Mechanical Products Reliability Assessment Based on the Structural Performance Degradation Data

Wang Qiang, Feng Jing, Sun Quan, Pan Zhengqiang, and Meng Jieru

***Abstract*—During mechanical products are in the process of testing or running, a number of key components will be wearing and aging, resulting in some sizes or gaps change. This kind of phenomena can be called the structural degradation. In order to obtain the degradation data, we need to dismantle and inspect the product in a planned way, which is usually a very complex work. However, it's seldom to carry out the research work based on structural degradation data in the research field of reliability assessment and life prediction. In this paper, the structural degradation data are described as a linear stochastic process model, considering the failure mechanism of the product, the reliability function can be obtained. At last a numerical example of a marine steam turbo-generator (MSTG) is given to illustrate the efficiency of this model.**

***Index Terms*—Reliability assessment, life prediction, structural performance degradation data, marine steam turbo-generator (MSTG).**

I. Introduction

Rub and impact between the static and dynamic components of MSTG is its common fault in the process of working. With the continuous improvement of power generation efficiency requirement and manufacturing processes, the gap between the static and dynamic component becomes smaller and smaller. Additionally, the MSTG usually works under variable conditions, and the support carrier of the STG is instability on the sea. Therefore, rub and impact fault is more likely to happen. The main parts are usually the surfaces of impeller and partitions, rotating blades and cylinder, shaft and steam seal, journal and bearing etc. Rub and impact makes labyrinth gap increase and bearing thickness reduce, ultimately leads to lower power efficiency, and even seriously affects the safe operation of the turbine. This change in the size of the MSTG itself can be called structural degradation, which may hinder the turbine's normal work performance. When degraded to a certain extent, the size does not meet the design requirements, we need to repair or replace the relevant components. Dismantling the components and measuring the sizes during the turbo-generator testing or running around can help us obtain the structural degradation data. Then we can carry out the research of reliability assessment and life prediction about some key components using the data. This work will help engineers to carry out maintenance and management, and to prevent the catastrophic failure happening.

Structural degradation of products is such a class of phenomena characterizes the components of product are gradually degrading over time due to the collision, abrasion and other forces. The mainly performance of the structural degradation is the change of the size of some components. The degradation of product's structure will lead to declining product's operating performance. Meng Xianghui modeled and analyzed for two typical wear phenomena, in order to examine the impact of structural degradation on performance degradation [1]. Due to the randomness of environmental stress and internal interaction, the structural degradation increment at a time is also random. Therefore, we can use some stochastic process models to describe the structural degradation of products.

At present, many domestic and foreign scholars have conducted research for the performance degradation. Gertsbackh and Kordonskiy proposed a simple linear model in which the slope and intercept are both random variables [2]. Feng Jing put forward a linear stochastic process model to describe the process of the product performance parameters approaching the critical value, then deduced the product's failure distribution function according to analyzing the failure mechanism carefully [3], [4]. In recent years, the reliability assessment and life prediction method based on performance degradation data has been widely used in electronics, machinery and other engineering fields [5], [6]. However, the literature about reliability assessment and lifetime prediction based on the structural degradation data obtained by dismantling and inspecting is rarely. This paper presents a linear stochastic process to describe the degradation process of the structural parameters of mechanical products, combined with the structural degradation data to research the reliability assessment problem of mechanical product components.

The remainder of this paper is organized as follows. Section II establishes a linear stochastic process degradation model and estimates model parameters. Section III establishes the life model of part level, then component level. Section IV provides a numerical experiment example to demonstrate the feasibility and effectiveness of this model. Finally, concluding remarks are given in Section V.

II. Degradation Model

A mechanical product has n-species typical wear components. For the i-th component, there are m_i parts existing structural degradation phenomena, where $i=1,2,\cdots,n$. We accurately measure the size of each part before and after the running attrition test. The wear rate of the j-th part of the i-th component is denoted by x_{ij} , which can be described as:

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$$x_{ij} = \frac{|X_j^{(i2)} - X_j^{(i1)}|}{\Delta T}, i = 1, \cdots, n; j = 1, \cdots, m_i \quad (1)$$

where $X_j^{(i1)}$ is the structure size measured before the test, $X_j^{(i2)}$ is the structure size measured after the test, ΔT is the interval time between two measurements.

Throughout this paper, the structural degradation performance of the i-th component can be characterized by the size change of its key parts, denoted by $X_i(t)$, which can be expressed as

$$X_i(t) = A_i + V_i t, i = 1, 2 \cdots n \quad (2)$$

where A_i is the initial value of the key part's size, and it is determined by production process and assembly process. Even with the same manufacturers out of the same batch of products, the size of the initial value will be some volatility. According to the central limit theorem, A_i is a normally distributed random variables, thus:

$$A_i = N(\mu_{A_i}, \sigma_{A_i}^2), i = 1, 2 \cdots n \quad (3)$$

And V_i is the wear rate of the key part's size, which is determined by work stress, material characteristics and other factors. Even with the same manufacturers out of the same batch of products, the size of the wear rate will be some volatility. According to the central limit theorem, V_i is a normally distributed random variables, thus:

$$V_i = N(\mu_{V_i}, \sigma_{V_i}^2), i = 1, 2 \cdots n \quad (4)$$

Obviously, Eq. (2) is a linear stochastic process model. $X_i(t)$ is a normally distributed random variable. Its expectation and variance as follow:

$$E[X_i(t)] = E[A_i + V_i t] = \mu_{A_i} + \mu_{V_i} \cdot t, i = 1, \cdots, n$$

$$D[X_i(t)] = D[A_i + V_i t] = \sigma_{A_i}^2 + \sigma_{V_i}^2 \cdot t^2, i = 1, \cdots, n$$

