

# An Evaluation Method of Accelerated Storage Life Test for Typical Mechanical and Electronic Products

Jinyong Yao, Hongzhi Li, Chao Du, Jiao Li

**Abstract**—Reliability of long-term storage products is related to the availability of the whole system, and the evaluation of storage life is of great necessity. These products are usually highly reliable and little failure information can be collected. In this paper, an analytical method based on data from accelerated storage life test is proposed to evaluate the reliability index of the long-term storage products. Firstly, singularities are eliminated by data normalization and residual analysis. Secondly, with the preprocessed data, the degradation path model is built to obtain the pseudo life values. Then by life distribution hypothesis, we can get the estimator of parameters in high stress levels and verify failure mechanism consistency. Finally, the life distribution under the normal stress level is extrapolated via the acceleration model and evaluation of the actual average life is available. An application example with the camera stabilization device is provided to illustrate the methodology we proposed.

**Keywords**—Accelerated storage life test, failure mechanism consistency, life distribution, reliability.

## I. INTRODUCTION

MANY products have the characteristic of a long-term storage and single-use. That is, during the most time of the whole life cycle, they are in storage or as standby. Therefore, storage life and storage reliability are the most important technical indexes, which not only relate to safe storage and effective use of products, but avoid economic losses caused by irrational scrapping. Thus, it is of important significance to study storage life of long-term storage products.

Since the long-term storage products are usually high reliable and little failure information is available, accelerated storage life test [1] is requisite. Two conventional reliability evaluation methods of accelerated storage life test are respectively based on degradation path model [2] and degradation amount distribution [3]. The former is a more mature and intuitive method. The basic idea is to establish the degradation path model and determine pseudo life values by setting a threshold. Its core is to acquire a degradation path based on statistical information or physical models. In fact, currently most studies on the degradation model are based on regression analysis. Gopikrishnan [4] analyzed statistical inference of random intercept and random slope of linear degenerate orbit. Meeker et al. [5] established the degradation path using nonlinear model and employed maximum likelihood function to estimate parameters. As for reliability evaluation of

storage life, Ma X. B. et al. [6] carried out estimators of the model parameters by analyzing some sub module electronic products and utilized Fisher information to conclude reliability confidence interval estimation under the normal stress level. Zhao Y. T. [7] analyzed the failure mechanism of the electromagnetic valve and deduced the storage life based on the minimum variance unbiased estimate (MVUE) and the least square method (LSM). In this paper, we introduce the method of combining the degradation path with acceleration model to evaluate reliability under the normal stress. By non-linear fitting, degradation path model is established with the preprocessed test data and parameters of life distribution under high stress levels are estimated using the best linear unbiased estimate (BLUE). With acceleration model, the life distribution under the normal stress level is determined, and the average storage life is concluded.

## II. EVALUATION METHOD

The accelerated storage life test evaluation includes the following several parts: original data preprocessing, statistical analysis of test data, evaluation result analysis and evaluation result verification. Fig. 1 is the flowchart of evaluation method.

### A. Data Normalization

Data normalization [8] is a method of processing the original data to make sure they are limited to a certain range we need. Through data normalization, physical expressions or data are transferred to scalar quantities which have some kind of relative relationship. A dimensionless expression derived from the dimensional expression will make the calculation and analysis much more efficient.

### B. Residual Analysis

In practical engineering, due to accidental factor interference or careless observation, the data we get are frequently not completely reliable, i.e. there are specific abnormal data, causing residual value particularly large. The so-called residual is the difference between actual observations and regression estimates, i.e.

$$e_i = y_i - \hat{y}_i \quad (i = 1, 2, \dots, n) \quad (1)$$

In order to improve the effect of the regression analysis, once abnormal data occur, they should be removed, and the remaining data can be better used to establish the regression equation [9]. Even if the regression equation is proved reliable by F criterion or correlation coefficient, we cannot exclude the probability of the presence of abnormal data. The purpose of

Jinyong Yao, Hongzhi Li, and Chao Du are with the School of Reliability and System Engineering, Beihang University, Beijing, 100191 China (phone: +8613521386504, +8613401156935, +8615011585728; e-mail: jinyongyao@buaa.edu.cn, lihongzhi01@sina.com, 455824352@qq.com, respectively).

