SCIENCE AND TECHNOLOGY

Article citation info:
WANG HW, GAO J. A reliability evaluation study based on competing failures for aircraft engines. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2014; 16 (2): 171–178.

HuaWei WANG
Jun GAO

A RELIABILITY EVALUATION STUDY BASED ON COMPETING FAILURES FOR AIRCRAFT ENGINES

BADANIA DOTYCZĄCE OCENY NIEZAWODNOŚCI SILNIKÓW LOTNICZYCH W OPARCIU O USZKODZENIA KONKURUJĄCE

Aircraft engine is a complex and repairable system, and the diversity of its failure modes increases the difficulty of reliability evaluation. It is necessary to establish a dynamic relationship among data, failure mode and system reliability, to achieve the scientific reliability evaluation for aircraft engines. This paper has used data fusion method to establish reliability evaluation models respectively for performance degradation failures and sudden failures. Furthermore, these two models have been integrated on the basis of competing failures' mechanism. Bayesian model averaging has been used to analyze the impacts of performance degradation failures and sudden failures on aircraft engines' reliability. As a result of above, the goal of an accurate evaluation of the reliability for aircraft engines has been achieved. Example shows the effectiveness of the proposed model.

Keywords: *aircraft engine, reliability evaluation, competing failures, Bayesian model averaging, data fusion.*

Silnik samolotu to złożony system naprawialny, w którym różnorodność przyczyn uszkodzeń zwiększa trudność oceny niezawodności. Dlatego też istnieje konieczność ustalenia dynamicznych związków pomiędzy danymi, przyczynami uszkodzenia i niezawodnością systemu, których znajomość pozwoliłaby przeprowadzać naukową ocenę niezawodności silników lotniczych. W prezentowanej pracy wykorzystano metodę fuzji danych do opracowania modeli oceny niezawodności w zakresie uszkodzeń wynikających z obniżenia charakterystyk oraz uszkodzeń nagłych. Ponadto, opracowane modele zintegrowano na podstawie mechanizmu uszkodzeń konkurujących. Do analizy wpływu dwóch omawianych typów uszkodzeń na niezawodność silników lotniczych wykorzystano procedurę bayesowskiego uśredniania modeli. Dzięki powyższym krokom, osiągnięto założony cel dokładnej oceny niezawodności silników samolotowych. Przykład pokazuje skuteczność proponowanego modelu.

Słowa kluczowe: *silnik lotniczy, ocena niezawodności, uszkodzenia konkurujące, bayesowskie uśrednianie modeli, fuzja danych.*

1. Introduction

The level of the aircraft engines' reliability affects flight safety directly. Estimating the reliability level scientifically and objectively is the foundation of reliability management and decision-making of maintenance for aircrafts. The difficulties of reliability evaluation for aircraft engines lie in two aspects. First, there are less failure data and rich condition monitoring data. Second, there is a problem of competing failures caused by the diversity of failure modes arising from the complexity of the system.

Extracting information about reliability from a large amount of monitoring information is a common concern issue in the current theoretical and engineering field. Researchers in the United States, Britain, Australia and other countries promote using HUMS (health and usage monitoring systems,) to monitor the health and use of engines, structure, etc, which can provide full-time health information and on-line monitoring, in order to make the diagnosis and prediction of the remaining life of the equipment, structure and operation [7]. HP Engine Company has developed an advanced life prediction system for gas turbine engines, which integrates fault prognostics and health management capacity [16] .Volponi [18] used data fusion technology for aircraft engine health management. Niu et al. [10] employed data fusion strategy for improving condition monitoring, health assessment and prognostics. Cobel [6] proposed using data fusion method, which fuses condition monitoring data and fault data effectively, to predict the remaining life, used genetic algorithm to select optimal monitoring parameters, applied GPM (General path model, GPM) to achieve that transform the traditional reliability analysis based on failure time to analysis based on failure process.