The parameters can be all estimated using the test data, as follow

$$\hat{\mu}_{A_i} = \frac{\sum_{j=1}^{n_i} X_j^{(i1)}}{n_i}, \hat{\sigma}_{A_i} = \sqrt{\frac{\sum_{j=1}^{n_i} (X_j^{(i1)} - \hat{\mu}_{A_i})^2}{n_i - 1}}, i = 1, \cdots, n \quad (5)$$

$$\hat{\mu}_{V_i} = \frac{\sum_{j=1}^{n_i} x_{ij}}{n_i}, \hat{\sigma}_{V_i} = \sqrt{\frac{\sum_{j=1}^{n_i} (x_{ij} - \hat{\mu}_{V_i})^2}{n_i - 1}}, i = 1, \cdots, n \quad (6)$$

where, n_i represents the number of the i-th component.

III. Life Prediction Model

Product degradation failure is generally defined as that the performance parameter drops below a certain threshold level. Suppose the threshold of the *i*-th component is $[D_{1i}, D_{2i}]$. The life of the *i*-th component is a random variable denoted by T_i. The cumulative distribution function of T_i denoted by $F_{T_i}(t)$, then the reliability function of the *i*-th component denoted by $R_{T_i}(t)$.

Assuming the component size unilaterally changes because of mechanical wear, so that this paper just considers the unilateral degenerate failure threshold. If the structure size parameter is monotonically decreasing, then the failure threshold is D_{1i}. The reliability function is given as:

$$\begin{aligned} R_{T_i}(t) &= 1 - F_{T_i}(t) \\ &= P\{T_i \geq t\} = P\{X_i(t) \geq D_{1i}\} \\ &= P\left\{ \frac{X_i(t) - (\mu_{A_i} + \mu_{V_i} t)}{\sqrt{\sigma_{A_i}^2 + \sigma_{V_i}^2 \cdot t^2}} \geq \frac{D_{1i} - (\mu_{A_i} + \mu_{V_i} t)}{\sqrt{\sigma_{A_i}^2 + \sigma_{V_i}^2 \cdot t^2}} \right\} \\ &= 1 - \Phi\left(\frac{D_{1i} - (\mu_{A_i} + \mu_{V_i} t)}{\sqrt{\sigma_{A_i}^2 + \sigma_{V_i}^2 \cdot t^2}} \right), i = 1, \cdots, n \end{aligned} \quad (7)$$

If the structure size parameter is monotonically increasing, then the failure threshold is D_{2i}. The reliability function is given as

$$\begin{aligned} R_{T_i}(t) &= 1 - F_{T_i}(t) \\ &= P\{T_i \geq t\} = P\{X_i(t) \leq D_{2i}\} \\ &= P\left\{ \frac{X_i(t) - (\mu_{A_i} + \mu_{V_i} t)}{\sqrt{\sigma_{A_i}^2 + \sigma_{V_i}^2 \cdot t^2}} \leq \frac{D_{2i} - (\mu_{A_i} + \mu_{V_i} t)}{\sqrt{\sigma_{A_i}^2 + \sigma_{V_i}^2 \cdot t^2}} \right\} \\ &= \Phi\left(\frac{D_{2i} - (\mu_{A_i} + \mu_{V_i} t)}{\sqrt{\sigma_{A_i}^2 + \sigma_{V_i}^2 \cdot t^2}} \right), i = 1, \cdots, n \end{aligned} \quad (8)$$

where $\Phi(\bullet)$ is the cumulative distribution function (*cdf*) of the standard normal distribution.

Using Eq. (7) and Eq. (8), we just obtain the reliability function of every parts of a component. Then, we need to determine the reliability function of the key components. We focus on the following two cases:

Case I: The component only has a key wear part, so the reliability function of the component is the reliability function of the key part.

Case II: The component has several key wear parts, we should consider their reliability logical structure relationship.

