A Multi-parameter Accelerated Degradation Prediction Method for the Storage Life of Aerospace Relays (Postprint)

Authors: Li Wenhua, Shen Peigen, Ma Sining

Date: 2019-03-05T00:00:00+00:00

Abstract

Aerospace relays are extensively utilized in critical fields such as national defense and the aerospace industry. Consequently, investigating their storage life is of paramount importance for enhancing the reliability of aerospace relays. At present, the majority of literature based on performance degradation data is confined to the study of single characteristic parameters, whereas numerous products feature multiple performance degradation indicators. Addressing the characteristic that aerospace relays possess multiple performance parameters, this paper proposes a degradation distance analysis method, incorporates principal component analysis (PCA) to integrate multiple characteristic parameters, and provides a method for solving parameter weighting factors. The contact resistance Rj, pull-in time Tx, and release voltage Us of aerospace relays are selected as the three parameters in this study, through which storage life prediction is realized, and the method is validated using actual measurement data.

Full Text

Study on Multi-Parameters Storage Life Prediction Method for Aerospace Relay in Accelerated Degradation

Li Wenhua, Shen Peigen, Ma Sining
School of Electrical Engineering, Hebei University of Technology, Tianjin 300130, China

Li Wenhua (male, born 1973) is a professor whose research focuses on electrical apparatus reliability and detection technology, new energy power generation, and grid integration technology.

Shen Peigen (male, born 1990) is a master’ s student whose research focuses on electrical apparatus reliability and detection technology.

Abstract

Aerospace relays are widely used in critical fields such as national defense and aerospace industries. Studying their storage life is therefore of great significance for improving reliability. Currently, most literature based on performance degradation data is limited to single characteristic parameters, whereas many products exhibit multiple performance degradation features. Addressing the multi-parameter characteristics of aerospace relays, this paper proposes a degradation distance analysis method and introduces Principal Component Analysis (PCA) to fuse multiple characteristic parameters, providing a method for solving parameter weighting factors. The contact resistance Rj, pick-up time Tx, and release voltage Us of aerospace relays are selected as parameters for storage life prediction, and the method is validated using measured data.

Keywords: Life prediction, degradation distance, multiple characteristic parameters, principal component analysis
Classification: V442; TM5

Key Project of Science and Technology Research in Higher Education Institutions of Hebei Province (ZD20155051).

1 Introduction

Aerospace relays are extensively employed in critical equipment for national defense and aerospace applications, where they must perform vital functions such as electrical signal transmission, circuit isolation, and relay protection under harsh environmental conditions including extreme temperatures, high humidity, and high-frequency vibration. In practical operation, the failure of a single relay can cause complete system paralysis, necessitating reliable long-term performance. For some relays, storage duration far exceeds actual service time [1]. During storage, continuously changing environmental conditions cause performance degradation, potentially rendering relays non-operational when finally deployed. Therefore, predicting the storage life of aerospace relays is crucial for ensuring extremely high reliability and longevity requirements in special environments and for avoiding significant economic losses from potential failures [2].

Traditional life testing methods for relay reliability assessment and lifetime prediction face numerous challenges, including high costs and limited failure data, often yielding ineffective results. Since failure mechanisms in service can ultimately be traced to underlying performance degradation processes, degradation data analysis has become an effective and cost-efficient approach for performance evaluation [3].

2 Problem Description

Product performance degradation may cause changes in one or several characteristic parameters, requiring evaluation of key parameters based on product functionality and comprehensive consideration of these parameters to assess operational status or performance. Particularly for complex systems, performance must often be reflected through multiple parameters that require integrated evaluation [4]. In research on performance degradation data analysis, literature addressing multiple degradation parameters typically assumes that joint probability density functions follow certain multivariate distributions. For example, reference [3] assumes multivariate performance degradation data at inspection times follows a multivariate normal distribution, while reference [5] uses joint probability density functions to characterize product failure probability density. Other approaches assume degradation patterns follow Wiener or Poisson processes and calculate failure times using predetermined single-parameter failure thresholds [6-8], thereby neglecting scenarios where failure thresholds may vary under correlated multi-parameter degradation conditions.