For complex systems, the reliability evaluation of single failure mode or single point of failure is an ideal assumption. But in terms of practical situation of aircraft engines, the failure modes are various and multi-failure modes often coexist. The failure modes can be divided into degradation failure and sudden failure only on the basis of major categories of classification. Different failure modes interact with each other, constantly change their forms of expression and mechanism of action in different stages of the running system. It is a problem of competing failures in essence, increasing the complexity of the reliability evaluation. The problem of competing failures has drawn a lot of concern in the field of reliability engineering. Bedford [2] analyzed the characters of reliability evaluation models for various competing failures from a statistical point. Lehmann [9] surveyed some approaches to model the relationship between failure time data and covariate data like internal degradation and external environment models. Bagdonavičius et al [1] made use of the half updating process of the linear degradation model to study the non-parameter estimation method of competing failure model, and to simplify the using decomposition method. Pareek et al. [11] studied the problem of censored data processing for competing failures. Bedford et al. [3] presented a competing risks reliability model for a system that releases signals each time on its condition deteriorates and provided a framework for the determination of the underlying system time from right-censored data. Su et al. [17] regarded the incidence of sudden failure as the function of performance degradation amount, made use of Wiener process to describe the degradation process, and proposed a reliability evaluation model for competing failures. Bocchetti et al. [4] proposed a competing risk model to describe the reliability of the cylinder liners of a marine Diesel engine, in which the wear process is described by through a stochastic process and the failure time due to the thermal cracking is described by the Weibull distribution. Park et al. [12] and Kundu et al. [8] considered the analysis of incomplete data in the presence of competing risks among several groups. Chen et al. [5] developed methods for competing risks when individual events are correlated with clusters. Wang et al. [19] used Bivariate exponential models to analysis of competing risks data involving two correlated risk components. Xing et al. (2010) [20] presented a combinatorial method for the reliability analysis of system subject to competing propagated failures and failure isolation effect. Salinas-Torres et al. (2002) [15] and Polpo et al. (2011) [14] proposed the Bayesian nonparametric estimator of the reliability of a series system under a competing risk scenario. Peng et al. (2011) developed reliability models and preventive maintenance policies for systems subject to multiple Dependent Competing Failure Process (MDCFP) .

For the problem of aircraft engines' competing failures, the information fusion technology will be referenced to the aircraft engines' reliability modeling and the input variables of the reliability model will be determined by information fusion. The impacts of competing failure modes on system reliability will be analyzed through data. This paper will use Bayesian model averaging method to study the data, to select the optimal model, and to propose a reliability evaluation model for aircraft engines based on competing failures.

2. The modeling framework of reliability evaluation for aircraft engines based on competing failures

2.1. The modelling process of reliability evaluation based on competing failures

This paper intends to combine the recent research results concerning reliability evaluation and competing failures based on information fusion, and to propose reliability evaluation methods based on competing failures for aircraft engines. Its characteristics are reflected in the following aspects. First, it takes into account both the characteristics of information and failure mechanism, establishing the reliability evaluation models respectively for the performance degradation and sudden failures. Second, in the case of sudden failures and performance degradation failures coexist, the reliability evaluation model based on competing failures is established. Third, the impacts of different failure modes' mechanism on the reliability are analyzed. The modeling process is shown in Fig.1.

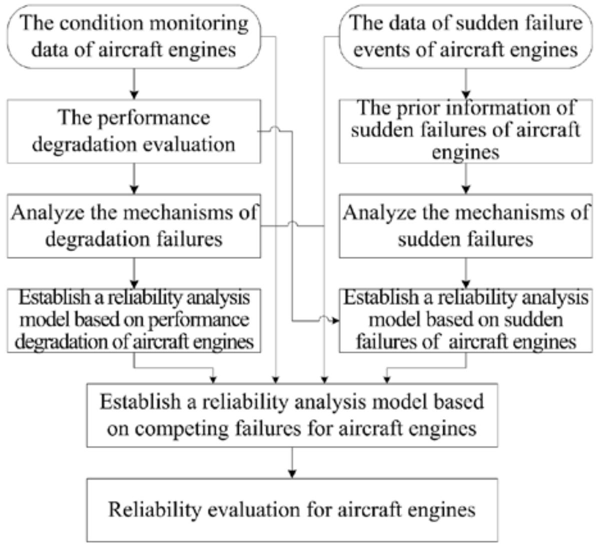

Fig 1. The flow diagram of reliability evaluation for aircraft engines based on competing failures

2.2. The reliability modeling methods of aircraft engines based on competing failures

The reliability modeling methods of aircraft engines based on competing failures include the following three-part.

2.2.1. The reliability evaluation of performance degradation failures for aircraft engines

The performance monitoring of aircraft engines includes three categories, namely, gas path performance monitoring, oil monitoring and vibration monitoring. The engines' performance degradation (or reduced efficiency) will usually be reflected in changes of monitoring parameters. The main monitoring parameters are: the turbine gas temperature (EGT), fuel flow (WF), oil pressure (OP), oil temperature (OT) and the oil consumption rate (OCR), the deviation of the low-pressure rotor vibration value (DLPRV) and high-pressure rotor vibration value deviation (DHPRV) and so on. The excessive EGT, the WF increasing, the larger DLPRV and DHPRV, the higher OCR all can reflect the performance degradation of aircraft engines. Comprehensively using above parameters to reflect the performance degradation of aircraft engines from the multi-dimensional perspective will be more realistic. This paper use Bayesian linear model to fuse above monitoring information, and its advantages are reflected in the following aspects. The Bayesian linear model, which foothold is expectation, reflects the uncertainty in the form of variance. The Bayesian linear model can well represent the randomness of monitoring parameters and performance degradation variables. It can fuse the impacts of various sources of data on the performance degradation, while taking fully into account the correlation between the data to avoid the phenomenon of information overlap. It has a learning function and it can fully fuse the data of different timing points. Noise parameters can be designed to avoid performance degradation's uncertainty caused by the uncertainty of the monitoring data results. It's worthy noting that, the Bayesian linear model can also fuse various types of nonlinear parameters through appropriate transformation.