Jiao Li is with the Qingyun Cooperation, Beijing, 100191 China (phone: +8613522435933; e-mail: daydayhappy2009@sina.com).

residual analysis is to solve this problem.

### C. Life Distribution Hypothesis and Verification

First, analyze the trend of performance parameters degradation and fit the degradation path curve using nonlinear equations to deduce the pseudo-life, which refers to the time to reach the predetermined threshold [10], [11]. Under a certain stress level, the degradation path of the same type of product

sample can be described by the same form of nonlinear equations. Due to random fluctuation between different product samples, the degradation path equations of different product samples have various equation coefficients. However, such fluctuation also has some randomness, so we can use a certain distribution to describe the randomness of the pseudo-life, as shown in Fig. 2.

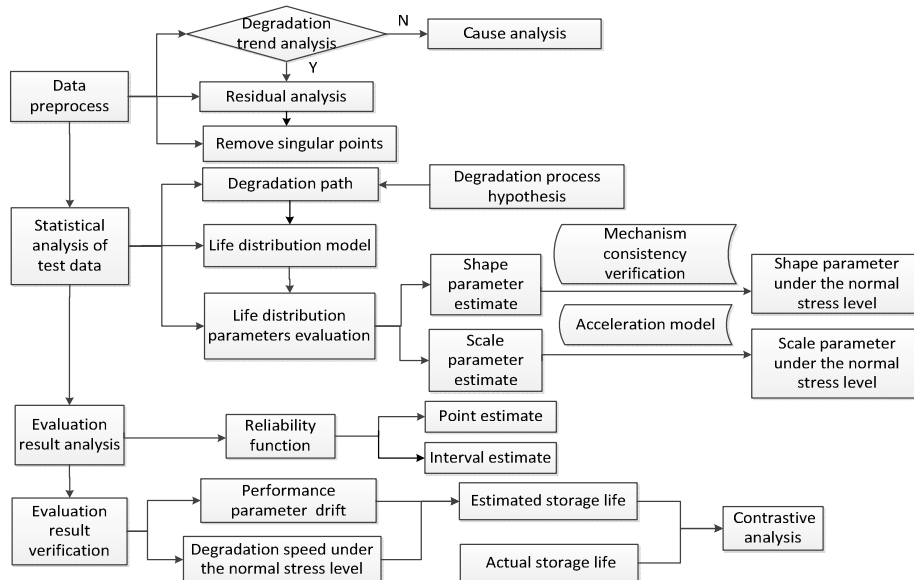


Fig. 1 Evaluation Method Flowchart

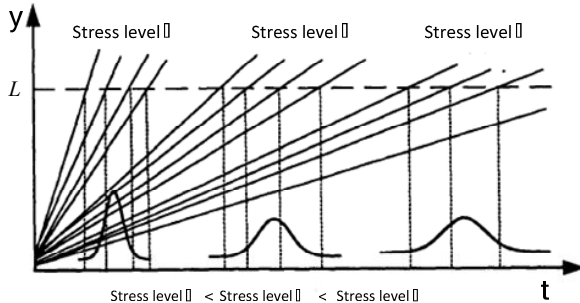


Fig. 2 Relationship between Performance Degradation Path and Life Distribution

Since the pseudo-life of samples declines when stress level rises, life distribution parameters are influenced by the stress level. Pseudo-life of products under the same stress level is obedient to the same distribution, but all or part of the parameters varies. With the acceleration model, the pseudo-life distribution parameters under the normal stress level can be extrapolated. Hence, it is feasible to evaluate the reliability of products and predict the average storage life under the normal stress level.

### D. Failure Mechanism Consistency Verification

There is a basic assumption in accelerated test, namely failure mechanism consistency. It means that the physical or

chemical change processes under different stress levels have the same essence. Meeting this condition is a prerequisite to ensure the correctness of the accelerated test results, so it is indispensable to verify the failure mechanism consistency of accelerated storage life test. Currently, there are three kinds of consistency judgment approaches: statistical analysis based constant parameters of acceleration model based and test observation based.

## III. APPLICATION EXAMPLE

As a key part of the downward-looking matching system in aircraft, the camera stabilization device, whose main function is capturing ground image for visual system real-time location, needs to endure the long storage process. It is a typical mechanical and electronic product. Since the sample size of these products is small, step stress accelerated storage life test [12] with three sequentially applied temperature stress levels 115°C, 105°C and 95°C is conducted to predict the actual storage life of camera stabilization device.

