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RESEARCH ARTICLE

The reliability prediction of torpedo electronic components in service life

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Abstract
For torpedo electronic components tested by functional verification, there are characteristics of a few samples and few failures. During service life, it is difficult to analyse and predict the changes in reliability. At present, management's observation of quality is mainly base on failure data, and it is difficult to make predictions about the moments without failure in service life. In this paper, according to the failure data, we consider such factors as performance degradation and detection and use the model of instantaneous failure rate to evaluate the reliability of the detection moments periodically, and predict the reliability of stages through the results of detection moments. The method proposed in this paper, on the one hand, considers the service experience, and on the other combines the detection data, to make the final evaluation result more credible. In addition, this paper predicts the changing trend of reliability between adjacent detection moments, which can provide a useful reference for quality management work.

1. Introduction

With the efficient development of reliability work in recent years, military equipment system has become highly reliable, which almost no failure during the storage period (Liu et al., 2017; Park et al., 2019; Lijuan et al., 2020). During long-term storage, weapons will be affected by temperature, humidity, and powering on/off (Yan, 2014; Wang et al., 2021). At the same time, weapons will undergo several actual drills due to cost and cycle factors during their service life, which will inevitably go through the stages of transportation, technical preparation, loading, etc. These stages will affect the reliability, maintainability and supportability (RMS) of torpedoes. Quality monitoring of torpedoes has become an important task for the logistics support department. The ability to predict reliability during the service period can help maintenance personnel to maintain the torpedo in time, improve the quality and extend the service life of the torpedo. However, predicting the reliability under the premise of a small amount of failure data is difficult (Meng et al., 2019; Bhargava, 2020). According to the statistics of the historical detection information, the performance degradation or failure of electronic components are mainly the manifestations of torpedo RMS (Li et al., 2019b). Therefore, it is important to study the reliability of torpedo electronic components in service life.

Figure 1 shows the structure of a typical torpedo. Systems composed of electronic components are collectively referred to as electronic systems. According to Figure 1, the electronic system includes sonar system, guidance system, control system, sensor, etc. As a complicated system, torpedo electronic systems are difficult to analyse and model directly (Zhang et al., 2019). These systems could be classified by the inspection methods in the routine maintenance process, and can be divided into two categories. The first category is general electronic components, which are tested through functional verification that

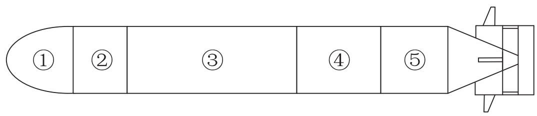

Figure 1. *Torpedo structure.*

generally has the characteristics of recording the condition through power-on, such as the sonar system, guiding system and control system. The second category is performance degradation components, which are tested through key parameter measurements, such as depth sensors. In this study, the reliability of the first category system prediction work was mainly carried out on general electronic components.

In most cases, the reliability of general electronic components was predicted by the statistics method. For torpedoes, the credibility calculated by this method will degrade due to the insufficient number of samples and failure data. Therefore, a comprehensive estimate of the reliability of general electronic components in this study which combined technical parameter data, performance degradation and detection was conducted. The reliability prediction methods for general electronic components include the bottom-up statistical method (BS), top-down similarity analysis method (TD) based on external failure data, and bottom-up failure physical method (BP). The first two methods are statistical analysis of failure data, while the latter is based on the failure physics (POF) model (Chen et al., 2013). According to the research of the BP method, the life of electronic components obeys the exponential model (Bain, 2017; Zhi et al., 2021). The average failure rate is used for reliability estimation in the traditional methods.

