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A Lifetime Prediction Method Based on Multi-performance Parameters

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Abstract: Lifetime prediction based on multi-performance parameters is a problem in the prediction field, to solve this problem and improve prediction accuracy, Dempster-Shafer theory is applied in this study. Firstly the multi-performance parameters information is taken as the evidences in D-S theory and a lifetime prediction method based on these is proposed. For the values of the performance parameters' information are different, a lifetime prediction method with weighting is proposed. Finally, a microwave component is taken as an example to explain the engineering application of the method proposed in this study.

Key words: Multi-performance parameters, lifetime prediction, dempster-shafer theory, weighting

INTRODUCTION

Lifetime prediction is a key technology which can improve the reliability, safety and maintainability of the products. Lifetime prediction based on performance degradation is a method that describes the performance degradation process by performance degradation data and then infers the product's lifetime by the performance degradation process; it has been an important method in the research area of lifetime prediction. The performance degradation data here usually come from a single performance parameter; however, the products have multiple performance parameters which can describe the products' performance degradation process. Sometimes, it is hard to distinguish the superior or inferior among the multiple parameters. And it is unilateral to use only one parameter to describe, for the failures are caused by multi-factors. If the multi-parameters can be utilized together, the problem would be solved. The method of PCA (principal component analysis) is usually used to solve the problem above (Cheng and Pecht, 2009), by reducing the parameters to one or a few uncorrelated reconstruction parameter. However, this method can't be used in all the situations, for the physical meaning, degradation process, failure threshold and lifetime model of the multi-parameters are different and the reduction process would lose some useful information. So it is necessary to propose a more available method to predict the lifetime with the multi-parameters.

If a parameter can be seen as evidence which can describe the failure situation, the lifetime prediction with multi-parameters can be seen as a composite process of multi-evidences and the Dempster-Shaper (D-S) evidence theory is just a appropriate method to compose multi-evidences. This method is proposed by Dempster and extended by Shafer and it is a useful method for information fusion in decision level. Although there are few researches in lifetime prediction with degradation data of D-S evidence theory, it had been researched in the field of failure diagnosis, Niu and Yang (2009) researched the prediction based on data with D-S linear regression model, Basir and Yuan (2007) utilized D-S evidence theory to study multi-sensors information fusion of engine, He *et al*. (2011) studied the failure diagnosis with D-S evidence theory and Bayesian theory, Xiao *et al*. (2012) utilized the fuzzy theory to obtain the weight and researched the D-S theory weighted fusion by it. Therefore, it is practicable to use D-S evidence theory to solve the problem of lifetime prediction with multi-parameters. So a lifetime prediction method with multi-parameters by D-S evidence theory is proposed here, firstly the D-S evidence theory is introduced, secondly the multi-parameters information fusion and lifetime prediction method is studied, then the weighted fusion method is also studied, finally the microwave component is taken as an example to explain the method above.

DEMPSTER-SHAFER THEORY

The main characteristics of Dempster-Shafer theory are: (1) It provides a method to describe the uncertainty which is smarter than probability; (2) It also provides a combination rule to combine different evidences. They are the theory foundation of combining lifetime information from product's different performance parameters and they would be introduced in detail as follow.

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Basic belief assignment function: Let Θ be a finite set of mutually exclusive and exhaustive hypotheses called the frame of discernment. For any proposition A, they all belong to the set of 2^{Θ}. In 2^{Θ}, define the basic belief assignment function m (mass function): $2^{\Theta} \to [0, 1]$ and it satisfies the two following conditions:

$$\begin{cases} \sum_{A \subseteq \Theta} m(A) = 1 \\ m(\phi) = 0 \end{cases} \tag{1}$$

The subsets A with nonzero masses are called the focal elements of m and m(A) indicates the degree of belief that is assigned to the exact set of A and not to any of its subsets.

Evidences combination rule: In the frame of discernment Θ, there are n basic belief assignment functions $m_1, m_2, \ldots, m_n$ from different sources, if the evidences of them are $E_1, E_2, \ldots E_n$, there is:

$$\begin{cases} m(\phi) = 0 \\ m(C) = (m_1 \oplus m_2 \oplus \cdots \oplus m_n)(C) \\ = \dfrac{\sum_{\cap_{i=1}^{n} E_i = A} m_1(E_1) m_2(E_2) \cdots m_n(E_n)}{1 - K} \quad \forall C \subseteq \Theta, C \neq \phi \end{cases} \tag{2}$$

Where:

$$K = \sum_{\cap_{i=1}^{n} E_i = \phi} m_1(E_1) m_2(E_2) \cdots m_n(E_n) > 0 \tag{3}$$

K is the measurement of the contradiction degree between different evidences, a bigger K indicate an intenser contradiction between evidences. And 1/(1-K)is the regularization factor which is to avoid giving non-zero belief to empty set Φ.

