Reliability evaluation of aerospace engines based on performance degradation distribution

Lin Zhao
Institute of Systems Engineering
China Aerospace Academy of Systems Science and Engineering
Beijing, China
caasse_lz@163.com

Hengshan Zong
Institute of Systems Engineering
China Aerospace Academy of Systems Science and Engineering
Beijing, China
zonghengshan@163.com

Xingyu Wang
Institute of Systems Engineering
China Aerospace Academy of Systems Science and Engineering
Beijing, China
caasse_xyw@163.com

Na Wang
Institute of Systems Engineering
China Aerospace Academy of Systems Science and Engineering
Beijing, China
caasse_nw@163.com

Zeyu Jiao*
Guangdong Key Laboratory of Modern Control Technology, Institute of Intelligent Manufacturing, GDAS
Guangzhou, China
zy.jiao@giim.ac.cn

***Abstract*—The aerospace engine is the most important part of the spacecraft, and it is related to whether the spacecraft can operate efficiently and stably. According to statistics, more than 90% of aerospace accidents are caused by the failure of aerospace engines. Therefore, predicting the remaining useful life (RUL) of aerospace engines is of great significance for ensuring the safety of astronauts and avoiding property losses. This study proposes a space engine reliability assessment method based on the distribution of performance degradation, which can be utilized to predict the remaining useful life of space engines based on historical data. The experimental results show that the method proposed in this study can numerically express the remaining useful life in the form of probability, which has great engineering and practical significance for aerospace engineering.**

***Keywords*—aerospace engine, reliability evaluation, remaining useful life, degradation distribution, historical data**

I. Introduction

The aerospace engine is the power source of the spacecraft and the most important part of the spacecraft [1]. The aerospace engine works in a high temperature and high pressure environment, which places extremely high requirements on the reliability of the engine [2]. Once the aerospace engine fails prematurely, it may lead to serious explosions, loss of power and lead to catastrophic results, not only causing major economic losses [3], but also endangering the personal safety of astronauts or ground personnel [4]. Therefore, how to evaluate the operating conditions of aerospace engines and predict the remaining useful life (RUL) of the engine is of great significance [5]. However, because aerospace engines are usually composed of tens of thousands of parts and are an extremely complex and systematic product, it is almost impossible to carry out reliability assessment of aerospace engine parts one by one. The reliability evaluation of aerospace engines can only be achieved by collecting data related to reliability based on the sensors on the aerospace engines [6].

The definition of degradation is a physical or chemical process that can cause a change in the performance of a aerospace engine. This change gradually develops over time and eventually leads to the failure of the aerospace engine system. If the aerospace engine is working or in storage, a certain performance gradually decreases with time until it reaches a state where it can't work normally (usually a critical value for judgment is specified, that is, the degradation failure standard or failure threshold), then it is said This phenomenon is a degenerate failure, such as the deterioration of the electrical performance of components, the wear of mechanical components, and the aging of insulating materials. The data that the performance parameters of aerospace engines degrade with the test time are called degradation data.

Based on the above-mentioned degradation data, this research proposes a data-driven aerospace engine reliability evaluation method based on the degradation distribution. First, multi-sensors deployed on aerospace engines have collected high-dimensional feature parameters that can characterize the operating state of the engine. Then, these parameters undergo a multiple linear regression to get a comprehensive health index. Based on historical data, the trend of aerospace engine degradation over time is represented by a sample mean function and a sample variance function. Finally, the coefficients in the function are estimated by the least square method, and the RUL of the aerospace engine is expressed by the corresponding function.

II. Related Work

Lu & Meeker's work in [7] discussed some problems of degenerate failure models, and under relatively general conditions, proposed some methods to solve the problems, but this work assumes that the random parameter vector obeys a normal distribution. When the assumption is not true, the author tests the predicted values of the parameters or makes Box-Cox changes to make them obey the normal distribution. This can make mathematical processing very convenient but may affect the final estimation accuracy [8]. In addition, as pointed out by Ye et al. [9], it is unreasonable to require random coefficients to obey a multivariate normal distribution in some situations. Ye et al. studied the statistical