In the actual service process of weapons, the failure rate will gradually rise in dynamic changes due to environmental factors and other influences. In other words, that is the influence of environmental factors on the failure rate in the BS method (Bajeel and Kumar, 2017; Dinu, 2020). Under the assumption that the life of electronic components obeys the exponential model, this study built the inherent failure rate degradation model by combining BS and BP methods based on the bathtub curve model established by Xie and Lai (1996). Then the instantaneous failure rate and reliability were calculated by environmental factors, service life, periodic detection, repair, phase replacement and Bayes probability. The objectivity of evaluation results in this study makes full use of the service experience and detection information of components. The purpose is to help logistics support personnel to understand the changes in the quality status of a batch of torpedoes and formulate better maintenance plans, finally improving the availability of weapons and reducing maintenance costs and losses.

The rest of the paper is organised as follows: Section II is literature review, which introduces related concepts. Section III is methodology, the models of failure rate and reliability are given, and the parameters of the degradation model and detection degradation are estimated. The examples are found in Section IV and provide simulation results and analysis. Conclusions and suggestions for future studies that need improvement are found in Section V.

2. Literature review

Reliability R: The reliability mentioned in this paper is the use's reliability of components (Cai et al., 2018), which refers to the ability of products to maintain the specified function under the specified service conditions and service time. It mainly reflects the product to resist the influence of various factors and keep the product's function unchanged during the long-term service time. The stronger the ability of the product, the better the reliability, and conversely, the worse.

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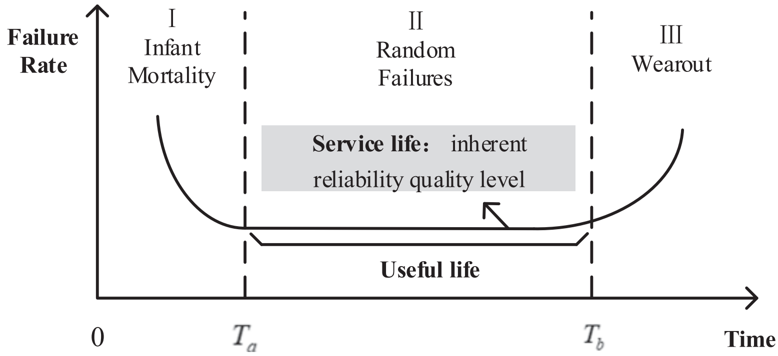

Figure 2. *Bathtub curve.*

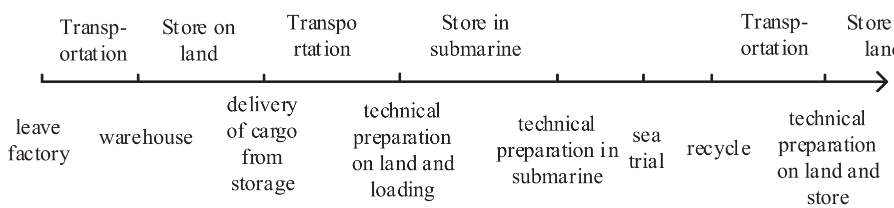

Figure 3. *Typical service life of torpedoes.*

Failure rate λ: The failure rate of the system usually depends on the variable of time and will change throughout the life cycle, which meets the bathtub curve (Ahsan et al., 2020; Majidi et al., 2020), as shown in Figure 2. Items in the same batch of in-service equipment have passed strict technical tests and qualifications before leaving the factory. This study considers that they have passed the early environmental stress screening and entered the random failures period (Han et al., 2019).

Exponential model: The exponential model, with only one unknown parameter (average failure rate $\bar{\lambda}$), is the simplest of all life distribution models. In this model, the relationship between reliability and average failure rate is $R = e^{-\bar{\lambda}t}$. It is widely used in the reliability prediction of electronic equipment (Jia and Yang, 2020).

Exponential-like model: The model is a modification of the exponential model. Considering the influence of internal/external factors on components, the failure rate changes dynamically in service life, either linearly or nonlinearly. Replace the average failure rate with the instantaneous failure rate (Li et al., 2020), that is $\int_{t_1=0}^{t} \lambda(t)dt = \bar{\lambda}t$. Then

$$R(t) = R_0 e^{-\int_{t_1=0}^{t} \lambda(t)dt} \tag{2.1}$$

where R_0 denotes product reliability at the time t_1, $\lambda(t)$ denotes failure rate function. It refers to the value of failure rate at the time t, $R(t)$Z – Product reliability at the time t.