2.2.2. The reliability evaluation of sudden failures for aircraft engines

The reliability analysis model based on the sudden failures includes two aspects. First, the reliability analysis of sudden failures, which is a reliability analysis problem of typical small-sample because the aircraft engine is high-reliability system and the fault information is rarely collected. The second are the correlation analysis between degradation failures and sudden failures, and quantifying the impacts of degradation failures on sudden failures. The reliability of sudden failures for aircraft engines is achieved by describing the law of its life changes. For the choice of sudden failures' distribution form, the final form is selected mainly through the combination of the failure mechanism analysis, following the fitting of the data validation and uncertainty analysis on the basis of the failure mechanism analysis. Because Weibull distribution model itself can reflect the impacts of the performance degradation on the law of life changes, so it is generally regarded as the main choice. The condition monitoring parameters of aircraft engines can not directly reflect the impacts that they pose on the sudden failures, but the performance degradation of aircraft engines can be extracted from the condition monitoring parameters. And then, the link between sudden failures and performance failures can be established by transforming the performance degradation as the shape parameters of the Weibull distribution appropriately.

Notice the actual situation that there are insufficient or even no failure data, this paper uses Bayesian methods to establish reliability analysis model of sudden failures.

2.2.3. The reliability evaluation of competing failures for aircraft engines

For the two major categories of failures, the research focused on the analysis of the relationship between sudden failures and performance degradation failures. For the mechanisms of the two failures between each other, the competing failures is usually regarded as a series model in the reliability analysis, but the reliability will be underestimated by using this method because a variety of competing causes of failures can not be real-time and simultaneous. If calculating the remaining life or reliability of different failures modes respectively and take the lowest as the reliability of competing failures, the reliability will be overestimated because to some extent the characteristics that a variety of competitive modes coexist in a certain period of time will be ignored. Competing failures needs considering the two failures modes' mechanisms comprehensively, but knowing how to act and change between the two modes can't rely solely on the failures mechanism analysis, the data is the key to understand it. To study the mechanism of two competing failures, this paper will use Bayesian model averaging method. Bayesian model averaging (Bayesian model averaging, BMA) is a probability forecast approach that is proposed recently and is used in multi-mode collection. The forecast probability density function (PDF) of a particular variable in BMA, is a weighted average of a single model forecast probability distribution after deviation correction, and the weight is the corresponding model's posterior probability which represents each model's relative forecast skill in the model training phase. The secondary use of condition monitoring data and event data can be achieved through BMA technology. And this not only solves the problem of reliability analysis based on a single failures mode, but also solves the problem of interaction of multiple failures modes. Based on the data re-learning, the goal of an accurate analysis of civil aircraft system reliability can be achieved.

3. The problem description of competing failures for aircraft engines

The problem description of competing failures for aircraft engines includes three aspects. The first is the process description of performance degradation failures, following the sudden failures description. And the third is competing failure description based on the sudden failures and performance degradation failures.

3.1. Performance degradation failures

Let $y(t)$ be the amount of performance degradation failures at time t and l be the failures threshold. When $y(t) \geq l$, aircraft engines will come up with performance degradation failures. Aircraft engines' performance degradation is irreversible, that is, the performance gradually decreases and the amount of performance degradation is constantly increasing with the use of time. Therefore, the Gamma process can be applied to describe the degradation process. Assume that y_0 is aircraft engines' initial performance, so $w(t) = y(t) - y(t_0)$ represents the accumulated deterioration at time t . Because degradation amount increases monotonically, for any t_i, t_j , if $t_j > t_i$, there must be $w(t_j) - w(t_i) > 0$. Assume that degradation amount $w(t)$ obey $Ga(\mu(t), \lambda)$, its density function can be expressed as follows:

$$f_w(\xi, \alpha(t), \lambda) = \frac{\lambda^{\alpha(t)}}{\Gamma(\alpha(t))} \zeta^{\mu(t)-1} e^{-\lambda\zeta} \tag{1}$$

where, α and λ represent shape parameter and scale parameter respectively; $\Gamma(\alpha) = \int_0^\infty t^{\alpha-1} e^{-t} dt$ is Gamma function.

