Journal of Systems Engineering and Electronics
Vol. 34, No. 1, February 2023, pp.247 – 258

Remaining useful life prediction based on nonlinear random coefficient regression model with fusing failure time data

WANG Fengfei, TANG Shengjin*, SUN Xiaoyan, LI Liang, YU Chuanqiang, and SI Xiaosheng

Department of Mechanical Engineering, Rocket Force University of Engineering, Xi'an 710025, China

Abstract: Remaining useful life (RUL) prediction is one of the most crucial elements in prognostics and health management (PHM). Aiming at the imperfect prior information, this paper proposes an RUL prediction method based on a nonlinear random coefficient regression (RCR) model with fusing failure time data. Firstly, some interesting natures of parameters estimation based on the nonlinear RCR model are given. Based on these natures, the failure time data can be fused as the prior information reasonably. Specifically, the fixed parameters are calculated by the field degradation data of the evaluated equipment and the prior information of random coefficient is estimated with fusing the failure time data of congeneric equipment. Then, the prior information of the random coefficient is updated online under the Bayesian framework, the probability density function (PDF) of the RUL with considering the limitation of the failure threshold is performed. Finally, two case studies are used for experimental verification. Compared with the traditional Bayesian method, the proposed method can effectively reduce the influence of imperfect prior information and improve the accuracy of RUL prediction.

Keywords: remaining useful life (RUL) prediction, imperfect prior information, failure time data, nonlinear, random coefficient regression (RCR) model.

DOI: 10.23919/JSEE.2023.000006

1. Introduction

Engineering practice shows that prognostic and health management (PHM) can reduce the risk of failure events and improve the reliability and safety through both prognostic and health management [1–3]. It is widely used in mechanical, electronic, medical, and other high reliability fields [4–6]. Remaining useful life (RUL) prediction is one of the most crucial parts in PHM [7,8]. In recent years, with the improvement of reliability for complex equipment, RUL prediction has attracted great attention by the scholars [9,10].

There are two common RUL prediction methods in PHM, namely physics-of-failure (PoF) and data-driven methods [10,11]. PoF approaches can provide more accurate RUL estimation based on the physics of underlying failure mechanisms [12]. However, it is typically difficult to obtain the physical failure mechanisms in advance for complex or large-scale engineering systems [13]. In contrast, the data-driven approaches can obtain the RUL of equipment through the condition monitoring (CM) data [14], such as vibration [15] and battery capacity [16], which are simpler than PoF approaches. The data-driven approaches include machine learning and statistical data-driven approaches [17]. Compared with machine learning approaches, the statistical data-driven approaches can derive an analytical expression of the probability density function (PDF) of RUL more easily. This is significant for determining the optimal maintenance time. In statistical data-driven approaches, the random coefficient regression (RCR) model is one of the earliest stochastic mathematical models for degradation modeling [14], which has been widely used in RUL prediction [18–21].

The CM data used by the data-driven approaches are mainly categorized into two classes, i.e., the historical degradation data of congeneric equipment and the field CM data of the evaluated equipment [2]. In general, the historical degradation data are used to estimate the fixed parameters [22] which describe the constant degradation features among all units of the population and the prior information of the random coefficient [23,24] that characterizes the unit-to-unit variability for a population of equipment. Then, under the Bayesian framework, the random coefficient is updated online by the field CM data. In this classical parameter estimation method, Bayesian theory is of paramount importance, which establishes a linkage between the historical degradation data and the field

Manuscript received March 10, 2021.
*Corresponding author.
This work was supported by National Natural Science Foundation of China (61703410;61873175;62073336;61873273;61773386;61922089).

CM data [2,10]. For the convenience of comparison, this classical parameter estimation method is called the traditional Bayesian method in this paper. More details of this traditional Bayesian method can be found in [10,18,25−27].

However, the traditional Bayesian methods in [10,18,25−27] mentioned above all rely on the prior information of fixed parameters and random coefficient in the model, which requires the existence of historical degradation data of congeneric equipment. Unfortunately, imperfect prior information often occurs, i.e., the historical degradation data of congeneric equipment are often inaccurate, incomplete [7,28] or even non-existent [13] in practical application. The main reason for this phenomenon is that the cost of building a complete historical degradation database is too high. In the existing literature research, there are two approaches to solve such problems. The first approach is the combination of the Kalman filter and the expectation maximization (EM) algorithm, which was first proposed by Wang et al. [29] and has been widely applied to RUL prediction based on the Wiener process [7,13,30−34]. Its main principle is that the posterior distribution of the hidden random coefficient is calculated by Kalman filtering based on the field CM data of the evaluated equipment and then the fixed parameters and random coefficient in the model are solved by the EM algorithm. This approach can overcome the impact of improper prior information on the RUL prediction. However, it also completely gets rid of the impact of prior information and only depends on the field CM data [10]. The second approach is to fuse failure time data of congeneric equipment to reduce the impact of incomplete historical degradation data. Compared with building a complete degradation database, the failure time data is easier to be obtained from historical maintenance (or repair) records [28]. The related research of fusing failure time data can be referred to Lehmann [35], Zhang et al. [36], Zhao et al. [37] and Sun et al. [38]. However, the random effects, i.e., the unit-to-unit variability, are not considered in these literature [28,35−38].

Through the relevant research of the above literature regarding fusing failure time data, we can find that there are still some problems to address for the degradation process based on the RCR model, which mainly include the following points.

(i) Gebraeel et al. [28] did not give the reason why the method of fusing failure time data works well and the estimation method of fixed parameters. After that, Tang et al. [2] gave a method to estimate the fixed parameters. In addition, Tang et al. [2] also explained why the method of fusing failure time data works well based on the natures of parameters estimation presented in the paper. However, [2] only aimed at the degradation process based on the Wiener process. Whether it is applicable to the degradation process based on the RCR model, including whether it has the same natures and whether the work with fusing failure time data is well, still remains to be solved.

(ii) The existing researches of fusing failure time data are mainly for the linear degradation process and the research on the RUL prediction based on the nonlinear RCR model with fusing failure time data still has not been presented. In actual conditions, many degradation trends are nonlinear.

(iii) The researches of fusing failure time data often ignore the existence of random effects. In 2009, Peng et al. [39] proved that the penalty of mis-fitting a random-effect model by a fixed-effect model was more serious than that of mis-fitting a fixed-effect model by a random-effect model.

(iv) The limitation of the failure threshold is not considered in most literature. For the equipment that does not fail at time t_k, it should be satisfied that $\omega - x_k > 0$ [1,10], where ω denotes the failure threshold and x_k denotes the actual degradation state of the equipment at time t_k.

To address the above problems, we first use the RCR model to model the nonlinear equipment degradation process. Then, the corresponding natures for parameters estimation of the RCR model are derived. This leads to the first contribution of this paper. Based on these natures of parameters estimation, we propose a parameters estimation method with fusing failure time data for the nonlinear RCR model. With the help of failure time data, this method uses the maximum likelihood estimation (MLE) to obtain the prior information of the random coefficient of the RCR model, which is the second contribution of this paper. Then, unlike the truncated cumulative distribution function (CDF) presented in Gebraeel et al. [18,19], we use the truncated normal distribution (TND) to model the failure threshold of equipment and the PDF of the RUL based on the nonlinear RCR model is derived, which is the third contribution of this paper. Finally, we use a numerical example and a case studies to verify the effectiveness of the RUL prediction method proposed in this paper, which can not only reduce the influence of imperfect prior information, but also effectively improve the accuracy of RUL prediction compared with the traditional Bayesian method.