LIFETIME PREDICTION METHOD BASED ON PERFORMANCE PARAMETERS FUSION

To predict a product's lifetime with performance parameter y, firstly the relevant degradation model should be built with the degradation data of y. According to the actual situation of y, the degradation model can be described with the method of neural networks, support vector machine and so on and also can be described with the mathematical model (Deng, 2006) which is:

$$y(t) = D(t, \theta) + \varepsilon \tag{4}$$

where y(t) is the value of y at the time of t, $D(t,\Theta)$ describes the degradation orbit of y, Θ and is the parameter of the model, is random error.

Secondly, the lifetime model is built according to the degradation model. If the failure threshold is defined as l, that means the product is failure when y(T) = l. According to the degradation model, the degradation failure distribution is:

$$F(t) = P\{T \le t\} \tag{5}$$

If the lifetime model can't derive a distribution, the lifetime prediction value t_f or interval value $[t_l, t_u]$ can also be obtained according to the lifetime model. The distribution, lifetime value and interval value are the decision information of performance parameter.

If take the decision information of multi-performance parameters as different evidences of lifetime prediction and use the Dempster-Shafer theory to combine the evidences, the lifetime prediction result based on multi-performance parameter would be obtained. Its fusion structure and process is shown in Fig. 1.

This structure can utilize the information and characteristic of multi-performance parameters adequately and it is more applicable, its detail process is shown as follow.

Suppose there are n performance parameters: $y_1, y_2, \ldots, y_n$ and their lifetime distributions are: $F_1(t), F_2(t), \ldots, F_n(t)$. If there are two proposition A and B in the frame of discernment Θ, proposition A is used to describe the product's reliable degree at time t, the smaller of m(A), the product is closer to the failure; proposition A is used to describe the product's unreliable degree at time

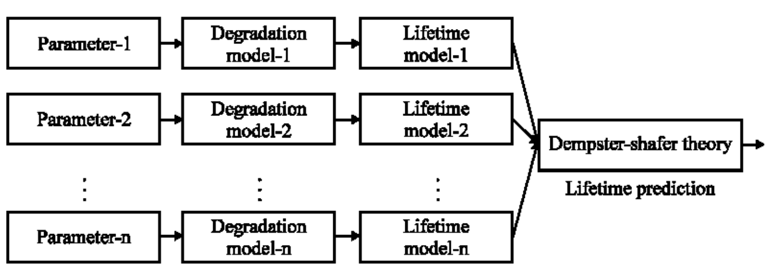

Fig. 1: Lifetime prediction process of multi-performance parameters

t, the bigger of m(B), the product is closer to the failure. According to the evidences combination rule, take the information from n performance parameters at time t as n evidences in D-S theory and which can be presented as: m_{t1}, m_{t2},..., m_{tn}, then the basic belief assignment function of performance parameter y_i is:

$$M_{ti}(A) = 1\text{-}Fi(t) \tag{6}$$

$$M_{ti}(B) = F_i(t) \tag{7}$$

With the evidences combination rule of D-S theory, the product's reliable degree C which combined n performance parameters' information can be obtained, its basic belief assignment function at time t is:

$$m_t(C) = m_{t1} \oplus m_{t2} \oplus \ldots \oplus m_{tn}(C) \tag{8}$$

where $m_t(C)$ is calculated according to formula and the m(C) at every time would be obtained, the curve that describes the change of product's reliable degree with time is plotted. Then the lifetime prediction value can also be obtained with the actual demand, if the demanded value is median-life, the lifetime prediction value is the time t when $m_t(C) = 50\%$.

If the decision information is lifetime prediction value t_f, the distribution can be derived with the prediction error $\varepsilon \sim N(0, \sigma^2)$ and:

$$t \sim N(t_f, \sigma_2) \tag{9}$$

If the decision information is interval value $[t_l, t_u]$, the interval can be seen as the 6Σ interval of normal distribution, then a normal distribution with mean of $u = t_l+(t_u-t_l)/2$ and variance of $\sigma^2 = ((t_u-t_l)/6$ is built, that is:

$$t \sim N(u, \sigma^2) \tag{10}$$

Then the lifetime prediction result would be obtained with the Eq. 6-10.

LIFETIME PREDICTION METHOD CONSIDERED WEIGHTING OF THE PARAMETERS

In the method above, all the performance parameters' importance are same. However, sometimes the importance of the performance parameters are different, the values of their information are different. To obtain a more accurate lifetime prediction result, the difference should be considered, so in this section, a weighting method is proposed to solve the problem above.