Generally assume that the scale parameter does not change in a performance monitoring process. Shape parameter changes with the change of the degradation process, because the extent and rate of the performance degradation experience an increasing trend, so we assume that shape parameter is proportional with expected degradation degree and time power, that is:

$$\alpha(t) = kt^v \tag{2}$$

Further, Eq. (2) can be transformed as following:

$$f_w(\xi, \alpha(t), \lambda) = \frac{\lambda^{kt^v}}{\Gamma(kt^v)} \zeta^{kt^v-1} e^{-\lambda x} I_{(0,\infty)}(\zeta) \tag{3}$$

Based on the theory of system reliability, the reliability for degradation failures can be depicted as following:

$$R(t) = P\{T > t\} \Rightarrow P\{w(t) < \varepsilon\} \tag{4}$$

where, ε is the failure threshold for performance degradation of an aircraft engine.
Then, the reliability evaluation for performance degradation of an aircraft engine can be depicted as following:

$$R(t) = \int_0^\varepsilon f_w(\zeta) d\zeta = \int_0^\varepsilon \frac{\lambda^{kt^v}}{\Gamma(kt^v)} \xi^{kt^v-1} e^{-\lambda\xi} d\xi \tag{5}$$

3.2. Sudden failures

The Weibull distribution is widely used in engineering fields. Through assigning different values to its parameters, it can fuse the impact of performance degradation on the law of life changes, so to some extent, it can describe the relationship between performance degradation failures and sudden failures.

Assume that the law of life changes for sudden failure of aircraft engines complies with the Weibull distribution, it can be expressed as:

$$f(t;\beta,\gamma)=\frac{\gamma}{\beta}\left(\frac{t}{\beta}\right)^{\gamma-1}\exp\left[-\left(\frac{t}{\beta}\right)^{\gamma}\right],\ \text{if } t>0 \tag{6}$$

Among that, $\beta>0$, $\gamma>0$ represent scale parameter and shape parameter respectively. And γ characterize the performance degradation.

When the shape parameter is known, the sudden failure reliability evaluation can be transformed to estimate scale parameter β. It is assumed that the scale parameter β has a conjugate gamma prior, that is:

$$\pi(\beta|c,d)=\begin{cases}\dfrac{d^c}{\Gamma(c)}\beta^{c-1}e^{-d\beta}, & if\ \ \beta>0\\ 0, & if\ \ \beta\le 0\end{cases} \tag{7}$$

where c and d are scale parameter' conjugate prior hyper parameters. The values of c and d can be calculated through the acquisition of the scale parameter' prior mean and variance. Further, it can calculate the posterior mean and variance of the scale parameter, to achieve the reliability evaluation of the sudden failure.

More generally, the conditional probability of sudden failure on the amount of degradation can be determined through data learning, in order to analyze the impact of degradation failure on sudden failure. Because the characteristics distribution of degradation amount is a function of time, so the process above can be simplified. Reliability can be calculated by the joint distribution function which based on the sudden failure's conditional probability and probability distribution, the relevant solution can use Monte Carlo simulation method.

The reliability of sudden failure can be expressed as follows:

$$R_s=1-\int_0^{T_s} f(t,\beta,r)dt \tag{8}$$

3.3. Competing failures

The basic assumptions for competing failure of aircraft engines are as follows.

I There are two random variables X and Y, where Y denote the degradation failure and X denote sudden failure. X and Y are competing failures for causing failure.

II The performance degradation failure is irreversible.

III There is correlation between performance degradation failure and the random variables of sudden failure.

So in the case of sudden failure, the reliability of aircraft engines in competing failures can be expressed as follow:

$$R_c(t)=P(T>t)=P(T_g>t,T_s>t)=\int_0^{\varepsilon}\exp\left[-\int_0^t\lambda_s(\tau|y)d\tau\right]f_w(y,\alpha,\lambda)dy \tag{9}$$

where $R_c(t)$ is the reliability under the competing failures at time t. Eq. (8) is a problem of high dimensional integral calculation, the calculation itself has no difficulty. However, competing failure is not synchronous, and the data of correlation between competing failure and sudden failure can not be collected. In a certain degree, performance degradation failure and sudden failure can not play a role at the same time; maybe one failure mode plays the main part. Assume that the corresponding reliability evaluation model of the performance degradation failure is M_1, the corresponding reliability evaluation model of the sudden failure is M_2, Eq. (9) for the reliability evaluation model based on the competing failures can be expressed as M_3. For the observational data collected, the expression of the various failure modes can be obtained through the study of observational data.

$$P(D|M_1,M_2,M_3)=\sum_{k-1}^{3}w_k g_k(D|M_k) \tag{10}$$

Conditional probability density function $g_k(D|M_k)$ represents the conditional probability of observed variable D which based on model M_k. w_k represents the posterior probability as the k th model is the best model, and w_k is non-negative and satisfies $\sum_{k=1}^{N}w_k=1$. The expression represents the relative contribution of each model to civil aircraft system reliability evaluation in the model training phase.