The remaining parts of this paper are organized as follows: Section 2 and Section 3 give some natures of parameters estimation. In Section 4, a parameter estimation method with fusing failure time data and the PDF of the RUL based on the nonlinear RCR model with considering the limitation of failure threshold are given. A numerical example and a case study are provided in Section 5. Section 6 draws the main conclusions.

2. Natures of parameters estimation for the evaluated equipment

First, the RCR model is used to model the nonlinear degradation process. The degradation process based on the nonlinear RCR model can be expressed as follows:

$$X(t) = x_0 + \lambda \Lambda(t;\theta) \tag{1}$$

where $X(t)$ denotes the actual degradation state at time t; x_0 is the initial degradation state; λ is the drift coefficient, which characterizes the rate of degradation; $\Lambda(t;\theta)$ is a monotone continuous nonlinear function with t, characterizing a nonlinear degradation process, in which θ is the fixed parameter, describing the nonlinear relationship between degradation state and time. The typical nonlinear functions are $\Lambda(t;\theta) = t^\theta$ and $\Lambda(t;\theta) = \mathrm{e}^{\theta t} - 1$ [40]. Without loss of generality, we set $x_0 = 0$.

Due to measurement error between the actual degradation state $X(t)$ and the observed degradation state $Y(t)$, the observed degradation process can be expressed as

$$Y(t) = X(t) + \varepsilon \tag{2}$$

where ε denotes the measurement error and is normally distributed with zero mean and standard deviation σ_ε. In addition, ε is assumed to be identically distributed and s-independent with λ.

Before studying the natures of parameters estimation for the evaluated equipment, we first give the parameters estimation results based on the field CM data of the evaluated equipment.

2.1 MLE of parameters for evaluated equipment

Suppose that at time t_k, $Y_{1:k} = \{y_1, y_2, \cdots, y_k\}$ are the field CM data at times $t_1, t_2, \cdots, t_k$, then based on (1) and (2), we can obtain that $y_j \sim \mathrm{N}(\lambda\Lambda(t_j;\theta), \sigma_\varepsilon^2)$. Note that in this case, the drift coefficient λ is a constant for specific evaluated equipment. Therefore, the log-likelihood function can be written as

$$\ln L(\lambda, \sigma_\varepsilon^2 | Y_{1:k}) = -\frac{k}{2}(\ln(2\pi) + \ln\sigma_\varepsilon^2) - \frac{1}{2\sigma_\varepsilon^2}\sum_{j=1}^{k}(y_j - \lambda\Lambda(t_j;\theta))^2. \tag{3}$$

Then, the parameters estimation of λ and σ_ε^2 can be obtained [41] as follows:

$$\hat{\lambda} = \frac{\sum_{j=1}^{k} y_j \Lambda(t_j;\theta)}{\sum_{j=1}^{k}\left(\Lambda(t_j;\theta)^2\right)}, \tag{4}$$

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{k}\sum_{j=1}^{k}\left(y_j - \hat{\lambda}\Lambda(t_j;\theta)\right)^2. \tag{5}$$

Remark 1 The existing methods cannot obtain the analytical expression of $\hat{\theta}$. In general, the estimated value of θ is obtained through the Matlab function "FMINSEARCH".

2.2 Natures of parameters estimation

For the parameters estimation shown in (4) and (5), we get some interesting natures, which are summed up in Theorem 1.

Theorem 1 For the parameters estimation of λ and σ_ε^2 given in (4) and (5), the expectations and variances of λ and σ_ε^2 can be calculated respectively as follows:

$$\mathrm{E}(\hat{\lambda}) = \lambda, \tag{6}$$

$$\mathrm{D}(\hat{\lambda}) = \sigma_\varepsilon^2 \frac{1}{\sum_{j=1}^{k}\Lambda(t_j;\theta)^2}, \tag{7}$$

$$\mathrm{E}(\hat{\sigma}_\varepsilon^2) = \left(1 - \frac{1}{k}\right)\sigma_\varepsilon^2, \tag{8}$$

$$\mathrm{D}(\hat{\sigma}_\varepsilon^2) = 2\left(\frac{k-1}{k^2}\right)\sigma_\varepsilon^4. \tag{9}$$

Proof From (1) and (2), we can obtain

$$y_j \sim \mathrm{N}\left(\lambda\Lambda(t_j;\theta), \sigma_\varepsilon^2\right). \tag{10}$$

According to the natures of the normal distribution, we have

$$\sum_{j=1}^{k} y_j \Lambda(t_j;\theta) \sim \mathrm{N}\left(\lambda\sum_{j=1}^{k}\Lambda(t_j;\theta)^2, \sigma_\varepsilon^2\sum_{j=1}^{k}\Lambda(t_j;\theta)^2\right). \tag{11}$$

Then,

$$\hat{\lambda} = \frac{\sum_{j=1}^{k} y_j\Lambda(t_j;\theta)}{\sum_{j=1}^{k}\Lambda(t_j;\theta)^2} \sim \mathrm{N}\left(\lambda, \frac{\sigma_\varepsilon^2}{\sum_{j=1}^{k}\Lambda(t_j;\theta)^2}\right). \tag{12}$$

Thus,

$$\mathrm{E}(\hat{\lambda}) = \lambda, \tag{13}$$

$$\mathrm{D}(\hat{\lambda}) = \sigma_\varepsilon^2 \frac{1}{\sum_{j=1}^{k}\Lambda(t_j;\theta)^2}. \tag{14}$$

For (8), we have

$$\mathrm{E}\left(\hat{\sigma}_\varepsilon^2\right)=\mathrm{E}\left(\frac{1}{k}\sum_{j=1}^{k}\left(y_j-\hat{\lambda}\Lambda(t_j;\theta)\right)^2\right)=$$
$$\frac{1}{k}\mathrm{E}\left(\sum_{j=1}^{k}\left((y_j-\lambda\Lambda(t_j;\theta))-\left(\hat{\lambda}\Lambda(t_j;\theta)-\lambda\Lambda(t_j;\theta)\right)\right)^2\right)=$$
$$\frac{1}{k}\sum_{j=1}^{k}\mathrm{E}(y_j-\lambda\Lambda(t_j;\theta))^2-\sum_{j=1}^{k}\Lambda(t_j;\theta)^2\mathrm{E}\left(\hat{\lambda}-\lambda\right)^2=$$
$$\frac{1}{k}\left(\sum_{j=1}^{k}\mathrm{D}(y_j)-\mathrm{D}\left(\hat{\lambda}\right)\sum_{j=1}^{k}\Lambda(t_j;\theta)^2\right)=\left(1-\frac{1}{k}\right)\sigma_\varepsilon^2. \tag{15}$$

In addition, it is easy to know that $y_j\sim\mathrm{N}(\lambda\Lambda(t_j;\theta),\sigma_\varepsilon^2)$ and

$$\hat{\lambda}=\sum_{j=1}^{k}y_j\Lambda(t_j;\theta)/\left(\sum_{j=1}^{k}\Lambda(t_j;\theta)^2\right)\sim\mathrm{N}\left(\lambda,\sigma_\varepsilon^2/\left(\sum_{j=1}^{k}\Lambda(t_j;\theta)^2\right)\right).$$

Then,

$$\frac{1}{\sigma_\varepsilon^2}\sum_{j=1}^{k}\left(y_j-\hat{\lambda}\Lambda(t_j;\theta)\right)^2\sim\chi^2(k-1), \tag{16}$$

$$\mathrm{D}\left(\hat{\sigma}_\varepsilon^2\right)=\mathrm{D}\left(\frac{1}{k}\sum_{j=1}^{k}\left(y_j-\hat{\lambda}\Lambda(t_j;\theta)\right)^2\right)=$$
$$\frac{1}{k^2}\mathrm{D}\left(\sum_{j=1}^{k}\left(y_j-\hat{\lambda}\Lambda(t_j;\theta)\right)^2\right)=2\left(\frac{k-1}{k^2}\right)\sigma_\varepsilon^4. \tag{17}$$

□

Remark 2 Since the estimation of θ cannot get the analytical expression, to further analyze the natures of parameters estimation, it is assumed that the estimation of θ is equal to the actual θ here. The corresponding nature of $\hat{\theta}$ is proved by simulation data in Subsection 5.1.

