Application Research of Tool Stability Based on Bayesian Theory

Liu Tian

AVIC Chengdu Aircraft Industrial (Group) Co., Ltd Chengdu 610091, China

Abstract. Due to high precision requirements and high machining value, the high-end aerospace manufacturing industry has put forward higher requirements for the stability of machining tools. In this paper, the Bayesian algorithm is used to obtain sample information through experiments, and the sample information and prior information are effectively fused to estimate the parameters. Finally, the stability of a domestic blade can be improved by 8.76%.

Keywords: Bayes; Tools; stability.

1. Introduction

In order to reduce the weight of aircraft, titanium alloy and composite materials are increasingly used in aircraft parts design, in addition to aluminum alloy. In the processing of aeronautical parts, the tool wear is large, and its stability is the main quality hidden danger in the processing of aeronautical structural parts. This method is applied to the intelligent diagnosis analysis of the failure/fault databases of two mechanical equipment. While obtaining high diagnostic recognition rate (the correct recognition rate of failure/fault modes reaches 96% and 86% respectively), it also identifies the key feature parameters that affect the failure/fault classification The analysis shows that the specific failure/fault mode is often determined by a few key characteristic parameters, while the key characteristic parameters of uncertain failure/fault mode are often distributed in a decentralized manner, The features with high monotonicity scores are fused with principal component analysis and health factors are constructed as observation data. The parameters of the degradation model are estimated based on Bayesian theory and Markov chain Monte Carlo sampling, and the parameters of the degradation model are updated online in real time to gradually approximate the tool wear degradation trend as time progresses and monitoring data are available sequentially. At the same time, the remaining life at each time is estimated iteratively [2-4] Some scholars, with the help of deep learning technology, can more fully mine the machine degradation information, and propose a new depth prediction network depth separable convolutional network (DSCN) for mechanical RUL prediction. [5-6] In order to reduce the weight of aircraft, titanium alloy and composite materials are increasingly used in aircraft parts design, in addition to aluminum alloy. At present, the quality problems caused by cutting tools for aeronautical structural parts account for a large proportion. The study of tool stability is an important direction to solve the processing quality of aeronautical parts.

2. Overview of stability evaluation methods

At present, the massive application of difficult to machine materials/new materials has become the biggest obstacle to the efficient machining of aircraft parts in China. The research on high-speed machining of titanium alloys and composite materials is the key to solving the problem of aircraft parts machining efficiency. As one of the main parts of machining, the tool plays a crucial role in it. At present, the cutting tool industry in China cannot fully meet the needs of high-end manufacturing industry in the aviation industry. The main market for high-precision, high-efficiency and highly reliable cutting tools required in the production of aircraft structural parts is still occupied by imported cutting tools, and the cost of imported cutting tools is very high.

Stability evaluation generally refers to the ability of the system to complete the required functions under given conditions. Tool stability refers to the ability of the tool to be used normally without failure under the specified tool life. It can also be understood as the probability that the tool will

process a specified number of qualified parts under the specified processing conditions (such as specific conditions such as machine tool, workpiece material and cutting parameters) and within the specified cutting time (durability). Stability evaluation is a basic research work in the use process of products. During the development, testing, production and application stages of products, its stability analysis helps to find weak areas and improve the predictive ability of product damage. Especially for large feed cutters, unexpected fluctuations may always occur during machining. Therefore, if the stability evaluation of large feed tool can be carried out, it is not only conducive to optimizing the tool design, but also can reduce production costs, reduce production failures and improve production efficiency.

There are many methods for stability evaluation, including the stability evaluation methods for mechanical products and the stability evaluation methods for units and systems. Through previous analysis, it can be summarized into two categories: Bayesian method and traditional method. The idea of Bayesian method is different from that of traditional methods. The biggest difference lies in the emphasis on the experience of "predecessors" before evaluation, that is, there is prior information, mainly from historical data and expert experience. The existence of prior information reduces the dependence on sample information and does not require large sample information. The sample information is obtained through experiments, and the sample information and prior information are effectively fused for parameter estimation, which can be evaluated by Bayesian small sample experiments. The disadvantage lies in the large amount of calculation, and it is difficult to determine a reasonable prior distribution, which is also a problem faced by Bayesian methods.

Due to the limitations of test conditions and production costs, some sample information is difficult to obtain, such as weapon system, simulation test information, test information of similar weapon systems, high-precision aerospace components and other reliability tests. The test samples will be very small, usually no more than five, or even only one to two. Therefore, such tests are called small sample tests. Due to the small number of samples, it is impossible to accurately evaluate the product information, which requires effective prior information and Bayesian small sample theory to evaluate the stability of the product.