4. Reliability evaluation algorithm for aircraft engines

4.1. Reliability evaluation algorithm for performance degradation failures

I Through the fusion of condition monitoring information, the expectation and variance of the degree of aircraft engines' performance degradation can be extracted to calculate the results;

Assume that the monitoring parameters of aircraft engines' performance degradation are expressed by matrix $\mathbf{X}=[\mathbf{X}_1,\mathbf{X}_2,\cdots,\mathbf{X}_k]$, where k represents monitoring parameters, e is deviation. The relationship between performance degradation and condition monitoring parameters can be expressed by the following stochastic equation:

$$\begin{cases}\mathbf{Y}=\mathbf{X}, +\mathbf{e}\\ \mathbf{e}\sim N(0,\sigma^2)\end{cases} \tag{11}$$

Among that, $\mathbf{Y}=\begin{bmatrix}y_1\\y_2\\\vdots\\y_n\end{bmatrix}$, $\mathbf{e}=\begin{bmatrix}e_1\\e_2\\\vdots\\e_n\end{bmatrix}$, $\mathbf{e}=\begin{bmatrix}e_1\\e_2\\\vdots\\e_n\end{bmatrix}$.

$\mathbf{e}_i$ is independent between each other and obey the normal distribution $N(0,\sigma^2)$, and σ^2 is known.

$\boldsymbol{\theta}$ can be calculated through monitoring parameters. The mean is $\boldsymbol{E}(\boldsymbol{\theta})$. And $\boldsymbol{C}(\boldsymbol{\theta})$ is covariance matrix.

For monitoring parameters, generally assume that they are in line with the inverse Gaussian distribution. Through continuous monitoring, the mean and variance are also constantly updating. The mean and covariance matrix can be expressed as follows.

$$\mathbf{E}(\theta|x,y)=\mu_\theta+\mathbf{C}(\theta)X^{\mathrm{T}}\left(\mathbf{X}\mathbf{C}(\theta)\mathbf{X}^{\mathrm{T}}+\mathbf{C}_e\right)^{-1}\left(y-\mathbf{X}\mu_\theta\right) \quad (12)$$

$$\mathbf{C}(\theta|x,y)=\mathbf{C}(\theta)-\mathbf{C}(\theta)\mathbf{X}^{\mathrm{T}}\left(\mathbf{X}\mathbf{C}(\theta)\mathbf{X}^{\mathrm{T}}+C_e\right)^{-1}\mathbf{X}\mathbf{C}(\theta) \quad (13)$$

With the increasing observational information, the Eq.(12), (13) can be used repeatedly to update the fusion results of the monitoring information for the performance degradation.

II Making use of the calculations results of mean and variance to calculate the scale parameter λ.

$$E\left(w(t)\right)=\frac{kt^{v}}{\lambda} \quad (14)$$

$$Var\left(w(t)\right)=\frac{kt^{v}}{\lambda^{2}} \quad (15)$$

Assume that μ_j, σ_j respectively represents the mean and variance of the accumulated degradation collected in the j th time. By the Eq. (14), (15) shows:

$$\hat{\lambda}_j=\frac{\hat{\mu}_j}{\hat{\sigma}_j^2} \quad (16)$$

From Eq. (16), we can know that λ is changing in the different monitoring stages.

III Calculating the parameter k and v of the shape parameter $\alpha(t)$.

$\alpha(t)$ is a time-varying parameter. According to monitoring the information's mean and collecting the monitoring information's time for several times, this model can be linear regressed after calculating the (15)'s logarithm to get $\hat{k}$ and $\hat{v}$.

IV Calculating performance reliability

Put the relevant parameters into the Eq. (5), the performance reliability can be calculated.

4.2. Reliability evaluation algorithm for sudden failures

I Calculating the hyper parameters of scale parameter β's prior distribution

By the Eq. (7), the prior mean and variance of the scale parameter β are:

$$E(\beta)=\frac{c}{d} \quad (17)$$

$$\sigma^2(\beta)=\frac{c}{d^2} \quad (18)$$

The reliability of sudden failure at time t_{R_0} is known, and then β can be expressed as:

$$\beta=\left[\frac{t_{R_0}}{\ln\left(1/R_0\right)^{1/r}}\right]^{1/r} \quad (19)$$

Put β's mean and variance into Eq. (17) and (18), the hyper parameters $\hat{c}$ and $\hat{d}$ can be calculated.

II Calculating the posterior mean and variance of the scale parameters

Collect the observational data of sudden failures $\{(t_1,n_1),(t_2,n_2),\cdots,(t_m,n_m)\}$, where t_i represents the happen time of sudden failures, and n_i represents the number of samples of sudden failures. The hyper parameters $\hat{c}$ and $\hat{d}$ are known, and then the posterior mean and variance of the scale parameters can be expressed as follows:

$$E(\beta')=\frac{c+\sum_{i=1}^{m}t_i}{d+\sum_{i=1}^{m}m_i} \quad (20)$$

$$\sigma^2(\beta')=\frac{c+\sum_{i=1}^{m}t_i}{\left(d+\sum_{i=1}^{m}m_i\right)^2} \quad (21)$$

III Calculating the reliability of sudden failures

Put $\hat{\gamma}$ which got by Eq. (11) and $\hat{\beta}$ which got by Eq. (19) into Eq. (8), the reliability of sudden failures can be calculated.

