Research on Remaining Useful Life Prediction for Aircraft Engine with a Fault Point

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Abstract. As a main power component, aircraft engine is a device with extremely high safety and reliability requirements, the engine’s failure often leads to failure of the whole flight system. The engine’s reliability and safety can be expressed by the engine’s remaining useful life (RUL), and RUL prediction the technology has widely used in aircraft engine. However, the engine usually subject to internal forces and imposed external sources under the complex environment, a fault may occur in degradation process. The occurrence of the fault will accelerate the degradation rate, causing the engine’s RUL shorten, so the general prediction method is not a good choice for aircraft engine. In this paper, we present a novel remaining useful prediction approach for aircraft engine considering a fault may occur in its degradation process. Finally, a case study is presented to demonstrate our method can improve the prediction accuracy.

Key words: Aircraft Engine; Remaining Useful Life; Fault Point; Degradation Process.

1. Introduction
The aircraft engine usually plays an important role in the aerospace field, which can be regarded as one of the most core components of a system. So the engine must keep high reliability safety, the engine’s RUL is directly related to their health states, and it’s also a key information for users. Predicting RUL has become an effective strategy to guarantee reliability of systems and reduce maintenance cost in the last decades. Therefore, many researches about RUL prediction of aircraft engines have drawn much attention. The RUL prediction methods of aircraft engine are classified into two types: mode-based and data-driven [1]. Nieto et al [2] use the particle swarm optimization (PSO) to improve the SVM, and the proposed hybrid PSO-SVM-based model is applied to RUL prediction of aircraft successfully. Zhao et al [3] investigate the relation between an arbitrary point of the degradation process and the correspondent RUL via the degradation pattern learning, and the proposed approach is applied to aircraft engines (aircraft engine is one of aircrafts) successfully. Yu et al [4] developed an a prognostics system based on logistic regression and state-space-model for engine health assessment and prediction, in which Bayesian state estimations are implemented to predict the future health of engines. More researches about aircraft RUL prediction can refer to [5]-[7].

The engine has its own degradation process, in which the value of its performance characteristic degraded over time until system failure. The degradation value of every machine’s performance characteristic represents the engine’s current health, and it degraded over time, the time series is called degradation trajectory or degradation path. The aircraft engine is a complex system, and its work
environment is very harsh, such as high temperature, different altitude. Therefore, the engine is operating normally at the start of its lifetime, and then develops a fault at a time point. The fault doesn’t stop the engine’s function, it can continue to operate. However, the occurrence of the fault will shorten the engine remaining useful life, specially change the rate of degradation trajectory. Many researches about RUL prediction of the aircraft engine don’t consider it is influenced by a FP (FP), which may cause decreasing the prediction accuracy, this paper will describe how to predict the RUL of aircraft engine with a FP.

2. Degradation Modeling

As a mathematical expression of Brown Motion (BM), Wiener process has been widely used in degradation modeling. Considering the fault may occur in the degradation process, which can be described by changing the drift parameter of Wiener process. When the fault occurs, it has a higher degradation rate than the case in the normal state. The FP separated the whole degradation process into two states, the whole process can be described by changing drift function, the diffusion coefficient $\sigma$ is assumed to be the same during the both states. The degradation process considering fault effects is then indicated as

$$X(t) = \begin{cases} 
\lambda_1 t + \sigma B(t) & t < \tau \\
\lambda_2 (t - \tau) + \lambda_\tau t + \sigma B(t) & t \geq \tau 
\end{cases}$$

(1)

Where $\tau$ is the FP, $\lambda_1$ and $\lambda_2$ are the degradation rates for $\tau > t$ and $\tau < t$ respectively. $X(t) \sim N(\lambda_1 t, \sigma^2 t)$ for $\tau > t$ and $X(t) \sim N(\lambda_2 (t-\tau) + \lambda_\tau, \sigma^2 \tau)$ for $\tau < t$.

Supposed the degradation observation as $\lambda_{ij}$ of engine i at $t_{ij}, \{i=1,2,...,m; j=1,2,...,n\}$, where $n_i$ is the number of inspection time of each engine. $\Delta X_{ij} = X_{ij+1} - X_{ij}$ from $\Delta t_{ij} = t_{ij+1} - t_{ij}$. The increment degradation model with a FP can be divided into three cases:

$$\Delta X_{ij} = \begin{cases} 
\lambda_{ij} \Delta t_{ij} + \sigma B(\Delta t_{ij}), & t_{ij+1} \geq \tau \\
\lambda_1 (t_{ij+1} - t_{ij}) + \lambda_2 (t_{ij+1} - \tau) + \sigma B(\Delta t_{ij}), & t_{ij} < \tau < t_{ij+1} \\
\lambda_2 \Delta t_{ij} + \sigma B(\Delta t_{ij}), & t_{ij} \leq \tau
\end{cases}$$

(2)

Where three cases respectively represent the FP occurs after the increment, FP occurs in the increment, FP occurs before the increment.