This paper proposes a degradation distance analysis method to address multi-parameter and multi-threshold challenges. The following assumptions are required for this analysis:

(1) The degradation of each performance parameter over time is irreversible [9].

(2) Multiple performance degradation parameters may be correlated or independent.

(3) Product failure is determined when any degradation parameter reaches its specified failure threshold.

3 Data Preprocessing

Accelerated storage degradation tests were conducted on 25 aerospace relays of a specific type under constant stress at 125°C, collecting three electrical characteristic parameters: contact resistance Rj, pick-up time Tx, and release voltage Us. The maximum value of contact resistance at the contacts was taken as the product' s contact resistance value. The specified thresholds were 50 mΩ, 8 ms, and 2.5 V, respectively. Table 1 presents the characteristic measurement data for relay #17 from the storage test.

Measurement devices inherently contain errors, and external environmental disturbances introduce noise into the measured characteristic variables. To reduce interference effects and minimize measurement randomness, it is necessary to perform smoothing preprocessing on the data. This paper employs moving average filtering to smooth each of the three characteristic parameters.

4 Parameter Degradation Distance Analysis

In most practical problems, the stable trend of performance parameters indicating product operational status is monotonically increasing or decreasing. From initial performance degradation to final failure, parameter values develop toward their failure thresholds. As test time extends, the distance between each performance parameter value and its failure threshold decreases. When the parameter value approaches the failure threshold infinitely closely (i.e., the distance approaches zero), product failure ultimately occurs. This phenomenon reflects the irreversibility of the degradation process. Figure 1 illustrates this degradation process using two performance parameters X and X .

Assuming a product has L performance degradation parameters X , X , ···, X , the distance between the performance degradation parameter value and its failure threshold at time t is |X (t) - X |, denoted as D(t). The distance between multiple performance parameters and their thresholds at time t is defined as:

$$D(t) = \sum_{j=1}^{L} w_j \left| X_j(t) - X_j^f \right|$$

where w (j = 1, 2, ···, L) are weighting factors assigned according to the practical importance of each characteristic parameter. Analysis of the distance between parameter values and failure thresholds at a given time effectively reflects product performance trends. Therefore, the key challenges in performance degradation analysis are identifying important parameters from numerous candidates, determining weighting factors among parameters, and establishing failure thresholds after data transformation.

4.1 Principal Component Analysis for Fusing Characteristic Parameters

Principal Component Analysis (PCA) is a commonly used feature extraction method that reduces multidimensional feature space while extracting correlations among all characteristic parameters. It has been widely applied in sensor signal extraction, power generation forecasting, and condenser fault diagnosis. PCA transforms original data linearly into principal components with lower dimensionality that retain maximal original information. For a data matrix X × where each column X corresponds to a feature vector and each row represents an observation sample, PCA essentially performs eigenvector analysis on its covariance matrix. When feature vectors have different units or significantly different magnitudes, the range transformation in Equation (2) is applied to normalize matrix elements between 0 and 1.

$$x'_{ij} = \frac{x_{ij} - \min_{1 \le k \le n} x_{kj}}{\max_{1 \le k \le n} x_{kj} - \min_{1 \le k \le n} x_{kj}}$$

In this paper, the three characteristic parameters—contact resistance Rj, pick-up time Tx, and release voltage Us—form the data matrix X × . PCA of X × yields three principal components Y (i = 1, 2, 3). When characteristic parameters are correlated, variation in X × is primarily captured by the first few principal components. PCA computation yields the following coefficient matrix for the three principal components:

$$\begin{bmatrix} 0.0444 & 0.8702 & -0.4907 \\ 0.0755 & 0.4868 & 0.8702 \\ 0.9966 & -0.0757 & -0.0441 \end{bmatrix}$$

When applying PCA for data compression and feature extraction, the cumulative contribution rate of retained principal components must exceed 85% to ensure that discarded information does not affect overall data analysis, as shown in Table 2.