From (7) and (9) in Theorem 1, the accuracy of parameters estimation of λ and σ_ε^2 is mainly effected by the number k of the detection time. The variances of parameters estimation of λ and σ_ε^2 become small as the number k increases.

3. Natures of drift coefficient with considering random effects

With considering the existence of the random effects, the drift coefficient λ is assumed to be a random variable that follows normal distribution, i.e., $\lambda\sim\mathrm{N}(\mu_\lambda,\sigma_\lambda^2)$, which describes the unit-to-unit variability among equipment. Theorem 1 only analyzes the natures of parameters estimation based on the evaluated equipment. Thus, in this section, we further analyze the natures of drift coefficient with considering the random effects.

3.1 Parameters estimation of drift coefficient with considering random effects

In order to address the problem of obtaining a negative variance of the drift parameter, Tang et al. [10] simplified the two-step MLE method proposed by Lu and Meeker [42] and applied it to the Wiener process. In addition, the analytical expressions of μ_λ and σ_λ^2 can be obtained by the two-step MLE method, which is more convenient to analyze the natures of drift coefficient than the traditional MLE method. Then, we apply it to the RCR model.

Without loss of generality, it is assumed that there are n items with the same type and the degradation data at time $t_1,t_2,\cdots,t_m$ of the ith item is $y_i=\{y_{i,1},y_{i,2},\cdots,y_{i,m}\}$.

Then, the parameters estimation of μ_λ and σ_λ^2 can be calculated by the two-step MLE as follows:

$$\hat{\mu}_\lambda=\frac{1}{n}\sum_{i=1}^{n}\frac{\sum_{j=1}^{m}y_{i,j}\Lambda(t_j;\theta)}{\sum_{j=1}^{m}\Lambda(t_j;\theta)^2}, \tag{18}$$

$$\hat{\sigma}_\lambda^2=\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{j=1}^{m}y_{i,j}\Lambda(t_j;\theta)}{\sum_{j=1}^{m}\Lambda(t_j;\theta)^2}-\hat{\mu}_\lambda\right)^2. \tag{19}$$

3.2 Natures of drift coefficient

Inspired by Tang et al. [2], we obtain some natures of drift coefficient based on the nonlinear RCR model with considering the random effects, which are summarized in Theorem 2.

Theorem 2 For the nonlinear RCR model described in (2), the expectations and variances of μ_λ and σ_λ^2 can be expressed respectively as follows:

$$\mathrm{E}(\hat{\mu}_\lambda)=\mu_\lambda, \tag{20}$$

$$\mathrm{D}(\hat{\mu}_\lambda)=\frac{1}{n}\cdot\frac{\sigma_\lambda^2\sum_{j=1}^{m}\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\sum_{j=1}^{m}\Lambda(t_j;\theta)^2}{\left(\sum_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^2}, \tag{21}$$

$$\mathrm{E}\left(\hat{\sigma}_\lambda^2\right)=\left(1-\frac{1}{n}\right)\cdot\frac{\left(\sigma_\lambda^2\sum_{j=1}^{m}\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\sum_{j=1}^{m}\Lambda(t_j;\theta)^2\right)}{\left(\sum_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^2}, \tag{22}$$

$$\mathrm{D}\left(\hat{\sigma}_\lambda^2\right)=\frac{(n-1)}{n^2}\cdot\frac{2\left(\sigma_\lambda^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^2}{\left(\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^4}. \tag{23}$$

Proof From (1) and (2), we can obtain $y_{i,j}=\lambda\Lambda(t_j;\theta)+\varepsilon$.

In addition, since $\lambda\sim\mathrm{N}(\mu_\lambda,\sigma_\lambda^2)$, $\varepsilon\sim\mathrm{N}(0,\sigma_\varepsilon^2)$, and ε is s-independent with λ, $y_{i,j}\sim\mathrm{N}\left(\mu_\lambda\Lambda(t_j;\theta),\sigma_\lambda^2\Lambda(t_j;\theta)^2+\sigma_\varepsilon^2\right)$ can be obtained.

Thus, $y_{i,j}\Lambda(t_j;\theta)$ also obeys a normal distribution:

$$y_{i,j}\Lambda(t_j;\theta)\sim\mathrm{N}\left(\mu_\lambda\Lambda(t_j;\theta)^2,\sigma_\lambda^2\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\Lambda(t_j;\theta)^2\right). \tag{24}$$

According to the natures of the normal distribution, we have

$$\frac{\sum\limits_{j=1}^{m}y_{i,j}\Lambda(t_j;\theta)}{\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2}\sim\mathrm{N}\left(\mu_\lambda,\frac{\sigma_\lambda^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2}{\left(\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^2}\right). \tag{25}$$

Thus,

$$\mathrm{E}\left(\hat{\mu}_\lambda\right)=\mathrm{E}\left(\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum\limits_{j=1}^{k}y_{i,j}\Lambda(t_j;\theta)}{\sum\limits_{j=1}^{k}\Lambda(t_j;\theta)^2}\right)\right)=\mu_\lambda, \tag{26}$$

$$\mathrm{D}\left(\hat{\mu}_\lambda\right)=\frac{1}{n}\frac{\sigma_\lambda^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2}{\left(\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^2}. \tag{27}$$

In addition, according to the natures of the Chi-squared distribution, we have

$$\frac{\left(\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^2}{\sigma_\lambda^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2}\cdot\sum_{i=1}^{n}\left(\frac{\sum\limits_{j=1}^{m}y_{i,j}\Lambda(t_j;\theta)}{\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2}-\mu_\lambda\right)^2\sim\chi^2(n-1). \tag{28}$$

Then, we can obtain

$$\mathrm{E}\left(\hat{\sigma}_\lambda^2\right)=\left(1-\frac{1}{n}\right)\cdot\frac{\left(\sigma_\lambda^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)}{\left(\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^2}, \tag{29}$$

$$\mathrm{D}\left(\hat{\sigma}_\lambda^2\right)=\frac{(n-1)}{n^2}\cdot\frac{2\left(\sigma_\lambda^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^4+\sigma_\varepsilon^2\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^2}{\left(\sum\limits_{j=1}^{m}\Lambda(t_j;\theta)^2\right)^4}. \tag{30}$$

□

Remark 3 From (21) and (23), the accuracy of parameters estimation of μ_λ and σ_λ^2 is mainly effected by number N of the congeneric equipment sample and number k of the detection time. When the detection time is fixed for equipment, increasing number N of sample can improve the accuracy of parameters estimation of μ_λ and σ_λ^2.

4. RUL prediction with fusing failure time data

In practical application, the traditional Bayesian method may be unable to obtain the accurate prior information of the unknown parameters in the model due to the imperfect prior information, which could decrease the RUL accuracy. In order to solve this problem, according to the natures of parameters estimation derived in Section 2 and Section 3, this section proposes an RUL prediction method based on the nonlinear RCR model that reasonably fuses the failure time data of congeneric equipment and the field CM data of the evaluated equipment. The flow chart of this method is shown in Fig. 1.