### A. Data Preprocess

#### 1. Degradation Trend Analysis

Camera stabilization device has four main performance indexes: transfer function, Signal Noise Ratio (SNR), uniformity, and positioning error. After observing and analyzing original test data, we find only transfer function

performance has a conspicuous trend of degradation. Fig. 3 shows the corresponding data curve.

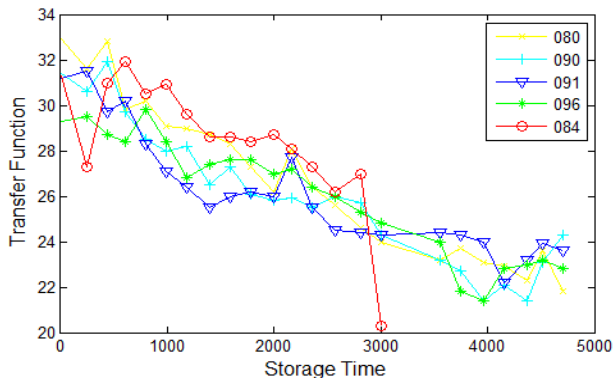


Fig. 3 Transfer Function Performance Data Curve

## 2. Residual Analysis

As shown in Fig. 3, the original test data are very coarse, so they cannot be used directly until singular points are removed by residual analysis. Fig. 4 is the processing result of 080 test data.

After process of eliminating abnormal points, each product's transfer function performance degradation curve is carried out, as shown in Fig. 5.

### B. Degradation Path Modeling and Parameters Estimating

From the degradation trend of the transfer function performance, nonlinear regression model is adopted to describe the degradation path:

$$y_{ij} = a_{ij}x^2 + b_{ij}x + c_{ij} \quad (2)$$

where  $a_{ij}, b_{ij}, c_{ij}$  are parameters of nonlinear model;  $y_{ij}$  is performance index measurement of product  $i$  ( $i=1,2,3,4,5$ ) under stress level  $j$  ( $j=1,2,3$ ).

Through the curve fitting method, we can obtain degradation paths under the three stress levels. For example, Fig. 6 shows the degradation path at 105°C.

For the single stress multi-level accelerated test, there is a cumulative degradation process, and the final degradation path is the result of accumulation of paths under respective stress levels. According to Wiener process characteristics, the failure time of a product can be considered as the time when a particle subject to Brownian motion passes through the predetermined value (failure threshold). Therefore, the product life  $T$  can be expressed as:

$$T = \inf\{t : t > 0, y(t) = L\} + \tau_{j_m j_n} \quad (3)$$

where  $\tau_{j_m j_n}$  is the equivalent life time under stress level  $S_{j_m}$  to life time under stress level  $S_{j_n}$ . The following is the calculation equation;