Bayesian method regards the parameter to be estimated as a random variable. According to people's previous experience, it can be determined that the parameter to be estimated follows a certain prior distribution. The principle is as follows:

Let the probability density function of the population be $\rho(x,\theta)$, θ Is the parameter to be estimated, which belongs to the parameter space θ, The sample information is xi=(x1, x2,... xn), $\pi(\theta)$ by θ Prior density function of, $\rho(x,\theta)$ Represents a given θ The conditional distribution of x after a certain value is also called the likelihood function $v(\theta)$, Then:

$$v(\theta)=\rho(x/\theta)=\prod_{i=1}^{n}\rho(x_i/\theta) \tag{1}$$

Parameters to be estimated θ the joint probability density with sample information x is w (x, θ)

$$\omega(x,\theta)=\rho(x/\theta)\ \pi(\theta) \tag{2}$$

π(θ) And w (x,θ) All include the parameters to be estimated θ The former is used when there is no sample information θ It is estimated that after the sample information is available, we can use w (x,θ) yes θ The estimation is made, therefore, for w (x, θ) Make a change:

$$\omega(x,\theta)=\varphi(x)\pi(\theta/x) \tag{3}$$

among φ (x) Is the marginal density function whose variables are x and θ irrelevant,

$$\varphi(x)=\int_{\Theta}\omega(x,\theta)d(\theta)=\int_{\Theta}\rho(x/\theta)\pi(\theta)d(\theta) \tag{4}$$

then:

$$\pi(x/\theta)=\frac{\rho(x/\theta)\ \pi(\theta)}{\int_{\Theta}\rho(x/\theta)\pi(\theta)d(\theta)} \tag{5}$$

π (θ/ x) Is the density function expression of Bayesian formula, θ the posterior distribution of refers to θ Is the conditional distribution on a given x. Prior distribution $\pi(\theta)$ It is the parameter to be estimated before processing test θ A kind of empirical knowledge of the posterior distribution $\pi(\theta/x)$ After observing the sample information x θ A modification of previous understanding. Therefore, the ideal evaluation effect of Bayesian method is precisely because the estimation of parameters not only depends on samples, but also integrates past experience and knowledge.

Prior distribution is the basis and starting point of Bayesian method theory, and also one of the key issues of Bayesian school research, so prior information $\pi(\theta)$ The key point of Bayesian small sample theory is to obtain. The common prior distribution can be generally divided into diffusion prior distribution, conjugate prior distribution and maximum entropy prior distribution. The higher the accuracy of the prior distribution, the more accurate the Bayesian small sample evaluation results. The common types of life distribution include log normal distribution, normal distribution, exponential distribution and distribution. Research shows that the maximum milling length of tools under normal wear follows log normal distribution.

3. Estimation of Blade Life Parameters Based on Bayesian Theory

The method of tool life parameter estimation based on Bayesian small sample theory is illustrated by an example of face milling titanium alloy TC4 with large feed inserts. Under certain cutting parameters (cutting speed is 80m/min, feed rate is 0.8mm/z, cutting depth is 0.8mm, cutting width is 12.5mm) and blunting standard (0.3mm is selected as the blunting standard), the milling length of the blade is about 4000mm.

Assume that the maximum milling length of the tool is l, obeys the logarithmic normal distribution, and the normal distribution density function is.

$$f(l)=\frac{1}{\sqrt{2\pi}\sigma}\exp\left[-\frac{\left(Y-\mu_y\right)^2}{2\sigma_y^2}\right] \tag{6}$$

Let Y=ln l, then Y follows the mean value μ y. The standard value is σ the normal distribution of y, then the probability density function of Y is:

$$f(e^y)=\frac{1}{\sqrt{2\pi}\sigma_y}\exp\left[-\frac{(Y-u_y)^2}{2\sigma_y^{\,2}}\right] \tag{7}$$

In which, the overall average value μy is obtained from the test sample information, μy is the unbiased estimator of the sample mean Y, while Y obeys the t distribution, and the degree of freedom is (n-1), so when the given 1-α on the confidence interval, the lower confidence limit of is:

$$u_y=\overline{Y}-t_{\frac{\alpha}{2}}(n-1)\frac{S_y}{\sqrt{n}} \tag{8}$$

$t_{a/2}$(n—1) —— t distribution α/2 Quantile.

S_y—— Sample standard deviation.

In this example, 4 large feed inserts are randomly selected for test, and the maximum wear of the rear cutter face is 0.3mm, which is the blunt standard. The maximum milling length of the blade is 4057mm, 3790mm, 3882mm and 3964mm respectively. The results after conversion to normal distribution are shown in Figure 1.

Table. 1 Test Results of a Large Feed Blade Sample

Max.milling length^l(mm)	4057	3790	3882	3964
Logarithmic length Y	8.3081	8.2401	8.2641	8.2850

so, Y=8.2743, S_y=0.0499, μ_y=8.1949.

Overall standard deviation σy Based on previous experience, it has the following relationship with tool life variation coefficient:

$$\sigma_y = \sqrt{\ln(1+C_v^2)} \tag{9}$$

C_v——Variation coefficient of tool life.

For large feed inserts, according to engineering experience, the life factor is taken as 0.25, so σy=0.2462.