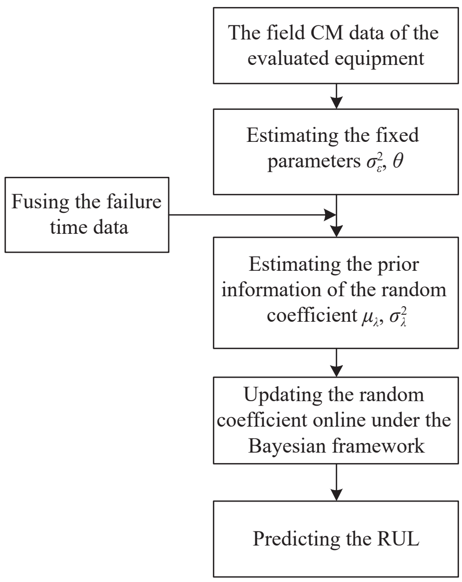


Fig. 1 Flow chart of RUL prediction with fusing failure time data

The main steps are as follows:

Step 1 Based on the field CM data of the evaluated equipment, the fixed parameters that describe constant degradation features among all units of the population can be obtained. Then, the prior information of the random coefficient that characterizes the unit-to-unit variability for a population of equipment can be calculated by fusing failure time data of congeneric equipment.

Step 2 The prior information of the random coefficient is updated online based on the field CM data of the evaluated equipment under Bayesian framework. Then, RUL of the evaluated equipment with considering the limitation of the failure threshold can be obtained.

Note that the method with fusing failure time data proposed in this paper only utilizes the failure time data and the field CM data, and avoids using the historical degradation data, which is the most obvious difference from the traditional Bayesian method. Next, according to the flow chart, calculate the RUL of the evaluated equipment.

4.1 Parameters estimation

The prior parameters in the degradation model based on the nonlinear RCR model are $\{\mu_\lambda,\sigma_\lambda^2,\sigma_\varepsilon^2,\theta\}$. In the following, the prior parameters are solved according to the flow chart, as shown in Fig. 1.

(i) Estimating the fixed parameters based on the field CM data of the evaluated equipment.

From (5), we have

$$\hat{\sigma}_\varepsilon^2\left(\hat{\theta}\right)=\frac{1}{k}\sum_{j=1}^{k}\left(y_j-\hat{\lambda}\Lambda(t_j;\theta)\right)^2. \tag{31}$$

Then, by substituting (4) and (31) into (3), after simplification, we obtain the profile log-likelihood function of θ as follows:

$$\ln L(\theta|Y_{1:k})=-\frac{k}{2}\ln(2\pi)-\frac{k}{2}\ln\left(\hat{\sigma}_\varepsilon^2\right)-\frac{k}{2}. \tag{32}$$

The estimation of θ can be obtained by maximizing the profile log-likelihood function in (32) through Matlab function “FMINSEARCH”. Then, the estimations of $\hat{\sigma}_\varepsilon^2$ can be obtained by bring $\hat{\theta}$ into (31).

(ii) Calculating the prior information of the random coefficient with fusing failure time data of congeneric equipment.

According to the natures of the nonlinear RCR model, the PDF of failure lifetime T_v of equipment can be written as

$$f_{T_v|\omega}(t_v|\omega)=\frac{\omega\Lambda'(t_v;\theta)}{\sqrt{2\pi\sigma_\lambda^2\Lambda(t_v;\theta)^4}}\bullet\exp\left(-\frac{(\omega-\mu_\lambda\Lambda(t_v;\theta))^2}{2\sigma_\lambda^2\Lambda(t_v;\theta)^2}\right). \tag{33}$$

Suppose that there are M items and their failure time data are $T_{1:M}=\{t_1,t_2,\cdots,t_m\}$, then, the log-likelihood function can be expressed as follows:

$$\ln L\left(\mu_\lambda,\sigma_\lambda^2|T_{1:M}\right)=m\ln\omega-m\ln\Lambda'(t_v;\theta)-\frac{m}{2}\ln(2\pi)-\frac{m}{2}\ln\sigma_\lambda^2-2m\ln\Lambda(t_v;\theta)-\frac{1}{2\sigma_\lambda^2}\sum_{v=1}^{m}\frac{(\omega-\mu_\lambda\Lambda(t_v;\theta))^2}{(\Lambda(t_v;\theta))^2}. \tag{34}$$

Taking the first partial derivatives of $\ln L(\mu_\lambda,\sigma_\lambda^2|T_{1:M})$ with respect to μ_λ and σ_λ^2 gives

$$\frac{\partial\ln L(\mu_\lambda,\sigma_\lambda^2|T_{1:M})}{\partial\mu_\lambda}=\frac{1}{\sigma_\lambda^2}\sum_{v=1}^{m}\frac{(\omega-\mu_\lambda\Lambda(t_v;\theta))\Lambda(t_v;\theta)}{(\Lambda(t_v;\theta))^2} \tag{35}$$

and

$$\frac{\partial\ln L(\mu_\lambda,\sigma_\lambda^2|T_{1:M})}{\partial\sigma_\lambda^2}=-\frac{m}{2}\frac{1}{\sigma_\lambda^2}+\frac{1}{2(\sigma_\lambda^2)^2}\bullet\sum_{v=1}^{m}\frac{(\omega-\mu_\lambda\Lambda(t_v;\theta))^2}{(\Lambda(t_v;\theta))^2}. \tag{36}$$

Then, by setting these derivatives to zeros, the parameters estimation of μ_λ and σ_λ^2 can be written as

$$\hat{\mu}_\lambda=\frac{\omega}{m}\sum_{v=1}^{m}\frac{1}{\Lambda(t_v;\theta)}, \tag{37}$$

$$\hat{\sigma}_\lambda^2=\frac{1}{m}\sum_{v=1}^{m}\frac{(\omega-\hat{\mu}_\lambda\Lambda(t_v;\theta))^2}{(\Lambda(t_v;\theta))^2}. \tag{38}$$

4.2 Online parameter updating

Let the parameters estimation of μ_λ and σ_λ^2 in the previous subsection be the prior information $\mu_{\lambda0}$ and $\sigma_{\lambda0}^2$ of the random coefficient, i.e., $\lambda\sim\mathrm{N}(\mu_{\lambda0},\sigma_{\lambda0}^2)$. Given the field CM data $y_{1:k}$, the posterior distribution can be calculated by Bayesian theory [43] as follows:

$$\lambda|y_{1:k}\sim\mathrm{N}(\mu_{\lambda,k},\sigma_{\lambda,k}^2) \tag{39}$$

where

$$\mu_{\lambda,k}=\frac{\sigma_{\lambda0}^2\sum_{i=1}^{k}y_i\Lambda(t_i;\theta)+\sigma_\varepsilon^2\mu_{\lambda0}}{\sigma_{\lambda0}^2\sum_{i=1}^{k}\Lambda(t_i;\theta)^2+\sigma_\varepsilon^2},$$

$$\sigma_{\lambda,k}^2=\frac{\sigma_{\lambda0}^2\sigma_\varepsilon^2}{\sigma_{\lambda0}^2\sum_{i=1}^{k}\Lambda(t_i;\theta)^2+\sigma_\varepsilon^2}. \tag{40}$$

4.3 RUL prediction

For the degradation process based on the RCR model, lifetime T can be defined as the time that the degradation process exceeds a pre-set failure threshold. Let $T=t_k+l_k$

denote the lifetime of equipment, where t_k denotes the current time and l_k denotes the RUL at time t_k. Then, the degradation process in (1) can be transformed into

$$Z(l_k) = X(l_k+t_k) - X(t_k) = \lambda\Delta\Lambda(l_k;\theta) \tag{41}$$

where $\Delta\Lambda(l_k;\theta) = \Lambda(l_k+t_k;\theta) - \Lambda(t_k;\theta)$. Without loss of generality, we set $Z(0) = 0$.