$$\tau_{j_m j_n} = \alpha_{j_m j_n} \cdot t_{j_n} \quad (4)$$

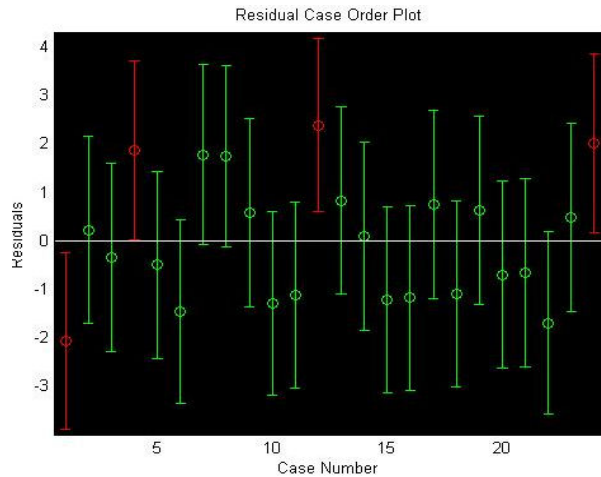


Fig. 4 080 Test Data Residual Analysis

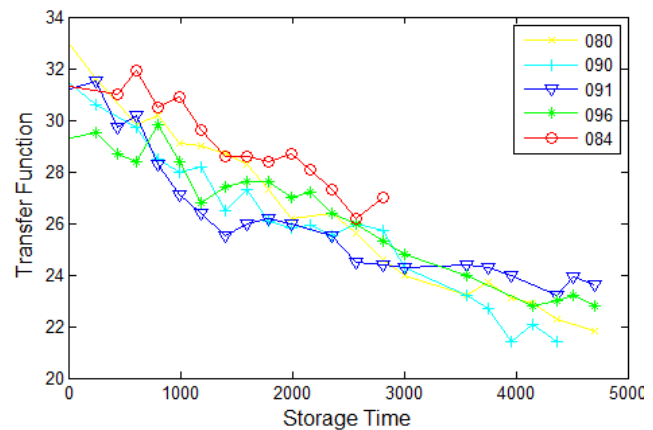


Fig. 5 Performance Degradation Curve after Processing

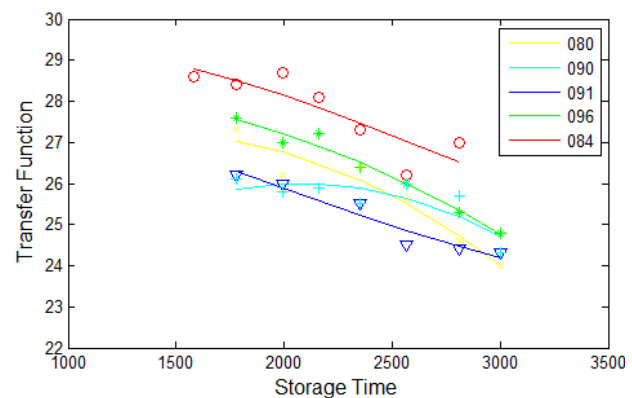


Fig. 6 Degradation Path at 105°C

where  $\alpha_{j_m j_n}$  is the acceleration factor under stress level  $S_{j_m}$  relative to  $S_{j_n}$ .

Since only temperature stress varies during the test,  $\alpha_{j_m j_n}$  should be calculated by the acceleration equation induced by Arrhenius reaction rate model,

$$\alpha_{j_m, j_n} = \exp\left[\frac{E_a}{k} \left(\frac{1}{T_{j_n}} - \frac{1}{T_{j_m}}\right)\right] \quad (5)$$

where  $T_{j_m}, T_{j_n}$  are absolute temperature (K),  $k$  is Boltzmann constant,  $k=8.617\text{E-}5\text{eV/K}$ ,  $E_a$  is the activation energy (0.4eV~1.2eV, here is 0.4eV).

Set a failure threshold value  $L$ , and the time when degradation path reaches  $L$  is considered as the failure time of products. Accordingly, the pseudo life values under temperature stress level 115°C, 105°C and 95°C can be obtained, as shown in Table I.

TABLE I  
PSEUDO LIFE UNDER DIFFERENT STRESS LEVELS

number	$T_1=115^\circ\text{C}$	$T_2=105^\circ\text{C}$	$T_3=95^\circ\text{C}$
080	3945.5	5626.8	7917.7
090	4012.6	5661.7	7859.9
096	4107.6	5466.6	7874.5
091	3857.7	5507.8	10591
084	4393.3	6245.5	

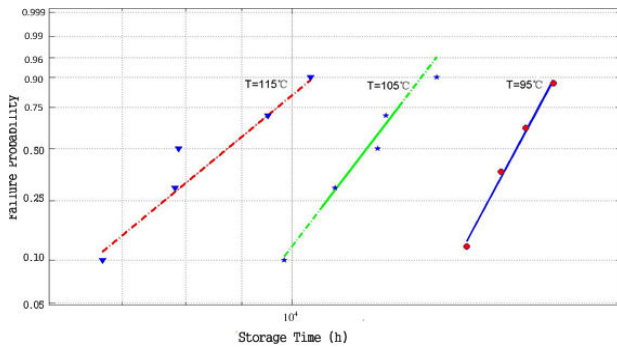


Fig. 7 Weibull Probability Paper

### C. Verification of Life Distribution Model Hypothesis

After obtaining the pseudo-life values under each stress level, in order to evaluate the storage life under the normal stress level, we need to suppose the life distribution of products. Since Weibull distribution has a wide applicability, we can assume the storage life follows a two-parameter Weibull distribution and utilize Weibull probability paper to verify the correctness of the assumption. Utilize the median rank formula

$$F(t_i) = \frac{i-0.3}{n+0.4} \text{ to estimate the failure probability } \hat{F}(t_i), \text{ and plot}$$

$(t_i, \hat{F}(t_i))$  onto the Weibull probability paper (Fig. 7). As shown in Fig. 7, the pseudo life values under the same stress level are distributed substantially in a straight line. Therefore, we can consider that the life distribution is obedient to a two-parameter Weibull distribution.