When the failure rate changes linearly, the exponential-like model is equivalent to the exponential model.

The complete service experience of the torpedo is: After leaving the supplier's factory, it is transported to the logistics support warehouse for storage. During the storage period, inspection and maintenance are regularly required. When there is a mission requirement, the torpedo is called out of the warehouse, transported to the designated location for technical preparation on the road and loaded into the ship or submarine. On submarines and other carriers, the torpedo is stored, tested and launched. Due to the high cost of torpedoes, most of the troops use exercise-head torpedo sections replacing warhead. After use, the torpedo must be recovered and restocked. The division of service life: Typical service life of a torpedo is shown in Figure 3.

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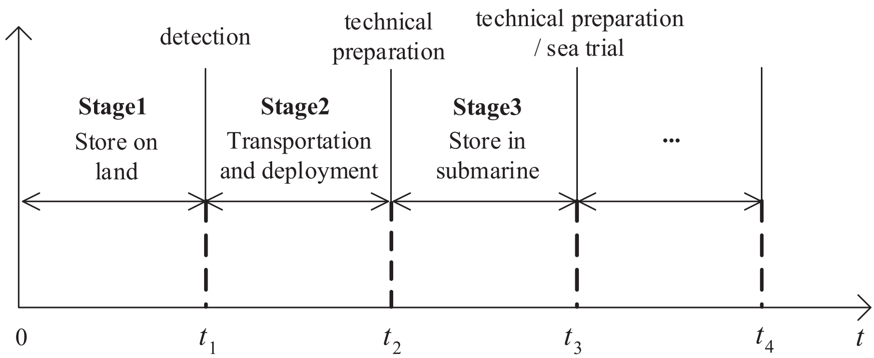

Figure 4. *Phase diagram.*

Assuming that the work during sea trial and the technical preparation process have the same mechanism that power-on for the impact on reliability, then the service life is simplified as shown in Figure 4. In Figure 4, the storage time is the starting point, the technical preparation is the boundary, and the onshore storage, onboard storage and transportation are the phase parts.

3. Methodology

The general electronic components of torpedoes include the homing system, wire-guided system, control system, etc. They generally have the characteristics of observing the working state and recording the condition through power-on. Traditional inspectors believe that normal function means high reliability. However, in the actual service life of the component, the reliability level shows in a downward trend. When the performance reaches a critical point, the function is abnormal. In this study, the initial reliability R_0 and critical reliability (failure threshold) R_{out} are defined and the reliability changes of the component are observed during service life.

3.1. Failure rate model

The bathtub curve is used to describe the change of failure rate of the repairable component. Its cumulative risk function model can be expressed by Equation (3.1) (Xie and Lai, 1996; Liu et al., 2019):

$$H(t) = (at)^b + (ct)^d, t, a, c \geq 0, b > 1, d < 1 \tag{3.1}$$

The failure rate function is

$$\lambda(t) = \frac{\partial H(t)}{\partial t} = ab(at)^{b-1} + cd(ct)^{d-1}, t > 0 \tag{3.2}$$

In the engineering application, in order to facilitate the determination of parameter, Equation (3.2) is simplified to obtain the two-parameter failure rate model (Xie and Lai, 1996), as

$$\lambda(t) = ab(at)^{b-1} + a(at)^{1/b-1}/\mathrm{b}\,,\ \mathrm{a}\ > 0, b > 1 \tag{3.3}$$

where $a = c$ determines the shape and $b = 1/d$ determines the height of the curve.

