A Reliability Evaluation Method for Non-electronic Product Storage Based on Inventory Rotation Data

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Abstract. Storage reliability refers to the ability of a product to maintain its specified functionality under specified conditions and for a specified storage time. To accurately evaluate the reliability of non-electronic product storage in a warehouse, this paper constructs a non-electronic product storage reliability evaluation model based on log normal distribution using inventory rotation data, designs a model solving algorithm, and provides calculation examples.

Keywords: Non-electronic products; Storage reliability; Lognormal distribution; Inventory rotation data; Evaluation methods

1 Introduction

Storage reliability refers to the ability of a product to maintain its specified functionality under specified conditions and for a specified storage time. It is an important capability indicator for many types of products. A certain warehouse is mainly responsible for the storage, supply, sealing and maintenance of non-electronic products. The warehouse will accept various materials allocated by the superior warehouse, and will also adjust the plan according to the superior's layout, receiving equipment and equipment from subordinate units for sealing. In recent years, with the expansion of business scope, the categories and quantities of warehouse inventory equipment and equipment have been increasing, making it difficult to effectively control the quality level of inventory products. Due to the possibility of product failure during the storage stage in the warehouse, it is necessary to effectively evaluate the storage reliability of the product and provide effective support for warehouse management decisions.

Non-electronic products enter the storage period after normal functional testing. Warehouse management personnel regularly inspect equipment and scrap any products found to have malfunctions. In addition, if the warehouse receives instructions to release the product, it will conduct pre-release testing on the product. If the product is in good condition, it will be released normally. If the product malfunctions, it will be scrapped. In actual product management, data is relatively scarce. If only product fault data is used to evaluate storage reliability, there will be significant errors compared to the actual situation. Therefore, it is necessary to treat all the incoming, outgoing, and

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fault data of products as inventory rotation data, and then use inventory rotation data to evaluate the storage reliability of non-electronic products.

At present, the biggest difficulty in conducting research on storage reliability assessment is the scarcity of failure data. Researchers can only construct models to evaluate the storage reliability of products based on different actual situations, such as no failure data[1], small sample failure data[2], deleted data, and sampling data[3]. In addition, some researchers have conducted storage reliability assessments on specific objects such as aviation ammunition[4], radio fuzzy detonation height[5], solid propellants[6], guided ammunition[7], missiles[8], etc. The existing research results have strong guiding significance for storage reliability assessment based on inventory rotation data[9, 10], but further research is needed on how to implement it.

This article focuses on the storage reliability evaluation requirements of non-electronic inventory products, constructs a storage reliability evaluation model based on inventory rotation data, provides application examples, and finally summarizes the entire article.

2 Mathematical Model

The typical feature of storage failure of non-electronic components is that there are fewer failures in the early stages of storage, but as the storage period increases, the risk of failure continues to increase, and high-frequency failure events may occur at a certain stage. For such situations, using a log normal distribution model for analysis is a very good choice.

The log normal distribution model is a continuous distribution model, characterized by the fact that although different equipment failure data may vary, they are mainly concentrated in a certain period of time. According to its probability density function, it shows a phenomenon of high in the middle and low at both ends. The aging and wear of non-electronic components can lead to a decrease in the performance of the components, and the failure time is relatively concentrated in the same environment. Generally, a logarithmic normal distribution model can be used to describe it, such as air extraction devices, reverse recoil devices, etc.

The probability density function of the logarithmic normal distribution is as follows.

$$f(t, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(lnt-\mu)^2}{2\sigma^2}} \tag{1}$$

Among them, μ represents the logarithmic mean of a variable, σ represents the standard deviation of the logarithm of a variable. From the above equation, it can be seen that the variable t of the logarithmic normal distribution must be greater than 0, which is very consistent with the physical meaning of describing component life. Therefore, its application in the field of reliability is extremely extensive. The calculation formula for reliability is as follows.

$$R(t) = \frac{1}{\sigma\sqrt{2\pi}} \int_t^\infty \frac{1}{x} exp\,(-\frac{(lnx-\mu)^2}{2\sigma^2}) dx \tag{2}$$

Assuming that a certain component has n records of storage data that can be collected, including data of failed components that have already been stored and data of non-failed components that have not been stored. The record of failed data is $r(r \le n)$, and the corresponding failure time is denoted as $t_1, t_2, \cdots, t_r$. There are $n - r$ records of non-failed data, and the corresponding storage time is denoted as $t_{r+1}, t_{r+2}, \cdots, t_n$.