According to specifications above, the probability density function (PDF) of the increment $\Delta X_{ij}$ as follows

$$f(\Delta X_{ij} | k) = \begin{cases} 
\frac{1}{\sqrt{2\pi \Delta t_{ij} \sigma}} \exp\left(\frac{(\Delta X_{ij} - \lambda_{ij} \Delta t_{ij})^2}{2\sigma^2 \Delta t_{ij}}\right), & k = 1 \\
\frac{1}{\sqrt{2\pi \Delta t_{ij} \sigma}} \exp\left(\frac{(\Delta X_{ij} - \lambda_1 (t_{ij+1} - t_{ij}) + \lambda_2 (t_{ij+1} - \tau))^2}{2\sigma^2 \Delta t_{ij}}\right), & k = 2 \\
\frac{1}{\sqrt{2\pi \Delta t_{ij} \sigma}} \exp\left(\frac{(\Delta X_{ij} - \lambda_2 \Delta t_{ij})^2}{2\sigma^2 \Delta t_{ij}}\right), & k = 3
\end{cases}$$

(3)

Where $k = 1, 2, 3$ denote the scenarios $\tau \geq t_{ij+1}$, $t_{ij} < \tau < t_{ij+1}$, and $t_{ij} \leq \tau$ respectively.
3. rul distribution with FP and parameter estimation

In general, finding its RUL distribution is key to predict engine’s RUL, and finally calculating the expectation value based on the distribution. Therefore, one of main goals is to obtain RUL distribution for the engine. Based on the concept of the first passage time, the engine is regarded as to be failure, when its degradation value exceeds the preset failure threshold. Suppose $w$ is the failure threshold, given that $X_{i,j}$ has not exceeded the failure threshold $w$. The lifetime $T$ under the concept of the first passage time is expressed as

$$T = \inf \{t : X(t) \geq w | X(0) < w\}$$

Therefore, let $L_{i,j}$ denote the RUL at time $t_{i,j}$, it can be expressed as

$$L_{i,j} = \inf \{l : X(t_{i,j} + l) \geq w | X_{i,j} < w\}$$

The Wiener process follows inverse Gaussian distribution, it’s easy to obtain the RUL distribution based on the concept of first passage time. However, the degradation process in (3) is divided into two parts by FP $\tau$, the PDF of RUL distribution should consist of two parts. If the FP is determined and known, the RUL distribution can be expressed as

$$f_{L_{i,j}}(t) = \begin{cases} \frac{w - Z_{i,j}}{\sqrt{2\pi\sigma^2 t^3}} \exp \left\{ \frac{-(w - Z_{i,j} - \lambda t)^2}{2\sigma^2 t} \right\}, & 0 < t < \tau \\ \frac{w - Z_{i,j}}{\sqrt{2\pi\sigma^2 (t - \tau)^3}} \exp \left\{ \frac{-(w - Z_{i,j} - \lambda (t - \tau) - \lambda \tau)^2}{2\sigma^2 (t - \tau)} \right\}, & t \geq \tau \end{cases}$$

Because the FP is unobservable, it is impossible to know its precise position. To derive the RUL distribution, the FP is regarded as a random variable, which is assumed that follows normal distribution $\tau \sim N(\mu, \sigma^2)$, and the PDF of the FP are expressed as $f_\tau(\tau, \theta)$, respectively, where $\theta$ is the set of unknown parameters of distribution function. The PDF of RUL distribution can be then expressed as

$$f_{L_{i,j}}(t) = \int_0^\tau \left\{ f_{L_{i,j}}(t | \tau, \lambda, \sigma^2, w) \right\} \cdot f_\tau(\tau, \theta) d\tau$$

According to (7), the unknown parameters consist of $\theta_\rho = \{\lambda_1, \lambda_2, \sigma\}$ and $\theta_\tau = \{\lambda_\tau, \sigma_\tau\}$. FP $\tau$ cannot be detected directly, which caused incomplete observation data. It can be regarded as a missing data in the observations, and in a missing-data problem for parameter estimation, EM algorithm is widely used to solve the problem of parameter estimation where likelihood function is not incomplete. The main idea of the EM algorithm is to convert a problem of maximizing a complex likelihood function into a series of simpler likelihood function problems [8], it consists of two steps: the expectation-step (E-step) computes the expectation of the log-likelihood with respect to the complete-data; the maximization step (M-step) then finds the maximizer of this expected likelihood. The two steps are repeated iteratively until the expectation value reach the minimum error or parameter value doesn’t change. The PDF of $\tau$ is given, and the complete data vector consists of $\{\Delta X, \Delta t, \tau\}$, where $\tau$ is set of the FP $\{\tau_1, \tau_2, ..., \tau_m\}$, the complete-data likelihood is then

\[\text{likelihood} = \prod_{i=1}^{m} f_{L_{i,j}}(t_{i,j} | \theta) \]
where \( \delta_{k,i,j} \) is an indicator variable for \( \tau \) and \( \Delta t_{i,j} \) in three scenarios, such that when scenario \( k = 1,2,3 \) occurs, corresponding to the \( \delta_{k,i,j} = 1, k \in 1,2,3 \), otherwise \( \delta_{k,i,j} = 0 \). \( I \{ \cdot \} \) is indicator function.