978-1-6654-1732-7/21/$31.00 ©2021 IEEE
DOI 10.1109/AIAM54119.2021.00009

inference technology of degradation data based on regression model, discussed the degradation failure problem under normal stress and stress, and obtained application in some practical problems. Huang gave a statistical analysis model of degradation data and used MLE to estimate the time-varying parameters in the statistical model [10]. The author used this model to study the thermal fatigue of welded joints on the metal surface and analyzed the existing life tests. The relationship between the data and the random intermetallic thickness. The results show that the random thickness of the intermetallic layer has a great influence on the MTBF and reliability of the solder joint in a high-temperature environment. Crk extended the work of the literature [7] and used multiple and multiple regression analysis to process the parameters of the degraded orbit [11]. Wu et al. used a model similar to that in [12] to study the performance changes of an electronic interface module using simulation methods. Su et al. [13] studied the statistical inference problem of the random coefficient degradation model under the random sample size [14]. Robinson & Crowder studied the Bayesian statistical inference of the growth curve degradation model under repeated measurement data [15]. Wu & Tsai used the fuzzy clustering method to study the problem of statistical inference of failure distribution based on the degradation model [16]. Gopikrishnan [17] discussed in detail the statistical inference of random slope and random intercept models under linear degenerate orbits and obtained applications in practical problems. There are generally two ways to establish a degraded trajectory. One is based on the failure mechanism of the avionics system and established by in-depth analysis of the failure physical and chemical reaction laws of the avionics system; the other is to directly perform curve fitting on the data. Degenerate orbit, this is an empirical method. Although this method can quickly establish a degenerate orbit, the accuracy may be poor, especially when a lot of extrapolation is required.

III. Method

This section introduces the method proposed by this study in detail, as shown in Figure 1. The proposed method can be divided into two stages, including the comprehensive health index expression and the solution of the degradation function.

A. Problem definition and hypothesis

Reliability modeling based on degradation distribution is based on the following assumptions:

Assumption 1: Degenerate quantity distribution family assumption. The degradation of all samples at some time of measurement follows the same distribution family, but the parameters of the distribution family may change with time.

Assumption 2: Distribution family parameter assumption. The parameters of the distribution family can be expressed as a function of time t and the external influencing factor S.

Assumption 3: Avionics system failure assumption. The failure threshold 1 of the sample is a constant. When the degradation amount $X(t)$ of the sample reaches the failure threshold for the first time, it is defined as the failure of the sample. The sample life $\xi = \inf(t|X(t) \geq 1)$ obeys a certain Life distribution type.

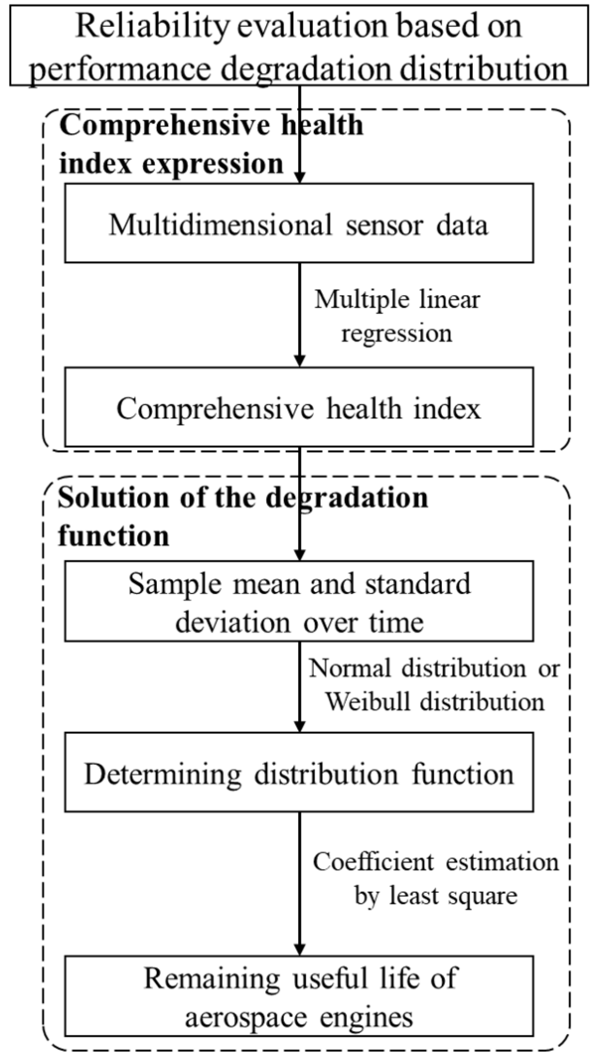

Fig. 1. Overall scheme of the proposed method

Assuming that the performance degradation amount y is a random distribution family that obeys a certain position-scale, then the position parameter and scale parameter at time t are respectively denoted as $\mu_y(t)$ and $\sigma_y^2(t)$, which can be used to determine the performance degradation distribution of the quantity at time t. Assuming that y obeys a normal distribution, and when $y \leq D_f$ (that is, the degradation curve is a monotonic decline), the aerospace engine fails, then the relationship between its reliability and the distribution of performance degradation is shown in the following equation:

$$R_t = 1 - P(y \leq D_f) = 1 - \Phi(\frac{D_f - \mu_y(t)}{\sigma_y(t)}) \qquad (1)$$