The two parameters of failure rate model are still difficult to determine. It takes a lot of time to choose the appropriate parameters to make the curve meet the bathtub curve. To reduce the time, this paper introduces the parameter T on the basis of Equation (3.3), as

$$\lambda(t) = ab(a(T-t))^{b-1} + a(a(T-t))^{1/b-1}/\mathrm{b}\,,\ 0\ < t < T,\ \mathrm{a}\ > 0, b > 1 \tag{3.4}$$

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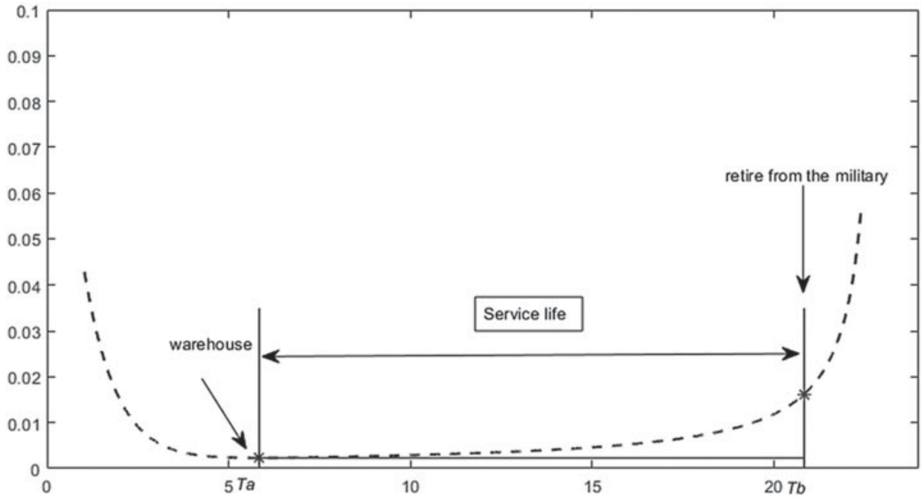

Figure 5. *Failure rate curve.*

where T is the upper limit of the maximum service life of the product, which determines the initial change trend of the bathtub curve. Assuming $a = 0.05$, $b = 4.6$, when $T = 23$ and the service life $T_{\text{use}} = T_b - T_a = 15$ years, the failure rate curve of Equation (3.4) is shown in Figure 5 that the horizontal axis is time and the vertical axis is failure rate. As seen in Figure 5, the failure rate model conforms to the bathtub curve, and the failure rate gradually increases during the service life $[T_a, T_b]$.

During the service life, environmental factors will accelerate the aging of electronic components (Hanif et al., 2018; Galbiati, 2019). For electronic components, it is impractical to directly analyse the impact of these factors from micro to macro because of the complex composition structure. So it is almost impossible to give the quantitative relationship between temperature, humidity, mold, salt spray and reliability.

This study introduces the environmental coefficient π_E, a semi-engineered and semi-quantitative approximate average processing method to characterise the degree of impact of environmental differences on reliability, which indicates the influence's degree of environmental stress in different environmental categories on component failure rate. In other words, its value represents the harsh multiple of the current environment relative to the baseline environment (good ground storage environment that maintains an environment with almost no mechanical stress under normal climatic conditions) (Dave and Wang, 2012). Under a definite environment, the instantaneous failure rate is

$$\lambda_{\text{new}}(t) = \int_{t_1}^{t} \pi_E \frac{d\lambda(t)}{dt} dt \tag{3.5}$$

According to China GJB/Z299, The classy environment categories and environmental coefficient related to torpedoes is showed in Table 1.

3.2. Parameter estimation

During service life, the reliability of components is mainly affected by two aspects: one is the performance degradation caused by the environment and the other is the increase of failure rate affected by detection and repair. According to the literature (Geng and Liu, 2009), the eventual outcome is the sum of the reliability caused by these two aspects. That is

$$R(t) = R_a(t) R_b(t). \tag{3.6}$$

where $R_a(t)$ is the reliability of performance degradation and $R_b(t)$ is the reliability of detection.