The cumulative contribution rate of the first and second principal components already exceeds 85%. PCA thus eliminates redundant and interfering information among multiple parameters while the first two principal components sufficiently reflect variation information from the original multidimensional features. Therefore, the third principal component can be omitted, achieving dimensionality reduction. The first principal component, with the largest contribution rate, preserves the majority of correlations among characteristic parameters and reflects their variation. The second principal component, when principal components with smaller contribution rates are ignored, represents a comprehensive embodiment of error information between original data and the first principal component, reflecting uncertainties and interference factors in parameter variation.

From the coefficient matrix, the expressions for the first principal component Y and second principal component Y are:

$$Y_1 = 0.0444x_1 + 0.8702x_2 - 0.4907x_3$$

$$Y_2 = 0.0755x_1 + 0.4868x_2 + 0.8702x_3$$

The time series of the first and second principal components can be further obtained from these equations.

4.2 Determination of Principal Component Weight Factors

The contribution rate of the j-th principal component represents the percentage of total system information contained in that component, indicating its relative importance. The weighting factor in Equation (1) represents the importance of each parameter, corresponding to its information content. When q principal components are selected, the weighting factor is calculated as:

$$\omega_j = \frac{\lambda_j}{\sum_{j=1}^{q} \lambda_j}$$

where is the eigenvalue of the j-th selected principal component. Here, two principal components Y and Y are extracted. Using Equation (5), the numerical values of weighting factors and can be calculated.

4.3 Determination of Multi-Parameter Failure Thresholds

During performance degradation data analysis, original data undergoes range transformation to eliminate dimensional differences among parameters, followed by principal component analysis. Consequently, when failure thresholds are specified for individual performance parameters, these thresholds cannot be used directly but must undergo corresponding transformations to remain valid.

During product degradation, performance 指标 values exhibit long-term increasing or decreasing trends, forming degradation trajectories. Each parameter' s failure threshold corresponds to the maximum or minimum value on its degradation trajectory. Based on the range transformation formula and data trends, specified failure thresholds can be transformed accordingly. The specified threshold vector for contact resistance Rj, pick-up time Tx, and release voltage Us is [50 mΩ, 8 ms, 2.5 V], which becomes [1, 1, 0] after range transformation. Through PCA analysis using Equations (3) and (4), the three-parameter threshold vector is transformed into two principal component thresholds: Y = 0.91 and Y = 0.56.

4.4 Principal Component Degradation Distance Analysis

Substituting the time series values Y (t) and Y (t) and the weighting factors from Equation (5) into Equation (1) yields the numerical results shown in Table 3.

Plotting these points and performing curve fitting using the least squares method produces the linear relationship shown in Figure 2. The discrete points are uniformly distributed on both sides of a straight line, allowing linear fitting:

$$D(t) = p_1 t + p_2$$

where the function coefficients are p = -0.0088679 and p = 1.1615.

Product failure occurs when the principal component parameter threshold distance function D(t) = 0. Solving this yields t = 130, indicating a pseudo-failure life of 130 weeks for the product under 125°C stress conditions. In practical applications, the lifetime variation among relays of the same type under identical test conditions is small. Therefore, this method was applied to degradation data from other aerospace relays for analogous validation. If similar lifetime values are obtained for other relays, the method demonstrates applicability and accuracy.

For validation, relays #3, #5, #8, and #13 were randomly selected from the 25 test relays. Applying the method to their measured data yielded the principal component degradation distance time series shown in Table 4.

Life prediction based on the time series for these four relays produced pseudo-lifetime values of $t = 117$, $t = 114$, $t = 140$, and $t = 150$ weeks. Letting the pseudo-lifetime value for relay #17 from Table 3 be t, the mean pseudo-lifetime for the five relays is $T = (t + t + t + t + t)/5 = 130.2$ weeks, with a standard deviation $D = \mathrm{std}(t) = 15.2$ weeks. These results demonstrate that the predicted lifetimes for randomly selected relays under 125°C stress conditions are similar, indicating that the method is applicable to other relay data with reasonable accuracy, enabling storage life prediction based on multi-parameter performance degradation of aerospace relays.