If the failure criterion is y{\geq D}_f (that is, the degradation curve is a monotonic rise), then the relationship between the reliability and the performance degradation distribution becomes:

$$R_t = 1 - P(y \geq D_f) = 1 - \Phi(\frac{D_f - \mu_y(t)}{\sigma_y(t)}) \qquad (2)$$

If y obeys the Weibull distribution with shape parameter θ_y and scale parameter η_y, then $\ln y$ obeys the extreme value distribution, and $\mu_y = \ln \eta_y$, $\sigma_y = 1/\theta_y$. If the avionics system fails at $y \le D_f$, the relationship between its reliability and the distribution of performance degradation is shown in the following equation:

$$R_t = 1 - P\left(y \le D_f\right) = \exp\left\{\frac{-\exp\left[\ln D_f - \mu_y(t)\right]}{\sigma_y(t)}\right\} \quad (3)$$

In order to use the above two expressions to evaluate the reliability of the avionics system during the design life t, the position and scale parameters of the performance degradation at time t must be known. Usually the position parameter and the scale parameter are taken as a function of time, which can be obtained by modeling and solving. Generally, it is assumed that the performance degradation of the aerospace engine obeys a normal distribution, and the reliability evaluation algorithm based on the performance degradation distribution described below is based on this assumption. When the amount of performance degradation obeys other distributions, similar methods can also be used for processing.

B. Comprehensive health index expression

After the performance degradation data of the aerospace engine at time $\{t_1, t_2, \ldots, t_n\}$ is collected, the sensor information needs to be fused to characterize the health status of the aerospace engine. It is assumed that the state of health value is a value between 0 and 1, with 0 representing engine damage and 1 representing complete engine health. The comprehensive health index of the aerospace engine can be expressed as the result of a multiple linear regression.

$$y_{ti} = a_1 x_1 + a_2 x_2 + a_3 x_3 + \cdots + a_n x_n + b \quad (4)$$

where y_{ti} is the comprehensive health index, *a* is the corresponding linear weight parameter, *b* is the bias, *x* is the value measured by each sensor at *ti* time.

C. Solution of the degradation function

After expressing the multi-dimensional sensor parameters as a comprehensive health index, the degradation law of aerospace engines over time can be described by the mean and variance. Generally, in the degradation process of aerospace engines, the mean and variance at a certain moment will obey the normal distribution or Weibull distribution, so both mean and variance are obtained from these two distributions.

When mean and variance obey normal distribution, the reliability of space engine can be expressed as

$$R_t = 1 - P\left(y \ge D_f\right) = \Phi\left(\frac{D_f - \mu_y(t)}{\sigma_y(t)}\right) \quad (5)$$

where $\Phi()$ is a normal distribution.

When mean and variance obey Weibull distribution, the reliability of space engine can be expressed as

$$f(t) = m/t_0 (t-\gamma)^{m-1} \exp\left[-(t-\gamma)^m / t_0\right] \quad (6)$$

where *m* is a shape parameter, which indicates the trend of the function. When $m>1$, it means that the failure rate increases with time, and $m<1$, which means that the failure rate decreases with time. t_0 is a parameter or characteristic lifetime, which represents the scaling of the function. γ is a positional parameter, and $\gamma > 0$; means that the device will not malfunction between $[0, \gamma]$.

D. Experimental setup

All experiments were performed in the Visual Studio Code environment of the Windows 10 operating system, based on the Matplotlib library, using Python language programming and Matlab. The main hardware configuration of the experimental environment is an Intel Core i7-9750H CPU; memory: 16G DDR4; GPU: NVIDIA Geforce GTX 1660 Ti GPU. PHM08 aerospace engine data set was used for the experimental data.

IV. Experiment Results

During the experiment, 21 sensors collected data at any one time, and the remaining useful life of the space engine was expressed as a number of cycles. After visualization with Matlab, 21 sensors reflect 6 different degradation features, as shown in Figure 2.