The corresponding RUL at time t_k can be written as

$$\begin{aligned} L_k = \{l_k : X(x_k+l_k) > \omega | x_0 < \omega\} = \\ \{l_k : Z(l_k) \geqslant \omega - x_k | Z(0) < \omega - x_k\}. \end{aligned} \tag{42}$$

Then, if $\omega - x_k$ is given, the PDF for the RUL of the equipment can be obtained as follows:

$$\begin{aligned} f_{L_k|\omega_k}(l_k|\omega_k) = \frac{\omega_k\Delta\Lambda'(l_k;\theta)}{\sqrt{2\pi\sigma_{\lambda,k}^2\Delta\Lambda(l_k;\theta)^4}}\cdot \\ \exp\left(-\frac{(\omega_k-\mu_{\lambda,k}\Delta\Lambda(l_k;\theta))^2}{2\sigma_{\lambda,k}^2\Delta\Lambda(l_k;\theta)^2}\right) \end{aligned} \tag{43}$$

where $\omega_k = \omega - x_k$ and x_k denotes the actual degradation state at time t_k.

From (2), we have $x_k \sim \mathrm{N}(y_k, \sigma_\varepsilon^2)$. Therefore, $(\omega - x_k) \sim \mathrm{N}(\omega - y_k, \sigma_\varepsilon^2)$. Then, in order to satisfy the condition that $\omega - x_k > 0$, we use the TND to model $\omega - x_k$, that is, $(\omega - x_k) \sim \mathrm{TN}(\omega - y_k, \sigma_\varepsilon^2)$.

Therefore, given the field CM data $y_{1:k}$, based on Lemma 1 proposed by Tang et al. [10], the PDF of the RUL based on the nonlinear RCR model with considering $\omega - x_k > 0$ can be derived by using the law of total probability as follows:

$$\begin{aligned} f_{L_k|y_{1:k}}(l_k|y_{1:k}) = \frac{\sqrt{G}\Delta\Lambda'(t;\theta)}{2\pi\Delta\Lambda(t;\theta)D\Phi(\mu\bullet\sigma_\varepsilon^{-1})}\cdot \\ \exp\left(-\frac{\mu_{\lambda,k}^2\Delta\Lambda(t;\theta)^2\sigma_\epsilon^2+\mu^2\sigma_{\lambda,k}^2\Delta\Lambda(t;\theta)^2}{2G}\right)+ \\ \frac{E\Delta\Lambda'(t;\theta)\Phi\left(\frac{E}{\sqrt{DG}}\right)}{\sqrt{2\pi\Delta\Lambda(t;\theta)^2D^3}\Phi(\mu\bullet\sigma_\varepsilon^{-1})}\cdot\exp\left(-\frac{(\mu-\mu_{\lambda,k}\Delta\Lambda(t;\theta))^2}{2D}\right) \end{aligned} \tag{44}$$

where

$$\mu = \omega - y_k, \tag{45}$$

$$D = \mu_{\lambda,k}^2\Delta\Lambda(t;\theta)^2 + \sigma_\varepsilon^2, \tag{46}$$

$$E = \mu_{\lambda,k}\Delta\Lambda(t;\theta)\sigma_\varepsilon^2 + \mu\sigma_{\lambda,k}^2\Delta\Lambda(t;\theta)^2, \tag{47}$$

$$G = \mu_{\lambda,k}^2\Delta\Lambda(t;\theta)^2\sigma_\varepsilon^2. \tag{48}$$

5. Experiment study

5.1 Simulation experiments

First, we use a numerical example to show the effectiveness of Theorem 1. Let $\Lambda(t;\theta) = t^b$. The parameters in the degradation process are assumed as $\lambda = 1$, $\sigma_\varepsilon^2 = 0.04$ and $b = 1.5$. Let $t_k = 1\,000$ and $\Delta t = 1$. The corresponding degradation path is shown in Fig. 2.

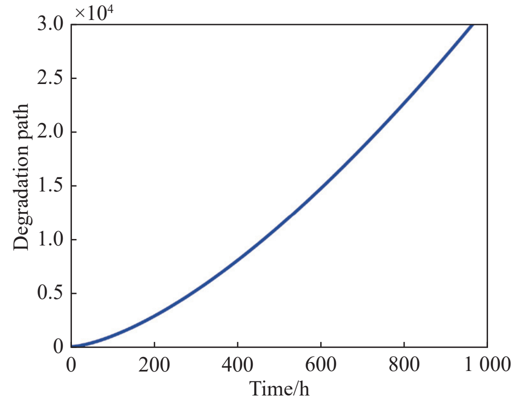


Fig. 2 Degradation path

Based on the simulated degradation data, the estimations of λ and σ_ε^2 with the change of t can be calculated respectively by (4) and (5) as shown in Fig. 3 and Fig. 4.

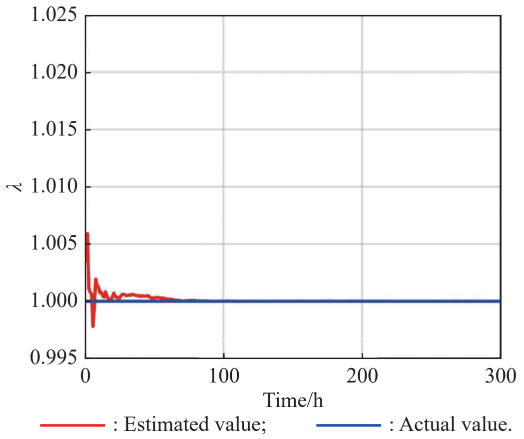


Fig. 3 Estimation of λ with the change of t

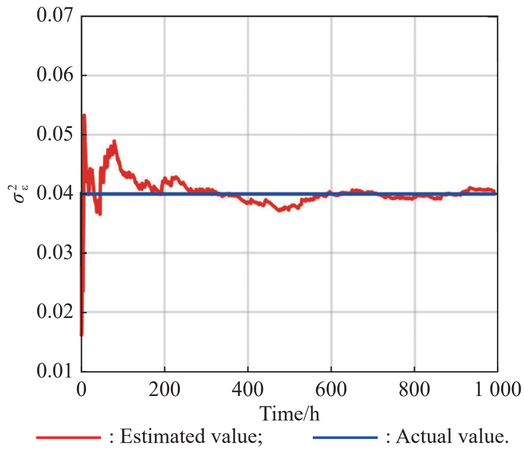


Fig. 4 Estimation of σ_ε^2 with the change of t

From Fig. 3 and Fig. 4, we can find that the estimations of λ and σ_ε^2 tend to the actual value as detection time t increases. In addition, the fluctuations of the estimations for λ and σ_ε^2 tend to be stable as detection time t gets larger, which also proves that increasing the number of on-site monitored degradation data can improve the accuracy of parameters estimation for fixed parameters. The estimation of θ with the change of t obtained through the Matlab function "FMINSEARCH" is shown in Fig. 5, which also shows that the estimation of b converges rapidly to the actual value as t increases. Although the nature of the fixed parameter θ cannot be analyzed by the analytical expression of $\hat{\theta}$ in theory, the simulation results indicate that the fixed parameter θ can be calculated based on the field CM data of the evaluated equipment.