Using component storage inventory rotation data $t_1, t_2, \cdots, t_n$, the maximum likelihood estimation method can be used to estimate unknown parameters μ and σ. When considering both failed and non-failed data, the maximum likelihood function calculation method is as follows.

$$L(\mu, \sigma | t_1, \cdots, t_n) = \prod_{i=1}^{r} f(\mu, \sigma | t_1, t_2, \cdots, t_r) \prod_{i=r+1}^{n} R(\mu, \sigma | t_i, x_1, \cdots, x_m) \quad (3)$$

To calculate μ, σ, the maximum likelihood estimation value can be based on the principle of maximum and minimum values, which means that at the extremum point, the first-order partial derivatives of the two parameters to be estimated are both 0. Therefore, it is possible to first take the logarithm on the right side of the above equation, and then calculate its relationship with each other separately the first order partial derivative of μ, σ, and finally construct the system of equations.

$$\begin{cases} \frac{\partial lnL(\mu,\sigma|t_1,\cdots,t_n)}{\partial \mu} = 0 \\ \frac{\partial lnL(\mu,\sigma|t_1,\cdots,t_n)}{\partial \sigma} = 0 \end{cases} \quad (4)$$

The above equation system is relatively complex, and it is difficult to solve it using analytical calculations. Therefore, computers can be used to solve problems through numerical analysis, and the solving algorithm is shown in Algorithm 1.

Algorithm 1: Model solving algorithm

Input: Inventory rotation data $t_1, t_2, \cdots, t_r, \cdots, t_n$, accuracy requirements for expected and variance approximation errors as α, β
calculate $\mu_0 = \frac{\sum_{i=1}^{n} t_i}{n}$ as the lower limit value of μ
calculate $\sigma_0 = \sqrt{\frac{\sum_{i=1}^{n}(\mu_0 - t_i)^2}{n}}$ as the initial value of σ;
Calculate the initial value L of the maximum likelihood function $\hat{L} = L(\mu_0, \sigma_0 | t_1, \cdots, t_n)$
sign the maximum likelihood estimate of μ, σ as $\hat{\mu} = \mu_0, \hat{\sigma} = \sigma_0$
$\Delta = ture$
$\mu = \mu_0$
While(Δ)
  $\Delta = False$
  $L_{before} = 0$
  For ($\sigma = 0, \sigma < \sigma_{max}, \sigma = \sigma + \beta$)
    Calculate the current maximum likelihood function value $L = L(\mu_0, \sigma_0 | t_1, \cdots, t_n)$
    If（$L > \hat{L}$）
      $\hat{\mu} = \mu$

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        σ̂ = σ
        L̂ = L
            Δ= ture
      End if
      If(L ≥ L_before)
        L_before = L
      Else
        σ = σ_max
      End if
    End for
End while
Output: μ̂, σ̂
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The core idea of Algorithm 1 is to first treat all non-failed data as failed data and calculate the mean as the lower limit of $\hat{\mu}$, which must be less than the optimal expected value. When the closer the value of μ is to the optimal solution, while finding the corresponding optimal value of σ, the value of the maximum likelihood function will inevitably be larger. For the same μ, the different value of σ will lead to different maximum likelihood estimates, but there will inevitably be an accompanying process of first decreasing and then increasing the value of σ. If the corresponding maximum likelihood estimate of μ can be found, it can be used to jump out of the current set of search process for σ. σ_{max} is pre-set based on the sample data situation for the maximum value of σ. Given the different situations of the sample data, there may be better results for the method of calculating σ_{max}. Therefore, this article recommends a calculation method for σ_{max} is as follows.

$$\sigma_{max} = \sqrt{\frac{\sum_{i=1}^{n}(t_{r,min} - t_i)^2}{n}} \tag{5}$$

Among them, $t_{r,min}$ represents the minimum value in the failed sample data. In this way, the smallest failed data is considered as the mean calculated σ_{max} , which will inevitably be much greater than the optimal solution $\hat{\sigma}$. Therefore, it can ensure the accuracy of the final calculation results. Base on the value of $\hat{\mu}$, $\hat{\sigma}$, it can be used to calculate the reliability under logarithmic normal distribution as follows:

$$R(t) = \frac{1}{\hat{\sigma}\sqrt{2\pi}} \int_{t}^{\infty} \frac{1}{x} exp\left(-\frac{(lnx - \hat{\mu})^2}{2\hat{\sigma}^2}\right) dx \tag{6}$$

3 Calculation Example

A certain product in the warehouse is a typical non electronic product and rarely experiences malfunctions during the initial storage period. A batch of data was collected and stored in 2018, as shown in the table 1.