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Table 1. *Environment.*

Environment category	Symbol	Environmental coefficient	Explanation
Good ground	G_B	1	Normal climatic conditions, mechanical stress close to zero, good temperature/humidity control, etc.
Move smoothly on the ground	G_{M1}	6.3	Relatively stable moving state with slight vibration and impact, such as special vehicles driving on the road and train.
submarine	N_{SB}	7.5	Environmental conditions in the submarine.
Fixed on general ground	G_{F1}	2.4	Environments that are less affected by vibration and shock, such as fixed frames.
Fixed on bad ground	G_{F2}	6.5	Relatively harsh, such as large temperature changes, mold, salt fog and chemical gas, etc.
Submarine launch tube	N_{SB1}	$N_{SB1} = N_{SB}\frac{G_{F2}}{G_{F1}} \approx 20$	User-defined: the submarine launch tube is a harsh environment, and the ratio of the harsh environment on the ground to the general ground environment is used as a coefficient to measure the environmental coefficient of the launch tube relative to the submarine cabin.

In this study, the inherent failure rate model and environmental coefficient are used to determine the impact of performance degradation, and the detection times model is used to determine the impact of detection on failure rate. This study uses the method of control variate to estimate the relevant parameters of $R_a(t)$ and $R_b(t)$, respectively, and the final evaluation result by Equation (3.5) is the lowest limit of reliability.

3.2.1. Parameters of failure rate model

For torpedoes, technical parameter data is an important indicator. This study uses the service life and design information to estimate the parameters of the inherent failure rate model, in which the degradation function is $\lambda_a(t)$.

Assume that the initial reliability is R_0, the failure threshold is R_{out} and the life in the standard storage environment is T_{use} years. Without considering the impact of detection and repair on the inherent failure rate ($R_b(t) = 1$), the parameters should make the model meet the following conditions:

1) The failure rate shows an increasing trend during the service life,
2) In the early and middle periods of life, the failure rate increases slowly. In the later period, it increases faster. The failure rate function approaches or reaches the inflection point when service ends,
3) Within the time range $[0,\ T_{\text{use}}]$, Equation (2.1) should satisfy $R(T_{\text{use}}) \approx R_{\text{out}}$ based on the Equations (3.4)– (3.6).

Parameter adjustment is similar to PID adjustment. According to Equation (3.1), the average failure rate inherently is $\bar{\lambda}_{gu} = -\ln(R_{\text{out}}/R_0)/T_{\text{use}}$.

Firstly, use the value of $\bar{\lambda}_{gu}$ to estimate $a,\ b$ roughly. The progress is:

- Let $a = 0.01$ and take the b form 1. With the increase of b value, the curve moves downwards until the average failure rate inherently $\bar{\lambda}_{gu}$ is between the first inflection point and the flat area.

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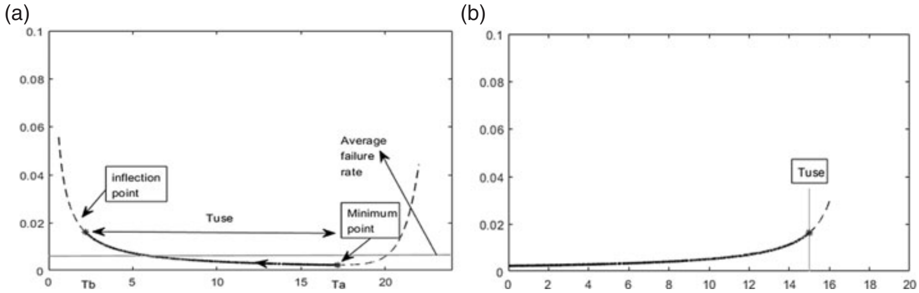

Figure 6. *Failure rate curve.*

- Then adjust the a value to control the shape until the length of the gentle area in the middle is close to life T_{use}.
- Take the point near the minimum value of the bathtub curve as the storage start time, and reversely take $T_a - T_{\text{use}}$ as the end time T_b.

Secondly, adjust the values of a and b exactly. The progress is:

- Making $\lambda(t)$, $T_b < t \leq T_a$ to satisfy 3), as shown in Figure 6(a).
- Let $T = T_a$, using the parameter T to adjust the time in order to obtain the inherent failure rate function model shown in Equation (3.4), as shown in Figure 6(b) that the horizontal axis is the service time and the vertical axis is failure rate.