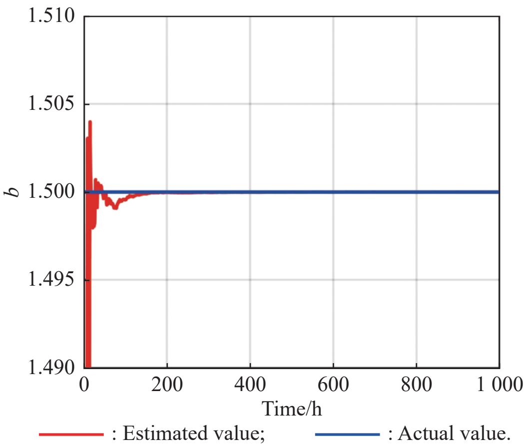


Fig. 5 Estimation of b with the change of t

Then, the parameters in the degradation process are assumed as $\mu_\lambda = 0.8$, $\sigma_\lambda^2 = 0.022\,5$, $\sigma_\varepsilon^2 = 1.44$, and $b = 1.5$. Let $t_k = 50$ and $N = 5, 10$, and 20. The corresponding partial degradation path is shown in Fig. 6.

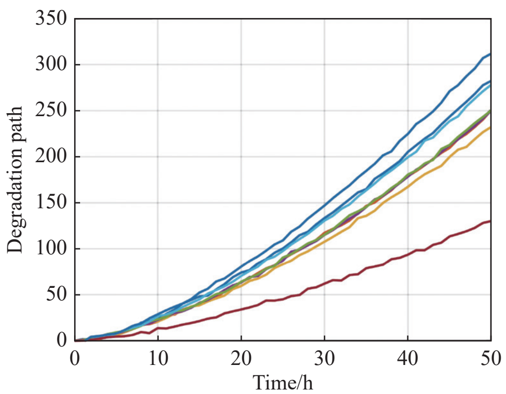


Fig. 6 Partial degradation path

Based on simulated degradation data, the estimations of μ_λ and σ_λ^2 with the change of t can be calculated respectively by (18) and (19) as shown in Fig. 7 and Fig. 8.

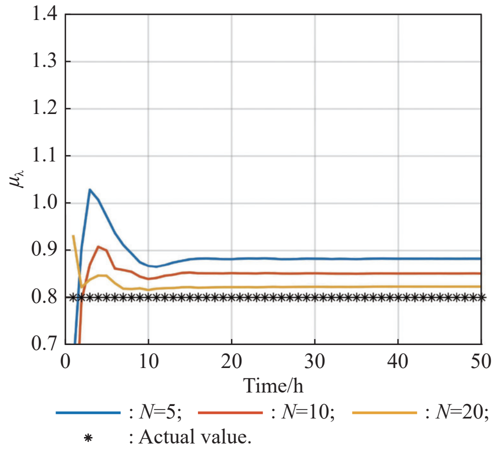


Fig. 7 Estimation of μ_λ with the change of N

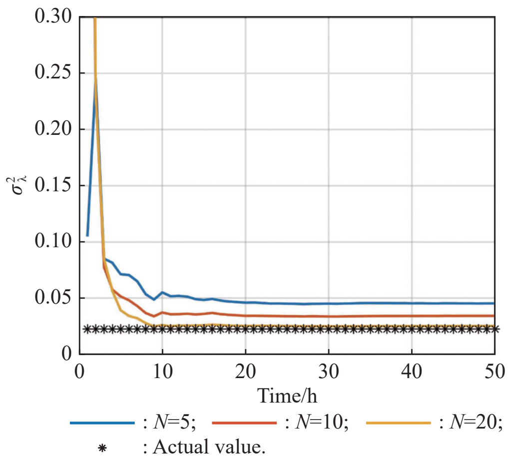


Fig. 8 Estimation of σ_λ^2 with the change of N

From Fig. 7 and Fig. 8, we can find that the estimations of μ_λ and σ_λ^2 tend to the actual value as the number of equipment sample N increases. In addition, the fluctuations of the estimations for μ_λ and σ_λ^2 tend to be stable as the number of equipment sample N gets larger, which also proves that increasing the number N of sample can improve the accuracy of parameters estimation for random coefficients.

5.2 Case study

In this subsection, we use the degradation data collected from the National Aeronautics and Space Administration (NASA) Ames Prognostics Center of Excellence to illustrate the effectiveness of the RUL prediction presented in this paper. The degradation data of lithium-ion batteries are shown in Fig. 9. The relaxation effect (RE) of battery capacity during the rest time [44] will affect the accuracy of RUL prediction. Thus, we use degradation data of lithium-ion batteries after eliminating the RE as shown in Fig. 10. The method of eliminating the RE can refer to Jin et al. [44] and Tang et al. [10].

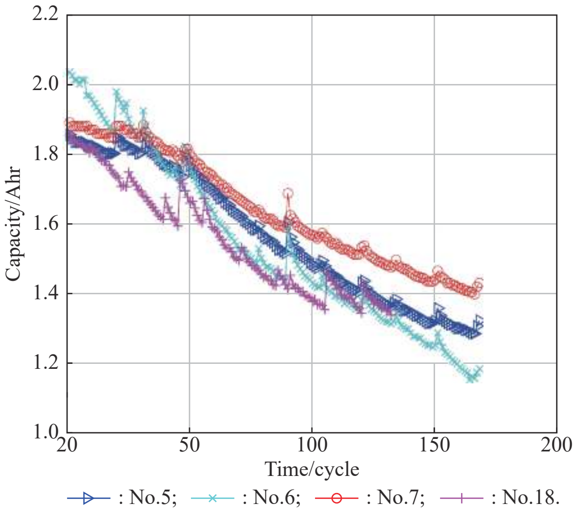


Fig. 9 Degradation data of lithium batteries

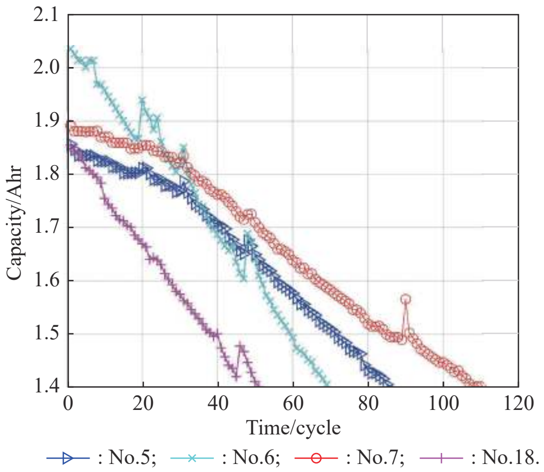


Fig. 10 Degradation path after eliminating the RE

The failure threshold of lithium-ion battery is defined as 70%—80% of its rated capacity. In this paper, the failure threshold is set as 70% capacity. Without loss of generality, let $\Lambda(t;\theta)=t^b$. In order to compare the method with fusing failure time data presented in this paper with the traditional Bayesian method, we select No.5 lithium-ion battery as the evaluated equipment and the degradation data of the other lithium-ion batteries are treated as historical degraded data of congeneric equipment to calculate the correct prior information of parameters in the traditional Bayesian method.

For simplicity, the method of RUL prediction based on the RCR model with fusing the failure time data is referred to M_0, the traditional Bayesian method based on the RCR model is referred to M_1 and the traditional Bayesian method based on the Wiener process is referred to M_2 [2]. First, based on the degradation data of No.6, No.7, and No.18 lithium-ion batteries, the prior information of parameters based on the RCR model can be calculated as follows: $\mu_\lambda = 0.004\,1$, $\sigma_\lambda^2 = 1.85\times10^{-6}$, $\sigma_\varepsilon^2 = 4.97\times10^{-4}$, and $b = 1.156\,5$. And, the failure lifetimes of No.6, No.7, and No.18 batteries are 69.5, 110.3, and 51 respectively.