### D. Model Parameters Estimating

When the sample size  $n \leq 25$ , the best linear unbiased estimate (BLUE) or the best linear time-invariant estimate (BLTLE) is widely adopted to give point estimate or of Weibull

distribution parameters  $m$  and  $\eta$ . The following is a detailed solving process to estimate  $m$  and  $\eta$  through BLUE method.

Firstly, sort sample pseudo-life value  $t_i$  into  $t_1 \leq t_2 \leq \dots \leq t_n$ . Then take log of  $t_i$  to obtain  $x_i: x_1 \leq x_2 \leq \dots \leq x_n$ , which are the corresponding values under the extreme-value distribution. The formula of BLUE method to estimate the extreme-value distribution parameters is as:

$$\begin{aligned} \hat{a} &= \sum_{j=1}^n D(n, n, j) x_j = \sum_{j=1}^n D(n, n, j) \ln t_j \\ \hat{\sigma} &= \sum_{j=1}^n C(n, n, j) x_j = \sum_{j=1}^n C(n, n, j) \ln t_j \end{aligned} \quad (6)$$

$D(n, n, j) x_j$ ,  $C(n, n, j) x_j$  are respectively BLUE coefficients for solving  $a$  and  $\sigma$  based on complete sample  $(n, n)$ .

When  $\hat{a}$  and  $\hat{\sigma}$  are obtained,  $m$  and  $\eta$  could be estimated through the point estimation:

$$\begin{cases} \hat{m} = \frac{g_{n,n}}{\hat{\sigma}} \\ \hat{\eta} = \exp(\hat{a}) \end{cases} \quad (7)$$

where  $g_{n,n}$  is the correction coefficient. Table II shows the result.

TABLE II  
WEIBULL DISTRIBUTION PARAMETER VALUE ESTIMATE

Stress level	$\hat{m}$	$\hat{\eta}$
$T_1=115^\circ\text{C}$	7.9	4458.7
$T_2=105^\circ\text{C}$	8.0	6226.6
$T_3=95^\circ\text{C}$	7.1	9104.3

### E. Failure Mechanism Consistency Verification

As shown in Table II, the estimators of Weibull distribution shape parameters under different stress levels are basically the same, indicating that the failure mechanism has not changed during the step stress accelerated storage life test.

### F. Extrapolation of Life Distribution under the Normal Stress Level

The weighted shape parameter is;

$$\hat{m}_0 = \frac{n_1 m_1 + n_2 m_2 + n_3 m_3}{n_1 + n_2 + n_3} = 7.6 \quad (8)$$

From Arrhenius reaction rate model, we can induce the relationship between life characteristic  $\eta_i$  with temperature  $T_i$ ,

$$\ln \eta_i = a + b/T_i \quad (9)$$

25°C is the ambient temperature for the storage of camera stabilization device. Substituting data of Table II into (9), we can get calculation results by the least square fitting,  $a = -4.73$ ,

$b = 5093.20$ ,  $\hat{\eta}_0 = 2.33E5$ . Hence, the product life is obedient to  $W(7.6, 2.33E5)$ . The corresponding reliability function  $R(t)$  is;

$$R(t) = \exp\left[-\left(\frac{t}{2.33E5}\right)^{7.6}\right] \quad (10)$$

The point estimator of average storage life  $\hat{t}_e$  is;

$$\hat{t}_e = \hat{\eta}_0 \cdot \Gamma\left(1 + \frac{1}{\hat{m}_0}\right) = 2.19E5 \quad (11)$$

Therefore, we can infer the actual average lifetime of camera stabilization device is 25.0 years.