Assuming that the initial reliability is $R(t_i{}^+)$ and the environmental coefficient is π_E in a stage, the reliability caused by performance degradation is:

$$R_a(t) = R(t_i{}^+)e^{-\int_{t_i}^{t} \pi_E \lambda_a(t)dt} \tag{3.7}$$

When the torpedo in the first stage of service life, $R(t_i{}^+) = R_0$.

3.2.2. Detection parameters of failure rate

The torpedo belongs to repairable components. Regular detection is necessary for long-term storage. The reliability $R_b(t)$ determined by the increase in failure rate due to detection is

$$\begin{aligned} R_b(t) &= e^{[-\Delta_{\lambda bk}(t-t_k)]} \\ \Delta_{\lambda bk} &= \lambda_b(k) - \lambda_b(k-1) \\ \lambda_b(k) &= \lambda_0(k+1)^\beta \end{aligned} \tag{3.8}$$

where λ_0 is inherent failure rate at the initial moment, $k$is detection times, $\lambda_b(k)$ is failure rate after the kth detection (Li et al., 2006), $t_k$is the time interval from the initial moment to the last detection and β reflects the increasing trend of the failure rate with the detection times. For the convenience of the following description, this study defines it as the detection parameters of failure rate.

According to the technical manual of torpedoes, regular detection is required for long-term storage. Assuming that the detection cycle is τ years, the reliability declines from R_0 to R_{out} during the service life without considering the impact of performance degradation. In this study, the $\lambda(t = 0)$ is taken as the initial failure rate λ_0, and the detection parameter β is estimated.

When the life of components is T_{use} in the standard storage environment, detection is carried out every τ year, the initial reliability is R_0, and the failure threshold is R_{out}, then the max number of detection in the service life is

$$k_{\max} = [T_{\text{use}}/\tau] \tag{3.9}$$

where [] indicates rounding, and the corresponding reliability is:

$$R_{\text{out}} = R_0 \mathrm{e}^{-[\lambda_0 + \sum_{i=1}^{k_{\max}-1} \lambda_b(i)]\tau} \tag{3.10}$$

We can get the parameter value $\hat{\beta}$ by solving Equation (3.10). If we consider the impact of performance degradation, the actual value β is less than $\hat{\beta}$. Then the range is: $0 < \beta < \hat{\beta}$.

3.3. Reliability prediction

As shown in Figure 4, during the service life, the service period can be divided into multiple stages, with technical detection as the limit. In this study, we calculate and predict reliability by Equation (3.6) in each stage and estimate the result of the detection moment through technical detection data. The evaluation result can correct the failure rate and reliability in the previous stage and predict the trend in the next stage. Then we use the recursive relationship between adjacent stages to describe the reliability change during the whole service life.

3.3.1. Relationship of the adjacent stage

At the time t_i of the ith detection, the personnel tests the components and the detection information is obtained. If a failure is found, the staff will repair it. If there is no failure, the component will continue to be stored. At the time t_i of the ith detection, the personnel tests the components and the detection information is obtained. If a failure is found, the staff will repair it. If there is no failure, the component will continue to be stored. When the end of the previous stage is t_i^-, the start of the next stage is t_i^+, the reliability of the detection moment is R_{ti}, the environmental coefficient is 1, the reliability of products that only under the condition of performance degradation is R_{guti}, then the relationship of reliability before and after detection is

$$R(t_i^+) = \begin{cases} R_{ti} & \text{no failure} \\ R_{\text{guti}} = R_0 \mathrm{e}^{-\int_0^{t_i} \lambda_a(t)dt} & \text{repairable failure} \end{cases} \tag{3.11}$$