4.3. Reliability evaluation algorithm for competing failures

I Description of the possibility of alternative model

The possibility of the model depends on the fitting function of the predicted values and experimental data for each model. And it can be expressed by deviation function and the measurement error. Assume that the output results of model M_k obey normal distribution, and their expectations can be a simple linear function of the original experimental results $a_k+b_kM_k$, the standard deviation is σ_k. Then, there is $g_k\left(D|M_k\right)\sim N\left(a_k+b_kM_k,\sigma_k^2\right)$.Among that, a_k and b_k are error correction items, which can be obtained through a simple linear regression.

II The weight calculation of alternative model

For the weight calculation of alternative model, this paper selects expectation maximization (EM) algorithm to accomplish it. The advantages of this method are that it is very effective for the problem of incomplete data, and it is in line with our civil aircraft system data collection, especially in the case of the incomplete observational data and the direct fault collection. In the calculation process, introduce a non-observed variable z. If the k th model is the best prediction in the model collection, set the value of

z as 1, otherwise 0. At any time, as long as there is a value is 1, others are 0. Initializing the weight and variance of each model, the algorithm begins to iterate between the expectation step and the maximum step. Its expression is:

$$z_k^j = \frac{w_k g\left(D \middle| f_k, \sigma_k^{j-1}\right)}{\sum_{l=1}^{N} w_l g\left(D \middle| f_l, \sigma_k^{j-1}\right)} \tag{22}$$

where, j represents the number of iterations. Then, $g\left(D \middle| f_k, \sigma_k^{(j-1)}\right)$ represents the conditional probability distribution of the k th model focusing on observing D. $g\left(D \middle| f_k, \sigma_j^{k-1}\right)$ is normal distribution, the mean is f_k and $\sigma_k^{(j-1)}$ is the variance. In the following maximization step, the BMA weight and variance are updated according to the latest $z_k^{(j)}$ until convergence is reached.

5. Example

Table 1 shows the 35 samples which have repaired and replaced engines. There are six parameters have been monitored, which are DEGT (the deviration exhaust gas tempreture), DWF (the deviration of fuel flow), DOP (the deviation of oil pressure), DHPRS (the deviation of high-pressure rotor speed), DLPRV (the deviation of the low-pressure rotor vibration value) and DHPRV (the deviation of high-pressure rotor vibration value). The engines' TSI (Time since installation) and FH (Fight hour) from the beginning of the monitoring moment can be obtained. The 36th sample is the engine still in the monitoring stage. From the data of table 1, the relationship between the various monitoring parameters can be extracted and be used as the basis of information fusion. Among that, the PDD (Performance degradation degree) is not the data collected directly, but the Gamma distribution shape parameter got by Monte-Carlo simulation method, according to engine remaining wing life, in the case of a given reliability threshold (90%), and in accordance with that its performance degradation meets Gamma random process.

Fuse the information and performance degradation degree according to the monitoring information collected and the algorithm proposed in section 2. The vector fused monitoring parameters is:

$$\hat{\beta} = [-0.0103, 0.1795, 0.0016, 0.0318, 0.0152, -0.0158, 0.0156]^{\mathrm{T}}$$

Table 1. Key performance monitoring parameters for some aircraft engines

NO	DEGT	DWF	DOP	DHPRS	DLPRV	DHPRV	TSI(FH)	PDD
1	7.51	2.54	1.89	-7.27	1.06	0.32	4055	0.1192
2	-4.74	3.52	1.92	-5.16	0.52	0.55	7095	0.0459
3	-0.03	2.03	1.19	-8.33	0.57	0.37	7801	0.0378
4	8.04	5.16	1.69	-7.74	0.24	0.57	3331	0.1176
5	7.77	7.80	2.12	-6.81	0.86	0.46	3832	0.1308
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
31	22.69	7.58	2.12	-1.07	0.64	0.99	1055	0.2000
32	4.23	4.83	1.96	-58.92	0.17	0.62	3397	0.0996
33	14.28	5.25	1.63	-2.03	0.78	0.94	1422	0.1572
34	11.38	3.14	1.63	4.19	0.23	0.74	1830	0.1465
35	8.24	3.17	2.18	9.78	1.05	0.76	1954	0.1185

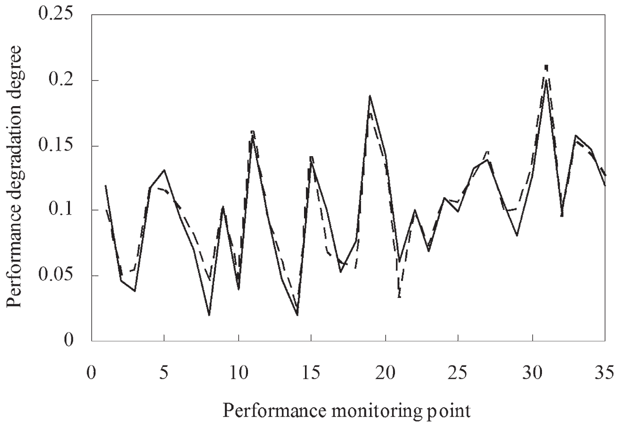

Fig. 2. The difference of performance degradation between real value and predictive value (The solid line shows the real value and the dashed line shows the predictive value)

The estimated values of performance degradation after fusion and the actual degradation values are compared in Figure 2.