Table I shows 14 pseudo life values in high stress levels. Using (4), (5), we can obtain 14 failure life values at 25°C, denoted by  $t_i$ ,  $t_1 \leq t_2 \leq \dots \leq t_n$ ,  $n=14$ . Then we establish a generalized pivot quantity  $t$  [13],

$$t = \exp(E(\ln(t_i)) - \hat{m}_0[E(\ln(t_i)) - \ln(\hat{\eta}_0)]s / v) \cdot \Gamma(1 + s / v) \quad (12)$$

where  $s^2 = \frac{1}{n} \sum_{i=1}^n (t_i - E(\ln(t_i)))^2$ ,  $v^2 = \hat{m}_0^2 s^2$ . Hence,  $\ln(t)$  is the  $1 - \alpha$  quantile of:

$$E(\ln(t_i)) - \hat{m}_0[E(\ln(t_i)) - \ln(\eta_0)]s / v + \ln \Gamma(1 + s / v) \quad (13)$$

Based on the Monte Carlo method to generate random numbers of standard extreme value distribution, it is realizable to infer the  $100(1 - \alpha)\%$  lower one-sided confidence interval on the average life, denoted by  $t_L$ . Through simulation calculation, we can determine  $t_L = 1.98E5$ , when  $(1 - \alpha) = 0.9$ . That is to say, the 90% lower one-sided confidence interval on the average life is 22.6 years.

#### IV. CONCLUSION

In this paper, we introduce the method to evaluate the reliability and predict life of long-term storage products through step stress accelerated storage life test. Small sample size and little failure information are the difficult problems in assessing storage products with high reliability and long lifetime. To solve these problems, main work of this paper is embodied in the following several aspects:

- (1) Inference of the pseudo life distribution through establishing a nonlinear degradation path of performance indexes under three high stress levels;
- (2) Verification of the life distribution hypothesis using probability paper, as well as failure mechanism consistency using shape parameter of Weibull distribution;
- (3) Extrapolation of failure life values under the normal stress level through combining pseudo life values under high stress levels with acceleration model.

#### ACKNOWLEDGMENT

The authors acknowledge the support by the National Natural Science Foundation of China under grant No. 61473017.

#### REFERENCES

- [1] Wang Z B, Ren W B, Li G F. Review of Accelerated Degradation Testing and Accelerated Life Testing. Low Voltage Apparatus, 2010, (1):1-6.
- [2] Gao C, Jiang M. Degradation Path Modeling Method Based on Time Series Analysis. Applied Mechanics and Material, 2012, 3(6):121-126.
- [3] Zhong Q H, Zhang Z H, Wang L. About model choice of degradation data analysis method. Systems engineering, 2009, 27(11): 111-114.
- [4] Gopikrishnan A. Reliability inference based on degradation and time to failure data: some models, methods and efficiency comparisons. The University of Michigan. 2004.
- [5] Meeker W Q, Escobar L A, Lu J C. Accelerated degradation tests: modeling and analysis (J). Technometrics. 1998, 40(2):89-99.
- [6] Ma X B, Wang J Z, Zhao Y. Based on the degradation data for life distribution reliability assessment method. Systems engineering and electronics. 2010, 33(2): 261-264 (in Chinese).
- [7] Zhao Y T. Electromagnetic valve storage life assessment (J) quality and reliability, 2010(5): 25-28.
- [8] Filzmoser, P. Walczak, B. What can go wrong at the data normalization step for identification of biomarkers? Journal of Chromatography A. Oct 3, 2014, Vol. 1362, p194, 12 p.
- [9] Carrasco, Jalmar MF, Ortega, Edwin MM, Paula, Gilberto A. Log-modified Weibull regression models with censored data: Sensitivity and residual analysis. Computational Statistics and Data Analysis, 2008 52(8): 4021-4039.
- [10] Kim Seong-Joon, Bae Suk Joo. Cost-effective degradation test plan for a nonlinear random-coefficients model. In Reliability Engineering and System Safety February 2013 110: 68-79.
- [11] Chaos M T. Degradation analysis and related topics: some thoughts and a review. Proc Natl Sci Counc. ROC(A), 1999, 23(5): 555-566 .
- [12] Wang Y H, Li X G. Study on Accelerated Storage Life Test of Initiating Explosive Device Based on Step Stress Method. Equipment Environmental Engineering. 2013, 10(1):38-40.
- [13] Li X J. Study on the Confidence Limits for the Mean of Weibull Distributions. Chinese Journal of Applied Probability and Statistics.