Then, the RUL distributions calculated by M_0, M_1 and M_2 at some points are shown in Fig. 11 where it can be found that the RUL distributions calculated by three methods can cover the actual RUL of the battery. However, the RULs predicted by M_0 are closer to the actual RUL and focused, which shows that the method proposed in this paper is more accurate.

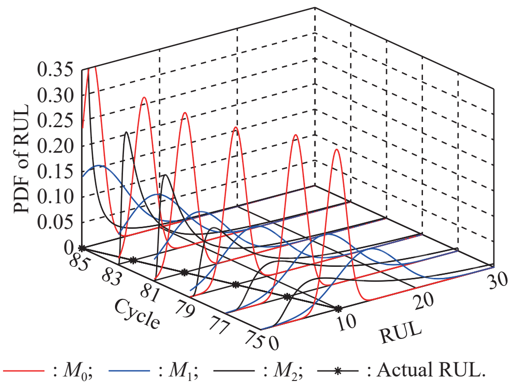


Fig. 11 Estimated PDFs of RUL by M_0, M_1, and M_2

In order to show the effectiveness of these methods more intuitively, we further calculate the mean squared errors (MSEs) and REs at some points as shown in Fig. 12 and Fig. 13.

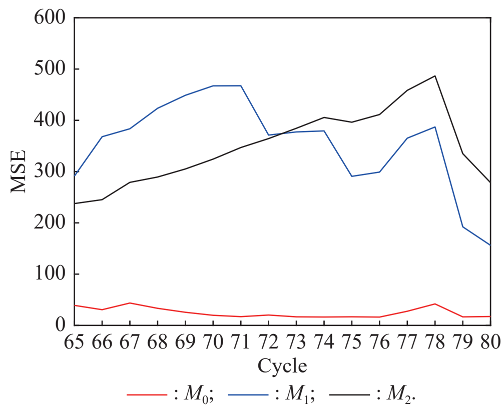


Fig. 12 MSEs at some CM points by M_0, M_1, and M_2

The MSEs and RE at each observation point are calculated as follows:

$$\mathrm{MSE}_k = \int_0^{+\infty} (l_k + t_k - T)^2 f_{L_k|y_{1:k}}(l_k|y_{1:k})\mathrm{d}l_k, \qquad (49)$$

$$\mathrm{RE}_k = |l_k + t_k - T|. \tag{50}$$

The results show that the MSEs and REs of RUL predicted by our method are better than those predicted by the traditional Bayesian method at all CM points, which reflects the superiority of our method.

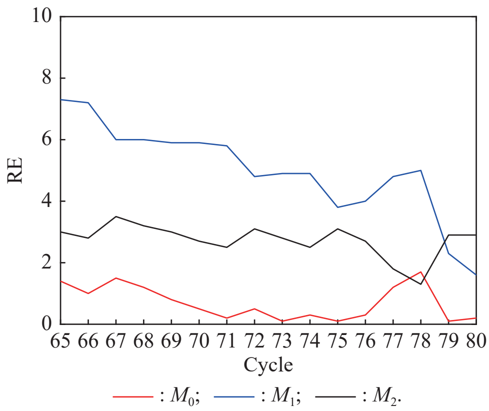


Fig. 13 REs at some CM points by M_0, M_1, and M_2

6. Conclusions

Improving the accuracy of RUL prediction is the core of RUL prediction. This paper proposes an RUL prediction method with fusing the failure time data to reduce the influence of imperfect prior information. First, some natures of parameters estimation based on the nonlinear RCR model are given. Second, based on the natures of parameters estimation, the fixed parameters and random coefficient are obtained. Then, an RUL prediction method with fusing failure time data is proposed. From above works, the main contributions can be summarized as follows:

(i) Based on the nonlinear RCR model, this paper gives the natures of parameters estimation. This gives the theoretical basis of the parameters estimation method with fusing failure time data.

(ii) Based on the natures of parameters estimation, we propose a parameter estimation method with fusing failure time data and field CM data for the degradation process based on the nonlinear RCR model with considering the random effects. This method utilizes the failure time data instead of the historical degradation data. Thus, it can reduce the impact of imperfect prior information.

(iii) TND is used to model the failure threshold in predicting the RUL to satisfy the limitation. The PDF of the RUL based on the nonlinear RCR model is derived.

References

[1] WANG Z Z, CHEN Y X, CAI Z Y, et al. Methods for predicting the remaining useful life of equipment in consideration of the random failure threshold. Journal of Systems Engineering and Electronics, 2020, 31(2): 415–431.

[2] TANG S J, XU X D, YU C Q, et al. Remaining useful life prediction with fusing failure time data and field degradation data with random effects. IEEE Access, 2020, 8: 11964–11978.

[3] ZHANG H W, CHEN M Y, ZHOU D H. Remaining useful life prediction for a nonlinear multi-degradation system with public noise. Journal of Systems Engineering and Electronics, 2018, 29(2): 429–435.

[4] ZHANG J L, LEE J. A review on prognostics and health monitoring of Li-ion battery. Journal of Power Sources, 2011, 196(15): 6007–6014.

[5] ARVIND S S V, BING L, MICHAEL P. Diagnostics and prognostics method for analog electronic circuits. IEEE Trans. on Industrial Electronics, 2013, 60(11): 5277–5291.

[6] CAI Z, CHEN Y X, ZHANG Q, et al. Residual lifetime prediction model of nonlinear accelerated degradation data with measurement error. Journal of Systems Engineering and Electronics, 2017, 28(5): 1028–1038.

[7] FAN Z L, LIU G B, SI X S. Degradation data-drive approach for remaining useful life estimation. Journal of Systems Engineering and Electronics, 2013, 24(1): 173–182.

[8] ZHANG J X, HU C H, HE X, et al. A novel lifetime estimation method for two-phase degrading systems. IEEE Trans. on Reliability, 2019, 68(2): 689–709.

[9] SI X S, WANG W B, HU C H, et al. Remaining useful life estimation based on a nonlinear diffusion degradation process. IEEE Trans. on Reliability, 2012, 61(1): 50–67.

[10] TANG S J, YU C Q, WANG X, et al. Remaining useful life prediction of lithium-ion batteries based on the wiener process with measurement error. Energies, 2014, 7(2): 520–547.

[11] CAI Z Y, CHEN Y X, GUO J S. Remaining lifetime prediction for nonlinear degradation device with random effect. Journal of Systems Engineering and Electronics, 2018, 29(5): 1101–1110.

[12] LEI Y G, LI N P, GUO L, et al. Machinery health prognostics: a systematic review from data acquisition to RUL prediction. Mechanical Systems and Signal Processing, 2018, 104: 799–834.

[13] SI X S, WANG W, HU C H, et al. A Wiener-process-based degradation model with a recursive filter algorithm for remaining useful life estimation. Mechanical Systems and Signal Processing, 2013, 35(1/2): 219–237.

[14] SI X S, WANG W, HU C H, et al. Remaining useful life estimation—a review on the statistical data driven approaches. European Journal of Operational Research, 2011, 213(1): 1–14.

[15] ZHANG Z X, SI X S, HU C H. An age- and state-dependent nonlinear prognostic model for degrading systems. IEEE Trans. on Reliability, 2015, 64(4): 1214–1228.

[16] TANG S J, GUO X S, ZHOU Z J. Mis-specification analysis of linear Wiener process-based degradation models for the remaining useful life estimation. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 2014, 228(5): 478–487.

[17] CAI Z Y, ZHOU W Z, XIANG C Y. Remaining useful lifetime prediction for equipment based on nonlinear implicit degradation modeling. Journal of Systems Engineering and

Electronics, 2020, 31(1): 194–205.