According to monitoring information and maintenance information, the prior value of sudden failures can be determined as $E(R_{3000}) = 0.97$, $\sigma^2(R_{3000}) = 3.76\times10^{-4}$. $E(\beta)$ and $\sigma^2(\beta)$ can be computed by Eq.(19). $\hat{c}$ and $\hat{d}$ can computed by Eq.(17) and Eq.(18). The posterior mean and variance of $\hat{\beta}$ can be computed by Eq. (20) and Eq. (21). Then combining the results of performance degradation evaluation, the reliability of sudden failures can be computed by Eq. (8). Figure 3 shows the changing trend of the probability density function of sudden failures.

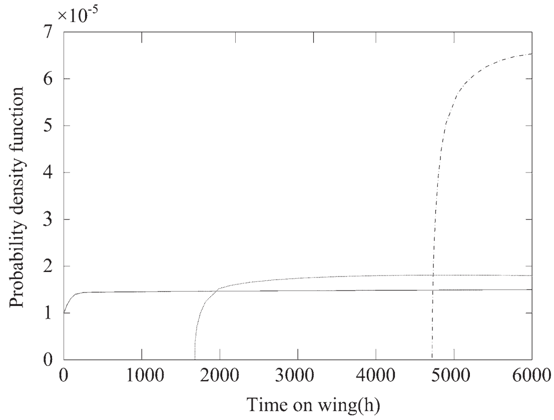

Fig. 3. The changing trend of the probability density function of sudden failures (The solid line shows the firs phase, the dotted line shows the second phase and the dashed line shows last phase)

Table 2 gives one engine's wing time and key monitoring parameters. For the above data, use different models to calculate the results of reliability evaluation. The comparison of each model is shown in Table 3.

For the three alternative models, namely, the reliability evaluation models of sudden failures, the performance degradation failures and competing failures, use Bayesian model averaging to calculate the weights of the three models respectively for three timing points. The calculation process is shown as Eq. (22). Estimate the reliability of aircraft engines, make the results compared with the actual values to calculate the deviation. The results are shown in Table 3.

The following conclusions can be drawn from Table 3. First, BMA can really analyze the mechanism of action between the different failure modes through learning different data. The advantages of the model are that it has higher fore-

Table 2. Key Monitoring parameters and main calculation results for on wing aircraft engines

NO \ Item	TSI (FH)	DEGT	DWF	DOP	DHPRS	DLPRV	DHPRV	$\hat{\beta}$	PDD
1	1707	–2.46	1.23	1.57	–0.12	0.33	0.94	55138	0.0567
2	4740	4.43	3.77	2.30	–2.78	0.52	0.48	46321	0.0832
3	5595	8.24	3.17	2.18	6.53	1.05	0.76	12334	0.1075

Table 3. The comparison of reliability evaluation results using different models

NO \ Item	M_1		M_2		M_3		M		
	$\hat{R}_G$	Deviation	$\hat{R}_S$	Deviation	$\hat{R}_C$	Deviation	Weight	$\hat{R}$	Deviation
1	0.9717	0.12%	0.9749	0.45%	0.9473	-2.39%	0.92 0.05 0.03	0.9711	0.062%
2	0.9565	0.59%	0.9580	0.75%	0.9163	-3.64%	0.73 0.11 0.16	0.9506	-0.074%
3	0.9512	2.42%	0.9493	2.21%	0.9030	-2.76%	0.28	0.9252	-0.377%

cast accuracy and it can effectively avoid the reliability overestimate or underestimate. From the prediction results of BMA model, because the existence of both positive deviation and negative deviation, there is no systematic bias from the forecast perspective. Therefore, the results are more credible.

Second, when aircraft engines are in the phase of higher reliability, the factors which lead to failure or affect the reliability are mainly reflected in the failure of performance degradation. From the weight calculation results of BMA, the greater stage of high reliability we are in, the more proportion of share the performance degradation will occupy.

Third, when aircraft engines are in the phase of high reliability, the possibility of sudden failure is generally less than the degradation failure. This is mainly due to the effects of degradation failure degree on the reliability of degradation failure is greater than on the reliability of the sudden failure. As the first two monitoring points shown in Table 3, the reliability of sudden failures is higher than performance degradation failures.