Overall mean μyThe prior distribution and posterior distribution of are normal distribution, so its probability density function is:

$$f(\mu_y) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left[-\frac{(\mu_y-\mu)^2}{2\sigma^2}\right] \tag{10}$$

μ—— $\mu_{y\ mean}$ value.

σ—— σ_y the variance.

Joint formula μy posteriori estimate

$$\mu'' = \frac{\mu'(\sigma_y^2/\mathrm{n}) + \sigma'^2\sqrt{\mathrm{nt}}}{(\sigma_y^2/\mathrm{n}) + \sigma'^2} \tag{11}$$

$$\sigma'' = \sqrt{\frac{\sigma'^2(\sigma_y^2/\mathrm{n})}{\sigma'^2 + \sigma_y^2/\mathrm{n}}} \tag{12}$$

$\mu'.\ \sigma'$—— μ_yyMean value and standard value of prior normal distribution.

$\mu''.\ \sigma''$ —— μ_yMean value and standard value of posterior normal distribution.

According to the previous test data, the prior mean and standard deviation of the logarithmic life mean are: μ'=8.4542, σ'=0.082, so μ'' =8.6106, σ''=0.065.

For a given inspection level α, 1—α Under confidence level μy Estimator:

$$\hat{\mu}_y = \mu'' - \mathrm{Z}_\alpha\sigma'' \tag{13}$$

Z_a—— Standard normal distribution α Quantile.

Set the standard milling length of the blade design as l0, the maximum milling length corresponding to normal distribution is Y0, so Y=ln l0, the tool failure boundary condition is Y=Y0, the stability index can be obtained from the stability formula of normal distribution β:

$$\beta = \frac{\mu'' - Z_\alpha\sigma'' - \ln l_0}{\sigma_y} \tag{14}$$

The designed maximum milling length of the blade is 3000mm (cutting speed is 80m/min, feed rate is 0.8mm/z, cutting depth is 0.8mm, cutting width is 12.5mm), and the confidence level of large feed blade is 1 - α= At 95%, it can be obtained that the pretest and posttest stability indexes are 1.2 and 1.9 respectively.

from β the blade stability probability can be calculated Ps:

$$p_s = \Phi(\beta) \tag{15}$$

Blade failure probability P_f:

$$p_f = \Phi(-\beta) \tag{16}$$

From the above calculation results, we can get the stability evaluation results as shown in Table 2, and the normal distribution of pre and posttest and samples as shown in Figure 1. The pretest standard deviation is 0.082, and the posttest standard deviation is 0.065. The right shift of the posttest normal curve indicates that the posttest estimation of tool life increases. The fluctuation of the standard deviation of the blade tends to be stable, and the reliability of the posterior estimation increases. On the premise that the sample is small, the results reflected by the sample normal curve are not representative, that is, the sample information is "insufficient", so the shape of the posterior normal curve cannot be estimated based on it. Then, with the participation of the prior normal curve, the shape of the posterior normal curve will not be disturbed by the fluctuation of the sample normal curve. It can be seen that the accuracy of prior information directly determines the accuracy of posterior

estimation. However, although the sample size is small, it cannot be ignored. For a batch of products, only "listen to" the prior information without testing, the evaluation result is undoubtedly a guess based on "past experience", lacking scientific nature.

Table. 2 Stability Evaluation Results of Large Feed Blade

index	μ	σ	P_s	P_f
Before evaluation	8.4542	0.082	1.2	88.49%
After evaluation	8.6106	0.065	1.9	97.13%

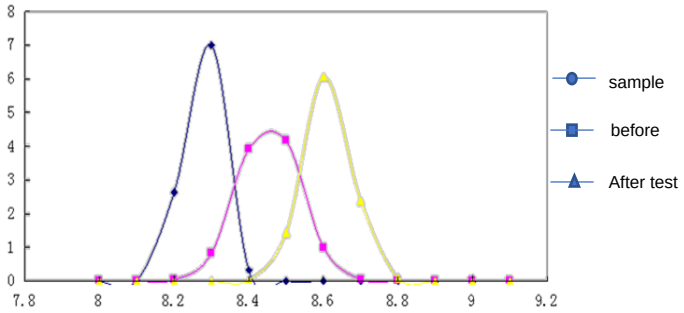


Fig. 1 Normal distribution of pretest and post test samples

In addition, if equation (14) is transformed and t0 is replaced by t, the tool life under given reliability can be obtained, that is.

$$t = \mu'' - Z_\alpha \sigma'' - \beta\sigma_y \tag{17}$$

4. Summary

When using Bayesian method to evaluate the stability of a blade, the previous test data is integrated in the evaluation, which ultimately improves the accuracy of the evaluation results. It can be seen from Table 2 that when the confidence level is 95%, the reliability of the blade increases from 88.49% before the test to 97.13% after the test, indicating that under the condition of accurate prior information, smaller test samples have obtained more accurate evaluation results.

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