[18] GEBRAEEL N Z, LAWLEY M A, LI R, et al. Residual-life distributions from component degradation signals: a Bayesian approach. IIE Transactions, 2005, 37(6): 543–557.

[19] GEBRAEEL N. Sensory-updated residual life distributions for components with exponential degradation patterns. IEEE Trans. on Automation Science and Engineering, 2006, 3(4): 382–393.

[20] GEBRAEEL N, PAN J. Prognostic degradation models for computing and updating residual life distributions in a time-varying environment. IEEE Trans. on Reliability, 2008, 57(4): 539–550.

[21] BAE S J, KVAM P H. A nonlinear random-coefficients model for degradation testing. Technometrics , 2004, 46(4): 460–469.

[22] HUI P D, BAO L J, ZHI Y W. A new result on lifetime estimation based on skew-Wiener degradation model. Statistics and Probability Letters, 2018, 138: 157–164.

[23] YE Z S, CHEN N, SHEN Y. A new class of Wiener process models for degradation analysis. Reliability Engineering & System Safety, 2015, 139: 58–67.

[24] YE Z S, WANG Y, TSUI K L, et al. Degradation data analysis using wiener processes with measurement errors. IEEE Trans. on Reliability, 2013, 62(4): 772–780.

[25] SI X S, WANG W, HU C H, et al. Estimating remaining useful life with three-source variability in degradation modeling. IEEE Trans. on Reliability, 2014, 63(1): 167–190.

[26] WANG Z Q, HU C H, FAN H D. Real-time remaining useful life prediction for a nonlinear degrading system in service: application to bearing data. IEEE/ASME Trans. on Mechatronics, 2018, 23(1): 211–222.

[27] TANG S J, GUO X S, YU C Q, et al. Real time remaining useful life prediction based on nonlinear Wiener based degradation processes with measurement errors. Journal of Central South University, 2014, 21(12): 4509–4517.

[28] GEBRAEEL N, ELWANY A, PAN J. Residual life predictions in the absence of prior degradation knowledge. IEEE Trans. on Reliability, 2009, 58(1): 106–117.

[29] WANG W B, CARR M, XU W J, et al. A model for residual life prediction based on Brownian motion with an adaptive drift. Microelectronics Reliability, 2011, 51(2): 285–293.

[30] SI X S. An adaptive prognostic approach via nonlinear degradation modeling: application to battery data. IEEE Trans. on Industrial Electronics, 2015, 62(8): 5082–5096.

[31] WANG X, HU C H, SI X S, et al. An adaptive prognostic approach for newly developed system with three-source variability. IEEE Access, 2019, 7: 53091–53102.

[32] FENG L, WANG H L, SI X S, et al. A state-space-based prognostic model for hidden and age-dependent nonlinear degradation process. IEEE Trans. on Automation Science and Engineering, 2013, 10(4): 1072–1086.

[33] HUANG Z Y, XU Z G, WANG W H, et al. Remaining useful life prediction for a nonlinear heterogeneous wiener process model with an adaptive drift. IEEE Trans. on Reliability, 2015, 64(2): 687–700.

[34] WANG Z Q, WANG W B, HU C H, et al. A real-time prognostic method for the drift errors in the inertial navigation system by a nonlinear random-coefficient regression model. Acta Astronautica, 2014, 103: 45–54.

[35] LEHMANN A. Joint modeling of degradation and failure time data. Journal of Statistical Planning and Inference, 2009, 139(5): 1693–1706.

[36] ZHANG Y, JIA X, GUO B. Bayesian framework for satellite rechargeable lithium battery synthesizing bivariate degradation and lifetime data. Journal of Central South University, 2018, 25(2): 418–431.

[37] ZHAO Q, JIA X, GUO B, et al. Real-time Bayes estimation of residual life based on multisource information fusion. Proc. of the Prognostics and System Health Management Conference, 2018: 215–222.

[38] SUN M, JING B, JIAO X X, et al. Research on life prediction of airborne fuel pump based on combination of degradation data and life data. Proc. of the Prognostics and System Health Management Conference, 2018: 664–668.

[39] PENG C Y, TSENG S T. Mis-specification analysis of linear degradation models. IEEE Trans. on Reliability, 2009, 58(3): 444–455.

[40] ZHANG Z X, SI X S, HU C H, et al. Degradation data analysis and remaining useful life estimation: a review on Wiener-process-based methods. European Journal of Operational Research, 2018, 271(3): 775–796.

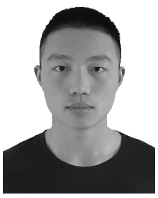
[41] WAN C H, LIU Z G, TANG S J, et al. Remaining useful life prediction based on the nonlinear random coefficient regression model under imperfect prior information. Journal of Beijing University of Aeronautics and Astronautics, 2021, 47(2): 2542–2551. (in Chinese)

[42] LU C J, MEEKER W Q. Using degradation measures to estimate a time-to-failure distribution. Technometrics, 1993, 35(2): 161−174.

[43] SI X S, WANG W, CHEN M Y, et al. A degradation path-dependent approach for remaining useful life estimation with an exact and closed-form solution. European Journal of Operational Research, 2013, 226(1): 53–66.

[44] JIN G, MATTHEWS D E, ZHOU Z B. A Bayesian framework for on-line degradation assessment and residual life prediction of secondary batteries in spacecraft. Reliability Engineering & System Safety, 2013, 113: 7–20.

Biographies



WANG Fengfei was born in 1997. He received his B.S. degree from Hefei University of Technology in 2019 and he is currently pursuing his M.S. degree in Rocket Force University of Engineering. His main research interests are prognostics and health management, remaining useful life prediction, and reliability assessment.
E-mail: 18755187114@163.com

TANG Shengjin was born in 1985. He received his B.S., M.S., and Ph.D. degrees in 2007, 2010, and 2015 from Rocket Force University of Engineering, Xi'an, China. He is currently an associate professor with the Rocket Force University of Engineering, Xi'an, China. His main research interests include prognostics and health management, reliability assessment, predictive maintenance, and image processing.
E-mail: tangshengjin27@126.com

SUN Xiaoyan was born in 1987. She received her B.S. degree in 2010 from Southeast University Chengxian College, Nanjing, China, and M.S. degree in 2013 from Xi’an Technological University, Xi’an, China. She is currently a lecturer with the Rocket Force University of Engineering, Xi’an, China. Her main research interests include prognostics and health management, image processing, and machine learning

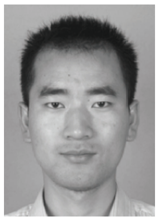
E-mail: sunxiaoyantsj@126.com

LI Liang was born in 1984. He received his B.S., M.S. and Ph.D. degrees from the Rocket Force University of Engineering, Xi ’an, China. He is currently a lecturer with the Rocket Force University of Engineering, Xi ’an, China. His main research interests include fault diagnosis of hydraulic system, hydraulic control theory and engineering.

E-mail: xzj_921@163.com

YU Chuanqiang was born in 1975. He received his B.S., M.S., and Ph.D. degrees from Xi’an Institute of High-Technology, Xi’an, China, in 2000, 2003, and 2007, respectively. He is currently a professor with the Rocket Force University of Engineering, Xi’an, China. His main research interests are reliability assessment, driverless cars, and image processing.

E-mail: fishychq@163.com



SI Xiaosheng was born in 1984. He received his B.S., M.S., and Ph.D. degrees from the Rocket Force University of Engineering, Xi’an, China, in 2006, 2009, and 2014, respectively. He is currently a professor with the Department of Mechanical Engineering. His research interests include evidence theory, expert system, prognostics and health management, reliability assessment, predictive maintenance, and lifetime estimation.

E-mail: sixiaosheng@gmail.com