Furthermore, when aircraft engines are in the operational phase of higher reliability, the probability of the occurrence of sudden failure will increase. As the third monitoring point, this is a real moment that two failure modes play a role at the same time, reflecting in the decreased evaluation deviation using traditional reliability evaluation model of competing failure.

6. Conclusions

In this paper, the mechanism of performance degradation and sudden failures of aircraft engines has been analyzed, a reliability evaluation model for competing failures has been proposed, and the traditional model of competing failures has been transformed. This method not only can make full use of condition monitoring information, but also can analyze the mechanism and transforming relationship between performance degradation failures and sudden failures through data learning. The method should be studied further.

***Acknowledgement**: The research work supported by National Natural Science Foundation and Aviation Fund of China (60879001,U1233115) and Qinglan Project.*

References

1. Bagdonavičius V, Bikelis A, Kazakevičius V et al. Analysis of joint multiple failure mode and linear degradation data with renewals. Journal of Statistical Plaaning and Inference, 2007;137(7): 2191–2207.
2. Bedford T. Competing risk modeling in reliability. In Modern statistical and mathematical methods in reliability. Edited by Wilson A, Limnios N, KellyMcNuly S et al.Word Scientific Publisher, New Jersey.
3. Bedford T, Dewan I, Meileijson I. The signal model: A model for competing risks of opportunistic maintenance. European Journal of Operational Research, 2011; 214(3): 665–673.
4. Bocchetti D, Giorgio M, Guida M et al. A competing risk model for the reliability of cylinder lines in marine Diesel engines. Reliability Engineering and System Safety, 2009; 94(8):1299–1307.
5. Chen BE, Lramer JL, Greene MH. Competing risk analysis of correlated failure time data. Biometrics, 2008;64(1):172–179.
6. Cobel JB. Merging data sources to predict remaining useful life-An automated method to identify prognostic parameters. University of Teenessee, Knoxville, 2010.
7. Kenneth P. Measuring the Performance of a HUM System – the Features that Count. Proceeding of Third International Conference on Health and Usage Monitoring – HUMS2003 . DSTO Platforms Sciences Laboratory, Australia 2003, 5–15.
8. Kundu D, Sarhan AM. Analysis of incomplete data in presence of competing risks among several groups. IEEE Transactions on Reliability 2006; 55(2): 262 – 269.
9. Lehmann A. Joint modeling of degradation and failure time data. Journal of Statistical Planning and Inference 2009;139(5): 1693–706.
10. Niu G, Yang BS, Pecht M. Development of an optimized-based maintenance system by data fusion and reliability-centered maintenance. Reliability Engineering and System Safety 2010; 95(7): 786–796.
11. Pareek B, Kundu D, Kumar S. On progressively competing risks data for Weibull distributions. Computational ststistics and data analysis 2009; 53(12–1): 4083–4094.
12. Park C, Kulasekera KB. Parametric inference of incomplete data with competing risks among several groups. IEEE Transactions on Reliability2004; 53(1): 11–21.
13. Peng H, Feng QM, Coit DW. Reliability and maintenance modeling for systems subject to multiple dependent competing failure process. IIE Transactions 2011,43(5): 12–22.
14. Polpo A, Sinha D.Correction in Bayesian nonparametric estimation in a series system or a competing-risk model. Statistics and Probability

Letters 2011; 81(12): 1756–1759.
15. Salinas-Torres V, Pereira C, Tiwari R. Bayesian nonparametric estimation in a series system or a competing risks model. Journal of Nonparametric Statistics 2002; 14(4): 449–458.
16. Suarez EL, Duffy MI, Gamache RN et al. Jet engine life prediction systems integrated with prognostics health management. Proceeding of IEEE Aerospace Conference 2004; 3596–3602.
17. Su C, Zhang Y. System reliability assessment based on Wiener process and competing failure analysis .Journal of Southeast University 2010; 26(4): 554–557.
18. Volponi A. Data fusion for enhanced aircraft engine prognostics and health management—Task 14: Program plan development. Pratt & Whitney Internal Memo 2001, 10.
19. Wang CP, Ghosh M. Bayesian analysis of bivariate competing risks model with covariates. Journal of Statistical Planning and Inference 2003; 115(2–1): 441–459.
20. Xing LD, Levitin G. Combinatorial analysis of systems with competing failures subject to failure isolation and propagation effects. Reliability Engineering and System Safety 2010; 95(11): 1210–1215.

HuaWei WANG
College of Civil Aviation
Nanjing University of Aeronautics and Astronautics
Nanjing, Jiangsu210016, China
E-mail: huaweiwang678@gmail.com

Jun GAO
Department of Management
Shijiazhuang Mechanical Engineering College
Shijiazhuang, Heibei050003, China
E-mail: guaguaguagua@163.com