5 Conclusion

(1) Accelerated storage tests can obtain critical information about relay characteristic degradation within relatively short timeframes, enabling storage life prediction for aerospace relays through degradation data analysis.

(2) This paper provides a novel approach for analyzing multi-parameter degradation data—the principal component parameter degradation distance analysis method. It defines the degradation distance between parameters and their corresponding thresholds, introduces PCA, and presents a method for determining weighting factors for different principal component parameters in degradation distance analysis. Finally, the method successfully predicts aerospace relay storage life.

(3) The proposed method addresses limitations of existing approaches based on multivariate joint probability density function assumptions and complex solution processes. Particularly as the number of performance parameters increases, the principal component degradation distance analysis method significantly reduces computational complexity.

(4) While linear fitting enables direct and rapid storage life prediction from principal component degradation distances, prediction accuracy directly depends on the quality and quantity of distance data, presenting certain limitations that require further research and improvement.

References

[1] Wang Zhaobin, Zhai Guofu, Huang Xiaoyi. Kinetic model of contact resis-

tance increment of electromagnetic relay in storage[J]. Transactions of China Electrotechnical Society, 2012, 27(5): 206-211.

[2] Lu Jianguo, Luo Yanyan, Li Wenhua, et al. Storage life test and failure analysis of aerospace relays[J]. Transactions of China Electrotechnical Society, 2009, 24(20): 54-59.

[3] Zhong Qianghui, Zhang Zhihua, Liang Shengjie. Reliability analysis approach based on multivariate degradation data[J]. Systems Engineering-Theory & Practice, 2011, 31(3): 544-551.

[4] Zhang Guolong, Cai Jinyan, Liang Yuying, et al. A fault prediction approach for multiple performance measures based on distance analysis[J]. Electronics Optics & Control, 2014(2): 32-35.

[5] Chao Daihong, Ma Jing, Chen Shuying. Assessment of storage reliability for FOGs by multivariate degradation data[J]. Optics and Precision Engineering, 2011, 19(1): 35-40.

[6] Mao Duanhai, Dong Jinlong, Wang Lixin, et al. Comprehensive assessment of FOG storage life based on multivariate degradation data[J]. Computer Measurement & Control, 2014, 22(2): 446-449.

[7] Wang Haowei, Xu Tinxue, Zhou Wei. Lifetime prediction method for missile electrical connector synthesizing degradation data and lifetime data[J]. Journal of Shanghai Jiao Tong University, 2014, 48(5): 702-706.

[8] Wang Haowei, Xu Tinxue, Zhao Xiaozhe. Residual life prediction method fusing accelerated degradation and field degradation data[J]. Acta Aeronautica et Astronautica Sinica, 2014, 35(12): 3350-3357.

[9] Zhao Zhicao, Song Baowei, Zhao Xiaozhe. Product reliability assessment by combining accelerated degradation test and accelerated life test[J]. Systems Engineering-Theory & Practice, 2014(7): 1916-1920.

[10] Wang Shujuan, Yu Qiong, Zhai Guofu. Discrimination method of contact failure mechanisms for electromagnetic apparatus[J]. Transactions of China Electrotechnical Society, 2010, 25(8): 38-44.

[11] Nie Peng, Chen Xin. Prediction of tool VB value based on PCA and BP neural network[J]. Journal of Beijing University of Aeronautics and Astronautics, 2011, 37(3): 364-367, 373.

[12] Jiang Hao, Hong Li, Zhang Guojiang. PV generation system forecasting model based on neutral network and principal components analysis[J]. Proceedings of the CSU-EPSA, 2013, 25(6): 102-105.

Note: Figure translations are in progress. See original paper for figures.