The complete-data loglikelihood is then written as

\[
\ln(L_c) = \sum_{i=1}^{m} \ln(f(\tau_i, \theta)) + \sum_{j=1}^{n-1} \sum_{k=1}^{3} \delta_{k,i,j} \cdot \ln f(\Delta X_{i,j} | (k); \lambda_1, \lambda_2, \tau_i, \sigma^2) \tag{8}
\]

(1) E-step, the goal of the E-step is to compute the expectation of the complete-data loglikelihood of the missing-data conditioned on the observed data. \( \tau_i \) must be linear separable with other unknown parameters. Then, \( \tau_i \) can be replaced by integrating expectation in (10).

\[
\begin{align*}
Q &= E\left( L_c | \Delta X \right) = Q_1 + Q_2 = \sum_{i=1}^{m} E\{f(\tau_i, \theta) \} + \sum_{i=1}^{m} \sum_{j=1}^{n-1} \sum_{k=1}^{3} E\{\delta_{k,i,j} \cdot \ln f(\Delta X_{i,j} | (k); \lambda_1, \lambda_2, \tau_i, \sigma^2) \} \tag{9}
\end{align*}
\]

where \( \theta^b \) and \( \theta_p^b \) denote the currently iterated estimates, \( b \) is number of iterations.

(2) M-step, once the conditional expectations of \( V \) are evaluated, new estimates for \( \theta^{b+1} \) can be generated by solving for the complete-data maximum likelihood estimation to \( Q \). As \( Q_1 \) only contains \( \theta \) and \( Q_2 \) only contains \( \theta_p^b \), the estimator vectors \( \theta^{b+1} \) and \( \theta_p^{b+1} \) can be calculated by (11), (12).

\[
\frac{\partial Q_1}{\partial \theta} = \frac{\partial}{\partial \theta} \left[ \sum_{i=1}^{m} E\left\{ \left. V_i^* | \Delta X \right\} \right] m_i^* (\theta) \right|_{\theta = \theta_p^b} = 0 \tag{11}
\]

\[
\frac{\partial Q_2}{\partial \theta_p} = \frac{\partial}{\partial \theta_p} \left[ \sum_{i=1}^{m} \sum_{j=1}^{n-1} \sum_{k=1}^{3} E\{\delta_{k,i,j} \cdot \left. V_{i,j,k}^* | \Delta X \right\} \right] m_{i,j,k}^* (\theta) \right|_{\theta = \theta_p} = 0 \tag{12}
\]

4. experiments and results analysis

There is a dataset FD001 by NASA about aircraft engine for predicting its RUL, the dataset contains training and test subsets. 100 engines are tested in two subsets, and 21 sensors is used to detect the degradation values of engine’s performance characteristic. Through observing its time series from training subset, the degradation process is divided into two phase by a FP. We select sensor 9 as our performance characteristic for the test, the original data obtained from the sensor contains a lot of noise, shown as fig.1. The moving average filter algorithm is used to eliminate the noise, and the result show in Fig.1 (b).
Figure 1. (a): Original data from sensor 9; (b): The data by moving average filter algorithm.

Then, the unknown parameters of the degradation model can be estimated by EM algorithm, the parameters of degradation model presented in Table 1. RUL distribution considering fault effects can be calculated by (7). As dataset is normalized by min-max normalization algorithm, the failure threshold of engine is 1. For comparative purposes, we use the general Wiener process to describe the engine’s degradation process without the FP, where the parameters are estimated by maximum likelihood estimation shown in Table 1. The prediction results of two methods are shown in Fig. 2(a), (b), the comparison results of three models at different observed time are shown in Table 2.

| Method            | $\lambda_1$ | $\lambda_2$ | $\sigma^2$ |
|-------------------|--------------|--------------|-------------|
| Proposed Method   | 0.0016       | 0.0136       | 1.1173e-04  |
| Conventional Method | 0.0055       | 0.0055       | 1.1234e-04  |

Table 2. The comparison results

| Results      | Time1 | Time2 | Time3 | Time4 | Time5 | Time6 | Time7 |
|--------------|-------|-------|-------|-------|-------|-------|-------|
| Actual Value | 59    | 44    | 31    | 23    | 19    | 14    | 9     |
| Proposed Method | 127   | 126   | 109   | 89    | 79    | 63    | 23    |
| Conventional Method | 60    | 54    | 42    | 34    | 30    | 15    | 8     |

Figure 2. (a): The results of the proposed method; (b): The results of the conventional method.
According to the results in Fig.2, as the observation time increases, the error between the predicted life and actual life becomes more and more smaller. The reason is that more observation data can be collected, the unknown parameters can be more precise. Meanwhile, the comparison results are shown in Table 2 and Fig.2, we can see that the proposed method is more accurate than conventional method at different time, so it’s necessary to consider the fault into the engine’s degradation process.

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