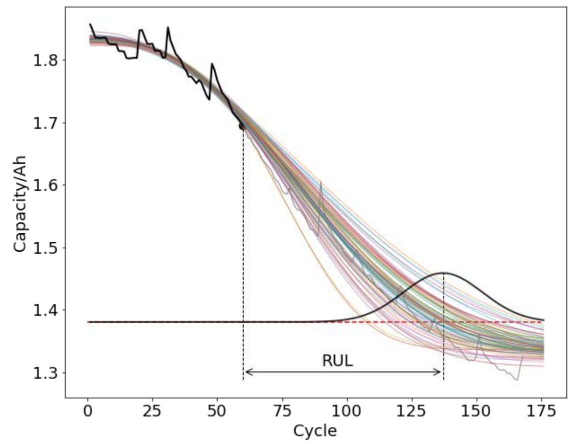

Figure 2. RUL prediction at starting point 60

3.3. Results

According to the three starting points, the predicted failure life and RUL is in Table 1.

Table 1. The RUL prediction error at the different starting point.

Staring point	Actual life/Actual RUL	Predicted life/Predicted RUL	RUL prediction error
60	128/68	138/78	10
80	128/48	114/34	14
100	128/28	131/31	3

The method with best performance is the method with lowest RUL prediction error. As shown in Table 2, the method of this study has a better performance than other studies except for result at starting point 80. It is better performance at starting point 60 when the data is insufficient.

Table 2. Comparison of other methods

Staring point	RUL prediction error			
	This study	PF (Zhang et al., 2018)	AR (Liu et al., 2014)	AR-RPF (Liu et al., 2014)
60	10	29	22	18
80	14	12	6	8
100	3	8	3	4

4. CONCLUSION

Accurate RUL prediction is critical to effective prognostic and health management (PHM) for improving reliability and safety of engineering systems. In this study, we proposed a novel RUL prediction method of lithium-ion battery. This method is useful to real-time RUL prediction by applying Bayesian estimation with Markov chain Monte Carlo (MCMC). The data-driven predictive model such as this model is useful for real-time RUL prediction because of characteristic of Bayesian updating.

In the empirical study, NASA battery data was applied in RUL prediction. This RUL prediction model was compared with three previous model. As a result, this model had a better performance than other previous models. Especially, it is better performance at starting point 60 when the data is insufficient. The RUL prediction model of this study can provide a better decision for predictive maintenance.

REFERENCES

Andre, D, A Nuhic, T Soczka-Guth, and Dirk Uwe Sauer. 2013. "Comparative study of a structured neural network and an extended Kalman filter for state of health determination of lithium-ion batteries in hybrid electricvehicles." *Engineering Applications of Artificial Intelligence* 26 (3): 951-961.

Andrieu, Christophe, Nando De Freitas, Arnaud Doucet, and Michael I Jordan. 2003. "An introduction to MCMC for machine learning." *Machine learning* 50 (1): 5-43.

He, Yi-Jun, Jia-Ni Shen, Ji-Fu Shen, and Zi-Feng Ma. 2015. "State of health estimation of lithium-ion batteries: A multiscale Gaussian process regression modeling approach." *AIChE Journal* 61 (5): 1589-1600.

Hu, Xiaosong, Changfu Zou, Caiping Zhang, and Yang Li. 2017. "Technological developments in batteries: a survey of principal roles, types, and management needs." *IEEE Power and Energy Magazine* 15 (5): 20-31.

Kim, TS, CS Park, and SE Ahn. 2008. "Determining the optimal maintenance action for a deteriorating repairable system." *Probabilistic engineering mechanics* 23 (1): 95-101.

Liu, Datong, Yue Luo, Jie Liu, Yu Peng, Limeng Guo, and Michael Pecht. 2014. "Lithium-ion battery remaining useful life estimation based on fusion nonlinear degradation AR model and RPF algorithm." *Neural Computing and Applications* 25 (3): 557-572.

Saha, B, and K Goebel. 2007. "Battery data set." *NASA AMES prognostics data repository*.

Waag, Wladislaw, Christian Fleischer, and Dirk Uwe Sauer. 2014. "Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles." *Journal of Power Sources* 258: 321-339.

Wang, Dong, Qiang Miao, and Michael Pecht. 2013. "Prognostics of lithium-ion batteries based on relevance vectors and a conditional three-parameter capacity degradation model." *Journal of Power Sources* 239: 253-264.

Zhang, Lijun, Zhongqiang Mu, and Changyan Sun. 2018. "Remaining useful life prediction for lithium-ion batteries based on exponential model and particle filter." *IEEE Access* 6: 17729-17740.

BIOGRAPHIES

Jihyun Park is currently working in Data Science team of Hyundai Mobis company.

Joonhyung Park is currently working in Data Science team of Hyundai Mobis company.