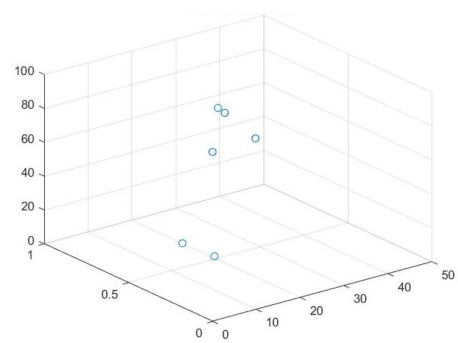

Fig. 2. Six typical degradation characteristics of aerospace engines

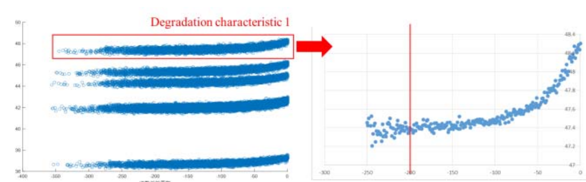

Fig. 3. Example of degradation characteristic

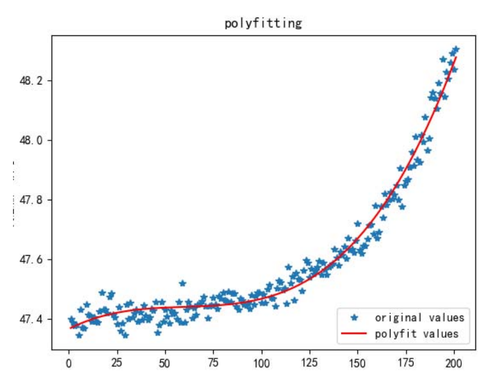

Fig. 4. Fitting results of degradation characteristics

As shown in Figure. 2-Figure. 4, the proposed method can well fit the degradation process of aerospace engines.

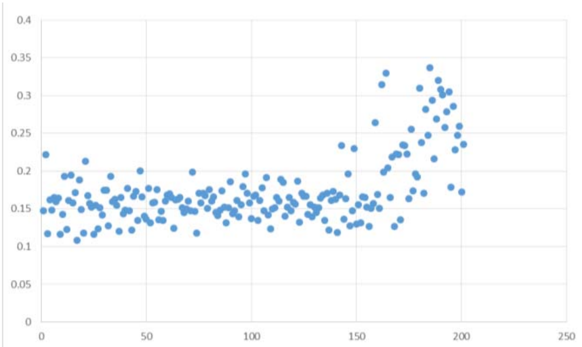

Fig. 5. Trends in the comprehensive health index

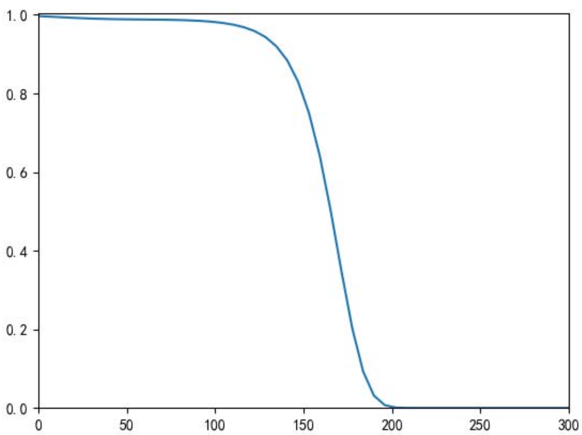

Fig. 6. Corresponding space engine reliability variation trend with time

According to Figure. 5 and Figure. 6, the degradation process of aerospace engine can be expressed as

$$R = 2.5 - 0.7T^3 - 0.5T^2 + 0.002T + 0.64 \quad (7)$$

The failure threshold D_f is 0.64 (that is, when the sensor 2 signal is greater than 0.64, the engine fails).

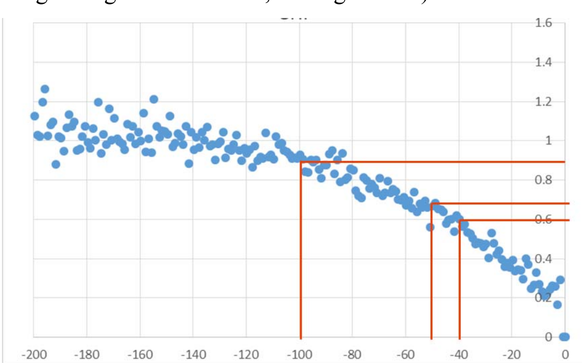

Fig. 7. Diagram of the relationship between remaining useful life and probability

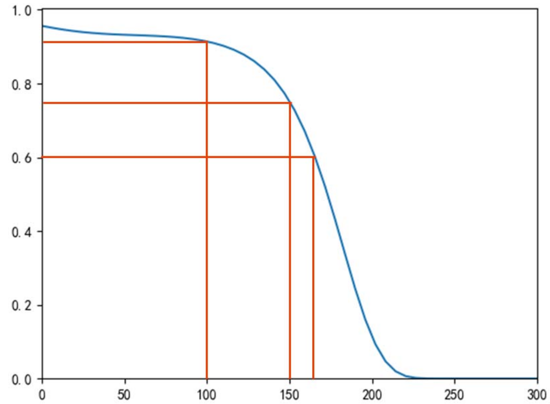

Fig. 8. Graphical representation of the degradation curve against the probability of remaining usable life

Figure. 7 and Figure. 8 illustrate the reliability evaluation results of aerospace engines based on degradation distribution, where the vertical axis represents the probability corresponding to the remaining available life value.