Table 1. Inventory rotation data record table

Sample number	Outbound status	Storage time
1	Failed	700
2	Failed	700
3	Failed	850
4	Failed	750
5	Non-failed	890
6	Non-failed	700
7	Non-failed	750
8	Non-failed	1000
9	Non-failed	1000

Using the method in section 2, a reliability evaluation model for the storage of air extraction devices based on inventory rotation data is constructed. Then, Algorithm 1 is used to analyze the inventory rotation data and solve the model. The key parameters of the model can be obtained as follows:

$$\hat{\mu} = 6.77$$
$$\hat{\sigma} = 0.12$$

Using the classic solution method, only considering fault data, the key parameters of the model obtained by solving the model are as follows:

$$\hat{\mu} = 6.61$$
$$\hat{\sigma} = 0.008$$

Due to the high proportion of non-failed data in the rotation data, but the difficulty in mastering the life data after the shipment, the non-failed data from the shipment can be equivalently regarded as faulty data, which is named the equivalent method in this article. Using the traditional calculation method, the corresponding model parameters for the equivalent method are calculated as follows:

$$\hat{\mu} = 6.69$$
$$\hat{\sigma} = 0.02$$

According to the model parameters calculated using three methods, draw the storage reliability variation curve as shown in Fig. 1.

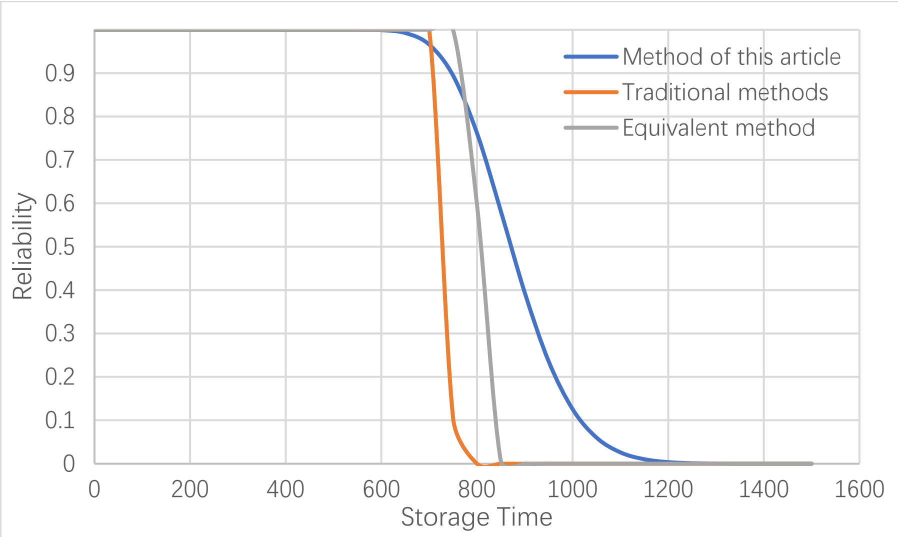

Fig. 1. Schematic diagram of reliability curve comparison

According to the above figure, the average storage life calculated by the method in this article is 870 days, and the reliability of storage for 750 and 800 days is 0.89 and 0.76, respectively; The average lifespan calculated by traditional methods is 747 days, and the reliability for storage of 750 and 800 days is 0.1 and 0, respectively; The average life calculated by the equivalent method is 807 days, and the reliability of storage for 750 and 800 days is 0.9 and 0.59, respectively. In practice, more than 60% of them are still intact after being stored for more than 800 days, and the average storage life far exceeds 750. Therefore, traditional methods that only consider storing data are not in line with the actual situation. In traditional methods, equating non fault data to fault data will inevitably result in the calculated average lifespan being lower than the actual lifespan level.

4 CONCLUSION

Storage reliability assessment is a very important issue that warehouse management needs to face, and accurately assessing the storage reliability of products is of great significance for warehouse management decisions. This article proposes a method for evaluating storage reliability based on inventory rotation data, constructs relevant models, and designs model solving algorithms. The application examples show that the method proposed in this article can effectively evaluate the storage reliability of products. The method in this article fully considers the value of non-failed data, making the evaluation results more reliable. If the invalid data is not particularly abundant, this method can make better use of limited data, and the evaluation effect will be better..

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