Assuming a component denoted by h includes k_h key wear parts. For simplicity, we assume that the reliability logical structure of all the wear key parts is in series. Then the life of the component T_h can be expressed as

$$T_h = \min_j \{T_{h_j}\}$$

Quickly we can obtain the reliability function of the component $R_h(t)$ as follow:

$$\begin{aligned} R_h(t) &= 1 - F_{T_h}(t) = P\{\min_j T_{h_j} \geq t\} \\ &= P\{T_{h_j} \geq t, j = 1, 2, \cdots, k_h\} \\ &= \prod_{j=1}^{k_h} R_{T_{h_j}}(t) \end{aligned} \quad (9)$$

Reliable life denoted by T_{R_0} is the continuous working time when the reliability of the component drops to R_0. The expression as follow:

$$R_h(t) = R_0$$

Its solution is

$$t = T_{R_0} = R^{-1}(R_0) \quad (10)$$

IV. Case Study

The stator winding end region of MSTG will undergo electromagnetic force in the normal working status. If the natural frequency of stator winding end region is the same as or near to the frequency of dominated electromagnetic force, then the stator winding end region will result in resonance or large amplitude vibration. It will affect the normal operation of the MSTG, even result in worse accident. Therefore, we choose the end region as an example to illustrate the efficiency of the model above.

In this paper, steam sealing clearance of the end region is selected to be the key structural parameter. There are 4 different kinds of steam sealing clearance, denoted as A, B, C, D, in every 3 similar key positions of the end region. The reliability test lasted 500 hours. Dismantle the turbo-generator before and after the test to measure every one kind of the steam sealing clearance repetitive twice.

In other words, we can consider that there are six samples of the end region, and each sample has the four kinds of steam sealing clearance respectively denoted by A, B, C, D. Fig. 1 shows the initial value and the final value of the four steam sealing clearance.

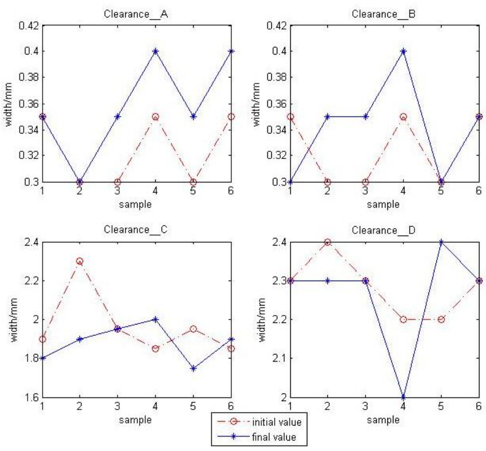

Fig. 1. The measured data of steam sealing clearance.

Using Eq. (5) and Eq. (6), we can get μ_{A_i}, σ_{A_i} and μ_{V_i}, σ_{V_i}. The estimation results and design thresholds are all presented in Table I. Then using Eq. (7) and Eq. (8), we can get the reliability function of each key part. Table II shows reliability assessment results of the steam sealing clearances. Finally using Eq. (9), we get the reliability function of the large marine turbo-generator's end region. Table III shows us the results. And Fig. 2 shows the reliability function curve of the end region.

TABLE I: Parameter Estimation Results of Each Clearance

No.	Threshold	μ_{A_i}	σ_{A_i}	μ_{V_i}	σ_{V_i}
A	0.3~0.45	0.3250	0.0274	0.0333	0.0258
B	0.3~0.45	0.3250	0.0274	0.0167	0.0408
C	1.6~2.3	1.9667	0.1693	-0.0833	0.1966
D	1.7~2.3	2.2833	0.0753	-0.0167	0.1329

TABLE II: Reliability Assessment Results of Each Clearance

No.	$T_{0.9}$(h)	$T_{0.8}$(h)	R(500)	R(1000)	R(1500)
A	900	1100	0.9926	0.8409	0.6195
B	900	1200	0.9862	0.8564	0.7250
C	400	700	0.8626	0.6798	0.5754
D	1500	2300	0.9999	0.9767	0.9056

TABLE III: Reliability Assessment results of the End Region

MTBF(h)	$T_{0.9}$(h)	$T_{0.8}$(h)	R(500)	R(1000)
1438	400	600	0.8443	0.4781

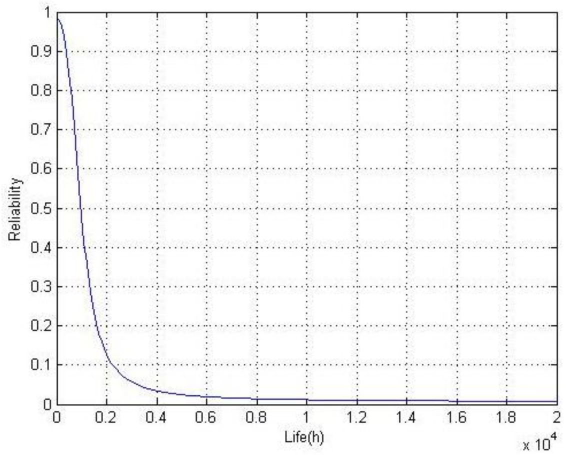

Fig. 2. The reliability function curve of the end region.

V. Conclusions

In this paper, we take the end region of a type of MSTG as an example. We select the steam sealing clearance as its key structural degradation parameter, and use the linear stochastic process theory to model its degradation process. Finally, we successfully obtain the reliability estimating results. This article takes a useful attempt to provide an easy operational engineering method for reliability estimation based on the structural degradation data.

In the future study, we can increase the frequency of dismantling and inspecting. And then we can try to use the wiener process to model the structural degradation performance, in purpose to improve predictive accuracy.

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