V. CONCLUSION

In this study, a reliability evaluation method for space engines based on performance degradation distribution is proposed, which can be used to predict the remaining service life of space engines based on historical data. First, multi-sensors deployed on aerospace engines have collected high-dimensional feature parameters that can characterize the operating state of the engine. Then, these parameters undergo a multiple linear regression to get a comprehensive health index. Based on historical data, the trend of aerospace engine degradation over time is represented by a sample mean function and a sample variance function. Finally, the coefficients in the function are estimated by the least square method, and the RUL of the aerospace engine is expressed by the corresponding function.

The experimental results show that the method presented in this paper can be used to express the residual life in the form of probability, which has important engineering and practical significance for aerospace engineering.

ACKNOWLEDGMENT

This work is supported by the financial support from Key-Area Research and Development Program of Guangdong Province(2020B090925002) and GDAS' Project of Science and Technology Development (No. 2021GDASYL-20210103090).

REFERENCES

[1] Petrescu, R. V., Aversa, R., Akash, B., Bucinell, R., Corchado, J., Apicella, A., & Petrescu, F. I. (2017). Modern propulsions for aerospace-part II. Journal of Aircraft and Spacecraft Technology, 1(1).

[2] Han, P. (2017). Additive design and manufacturing of jet engine parts. Engineering, 3(5), 648-652.

[3] John, S. K., Mishra, R. K., Hari, K., Ramesha, H. P., & Ram, K. K. (2020). Investigation of Bearing Failure in a Turbo Shaft Engine. Journal of Failure Analysis and Prevention, 20(1), 34-39.

[4] Kevorkova, O., & Popov, A. (2018, March). Discussing the 2015 NASA technology roadmap: Stethoscope or autonomous healthcare technology?. In 2018 IEEE Aerospace Conference (pp. 1-11). IEEE.

[5] Wu, Y., Yuan, M., Dong, S., Lin, L., & Liu, Y. (2018). Remaining useful life estimation of engineered systems using vanilla LSTM neural networks. Neurocomputing, 275, 167-179.

[6] Cai, B., Kong, X., Liu, Y., Lin, J., Yuan, X., Xu, H., & Ji, R. (2018). Application of Bayesian networks in reliability evaluation. IEEE Transactions on Industrial Informatics, 15(4), 2146-2157.

[7] Lu C. J., Meeker W. Q., Using degradation measures to estimate a time-to-failure distribution, Technometrics, 1993, 35(2):161-174

[8] Nelson W., Accelerated Testing: Statistical Models, Test Plans, and Data Analysis, John Wiley & Sons, New York, 1990

[9] Ye, Z. S., & Xie, M. (2015). Stochastic modelling and analysis of degradation for highly reliable products. Applied Stochastic Models in Business and Industry, 31(1), 16-32.

[10] Huang W., Reliability Analysis Considering Product Performance Degradation, PhD Thesis, The University of Arizona, 2002

[11] Crk V., Reliability assessment from degradation data, Proc. Annual Reliability and Maintainability Symposium, 2000

[12] Wu S.J, Reliability analysis using the least squares method in nonlinear mixed-effect degradation models, PhD Thesis, The University of Wisconsin-Madison, 1996

[13] Su C., Lu J.C., Chen D., et. al., A random coefficient degradation model with random sample size, Lifetime Data Analysis, 1999, 5:173-183

[14] Crk V., Product performance-evaluation using Monte-Carlo simulation: a case study, Proc. Annual Reliability and Maintainability Symposium, 2001

[15] Robinson M., Crowder M., Bayesian methods for a growth-curve degradation model with repeated measures, Lifetime Data Analysis, 2000, 6:357-374

[16] Wu S.Y., Tsai T.R., Estimation of time-to-failure distribution derived from a degradation model using fuzzy clustering, Quality and Reliability Engineering International, 2000, 16:261-267

[17] Gopikrishnan A., Reliability inference based on degradation and time to failure data: some models, methods and efficiency comparisoins, PhD Thesis, The University of Michigan, 2004