Evaluation method of the weightings: The weighting of one performance parameter represents the importance and proportion of its information among the whole information. If there is no history information to determine the weightings, their values should be evaluated with the information of performance parameters with an effective method. For the Principal Component Analysis method (PCA) can describe the importance and proportion of one parameter's information among the whole information efficiently, so a method based on PCA is proposed to evaluate the weightings of performance parameters, the process of this method is as follows:

- **Eigenvalue and eigenvector:** If $X = (x_1, x_2,\ldots, x_p)$ is a vector with p dimensions, $E(X) = \mu$, $Var(X) = \Sigma$, μ and Σ are known, the spectral decomposition of Σ is:

$$s = \sum_{i=1}^{p} \lambda_i a_i a_i' \tag{11}$$

and then $\lambda_1 = \lambda_2 = \ldots = \lambda_p = 0$ are the eigenvalues of Σ, a_1, a_2,..., a_p are the eigenvectors.

a_i is the ith principal axis of X and $z_i = a_i X$ is the ith principal component of X, i = 1,2,..., p. For the information content is in proportion to variance, so a_i should satisfy the maximization of $Var(z_i) = a_i'\Sigma a_i$, when $a_i' a_i = 1$ and $a_i' a_j = 0$.

The eigenvalue λ_i reflect the proportion of z_i in the variance of X, where $\lambda_i/(\lambda_1+\lambda_2+\ldots+\lambda_p)$ is the variance contribution ratio of z_i. The sum of the first k variance contribution ratio is the variance contribution ratio of z_1, z_2,..., z_k. Usually when $(\lambda_1+\lambda_2+\ldots+\lambda_k)/(\lambda_1+\lambda_2+\ldots+\lambda_p)$ attains the threshold (like 70-90%), the k principal component can displace X to describe the whole information.

For the n performance parameters y_1, y_2,..., y_n, they can be seen as the component of the whole information X, with the method of PCA, the eigenvalue $\lambda_1 = \lambda_2 = \ldots = \lambda_n = 0$ and eigenvector a_1, a_2, ..., a_n can be obtained and then they would be used to obtain the values of weightings.

- **Weighting value's evaluation:** When the eigenvalues and eigenvectors of performance parameter y_1, y_2,..., y_n are obtained, according to the variance contribution ratio of z_i, the proportion of z_i in the whole information is ξ_i:

$$\xi_i = \frac{\lambda_i}{\sum_{s=1}^{n} \lambda_s} \tag{12}$$

It is known that:

$$z_i = a_i'Y = a_{i1}y_1+\ldots+a_{ik}y_k+\ldots+a_{in}y_n$$

where, a_{ik} is the projection of y_k in z_i, it describes the influence of y_k to z_i, then the influence of y_k in the state space of $z_1, z_2, \ldots, z_n$ is:

$$u_k = \sqrt{\sum_{i=1}^{n} a_{ik}^2} \quad (13)$$

Consider the influence of ξ_i, equation is:

$$u_k' = \sqrt{\sum_{i=1}^{n} \xi_i a_{ik}^2} \quad (14)$$

u_k' is the quantification form of's influence in the whole information and then its weighting w_k is:

$$w_k = \frac{u_k'}{\sum_{i=1}^{n} u_i'} \quad (15)$$

Application method of the weightings: To apply the weightings to the lifetime prediction method based on performance parameters fusion, firstly the fusion result should support the high weighting parameter and the prediction result should be more accurate. In this respect, Fang (2006) had researched the application method of weightings based on D-S theory, whose expression is:

$$\begin{cases} m_k'(A_i) = \dfrac{[m_k(A_i)]^{w_k/w_{max}}}{\sum_j [m_k(A_j)]^{w_k/w_{max}}} \\ m_k'(\phi) = 0 \end{cases} \quad (16)$$

where, w_{max} is the maximum value of the weightings. For it can process and combine the basic belief assignment functions properly, so is used in this study to process and combine the information from multi-performance parameters and then lifetime prediction that considered weighting of the parameters is solved.

APPLICATION EXAMPLE

In the application of microwave component's lifetime prediction (at 25°C), Accelerated Degradation Testing (ADT) had been used to obtain the product's performance parameter degradation information. The samples' number is 3, the accelerated stress is temperature, the application method of the stress is step-stress (there are 4 steps: 60, 70, 80 and 85). There are 3 different performance parameters of the microwave component and they are all important, so the degradation data of the 3 parameters are collected simultaneously every 8 hours in ADT. The application time of temperature 60, 70, 80 and 85 are 1976, 1392, 1240 and 912 h and the degradation data numbers of different temperatures are shown in Table 1. The thresholds of the 3 parameters are 90, 95 and 80% of their standard value.

Table 1: Degradation data No.

Temperature (°C)	60	70	80	85
Degradation data No.	247	174	155	114

Table 2: Evaluation values of the parameters

Performance Parameter	1	2
Drift coefficient (25°C)	5.7215e-7	4.1375e-6
Diffusion coefficient	0.0035	0.0039

When all the ADT data are obtained, relevant degradation modeling method would be selected according to the pre-process result of the data. For the degradation increment of parameter 1 and parameter 2 followed normal distribution, so the Wiener process is used to describe the degradation process, the degradation model is (Li and Jiang, 2007):

$$Y(t) = \sigma B(t)+d(s)\cdot t+y_0 \quad (17)$$

where, $Y(t)$ is the performance degradation process of product, $B(t)$ is the standard Brownian motion with the mean value of 0 and the variance of t, denoted as $B(t)\sim N(0,\ t)$, Σ is the diffusion coefficient which is a constant and does not change with stress or time, y_0 is a known initial value of product performance and $d(s)$ is the drift coefficient which represents the degradation rate of product and is a function of stress. When the evaluation values of $d(s)$ and Σ are obtained, according to the property of Wiener process, the reliability followed the inverse Gaussian distribution, then the reliability and lifetime prediction values are obtained. The evaluation values of $d(s)$ and Σ (parameter 1 and parameter 2) are shown in Table 2.

The method of neural networks is used to parameter 3 to modeling the degradation process and predicting the product's lifetime (Zhang and Li, 2009), the lifetime prediction value is 110040 h, the prediction error is ε, where $\varepsilon\sim N(0,\ 300^2)$. According to, lifetime t follows the distribution as:

$$t\sim N(1100400,\ 300^2)$$

And then the principal component analysis method is applied to the 3 performance parameters, for the variance contribution ratio of the first principal component is 99%, so $\xi_i\approx 1$, their eigenvector is $a_1 = (-0.60818, -0.54726, -0.57501)$. With the Eq. 13~15, the weightings of the 3 performance parameters are evaluated, they are0.351, 0.317 and 0.332.

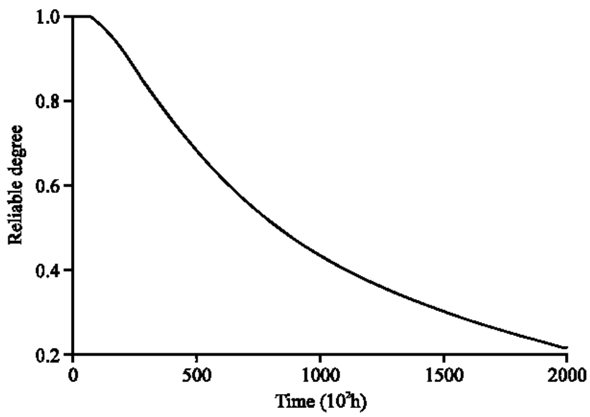

Fig. 2: Product's reliable degree at different times

Table 3: Lifetime prediction result

Method	Parameter 1	Parameter 2	Parameter 3	3-parameters fusion	Considered weightings
Lifetime (h)	80500	75800	110040	91600	83700

With the lifetime prediction method proposed in this paper, the information of the 3 performance parameters at time t are taken as different evidences of lifetime prediction and written as m_{t1}, m_{t2} and m_{t3}. Their basic belief assignment functions are $m_{t1}(A)$, $m_{t1}(B)$, $m_{t2}(A)$, $m_{t2}(B)$, $m_{t3}(A)$, $m_{t3}(B)$. Define the extent of t is 1 to 200 thousand hours, the time interval is 1hour and the basic belief assignment functions of the 200 thousand time point are evaluated, then the product's reliable degree at different times is described which is shown in Fig. 2.

If define the product's lifetime t is the time when its reliable degree is 50% and then the lifetime prediction result based on multi-performance parameters is obtained. The results of with single parameter, with 3 parameters and considered the weightings are shown in Table 3.

From this example, we can see that the method proposed in this paper can solve the problem of lifetime prediction based on multi-performance parameters.

CONCLUSION

The information from multi-performance parameters are utilized comprehensively with D-S theory and relevant degradation modeling method in this study to predict product's lifetime. And in order to predict the lifetime more accurately, a method based on PCA are proposed to obtain the weightings of the multi-performance parameters. Then the problem of lifetime prediction based on multi-performance parameters are solved. At the same time, this method can also solve the problem of lifetime prediction based on information from multi-sources, by taking the test information, field using information and simulation information etc., as the evidences of lifetime prediction.

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