3.3.2. Reliability estimation at detection moment

In this study, failure rate function, detection information and Bayes (Han, 2016; Wan et al., 2018; Li et al., 2019a) are applied to estimate the reliability at the detection moment. And these pieces of information are defined that the stage before the ith detection is i and the initial reliability is $R(t_{i-1}{}^+)$. Then in stage i, the value range of failure rate is

$$\begin{aligned} &\left(\lambda_{\min}(t) = \lambda(t_{i-1}) + \int_{t_{i-1}}^{t} \pi_E \frac{\lambda_a(t)}{dt}\right) < \lambda(t) \\ &\quad < \left(\lambda(t_{i-1}) + \int_{t_{i-1}}^{t} \pi_E \frac{\lambda_a(t)}{dt} + \Delta_{\lambda bk} = \lambda_{\max}(t)\right), t_{i-1} \le t < t_i \end{aligned} \tag{3.12}$$

The reliability in stage i is $R(t) = R(t_{i-1}{}^+)e^{-\int_{t_{i-1}}^{t} \lambda_{\max}(t)dt}$.

In the ith detection, the number of samples is n_i, and the number of failures is f_i. Under the binomial distribution and square loss, the Bayes assessment of reliability at the ith detection moment is (Han, 2005)

$$\hat{R}_i = \int_{R_{i1}}^{R_{i2}} \left(\frac{R^{n_i+q-r_i}(1-R)^{r_i}}{\int_{R_{i1}}^{R_{i2}} R^{n_i+q-r_i-1}(1-R)^{r_i} dR} \right) dR \tag{3.13}$$

where $R_{i1} = R(t_{i-1}{}^+)e^{-\int_{t_{i-1}}^{t} \lambda_{\min}(t)dt}$, $R_{i2} = R(t_{i-1}{}^+)e^{-\int_{t_{i-1}}^{t} \lambda_{\max}(t)dt}$, $q = R_{i2}/1 - R_{i2}$.

Table 2. *Model error.*

Model	Reliability $R_{\text{mod } i}$ of single condition in T_{use} years	Error between model and failure threshold $\lvert R_{\text{mod } i} - R_{\text{out}}\rvert$
Performance degradation	0.9251	0.0001
Detect degradation	0.9249	0.0001

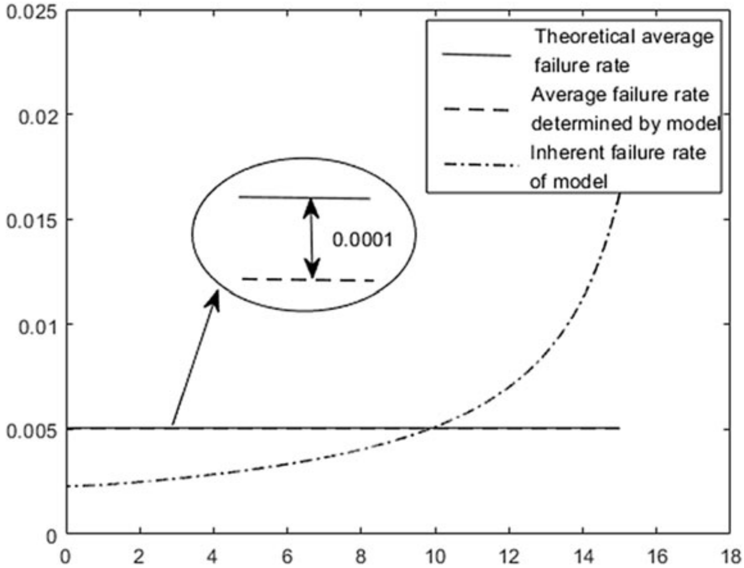

Figure 7. *Inherent failure rate model.*

The failure rate and reliability in stage i are corrected by the evaluation result $\hat{R}_i$ at the ith detection moment and the increment of failure rate at the $(i-1)$th detection moment is used to update the detection parameter $\hat{\beta}$. The process is as follows:

1) Calculate the average failure rate $\bar{\lambda}_i = -\ln(\hat{R}_i/R(t_{i-1}{}^{+}))/(t_i - t_{i-1})$ in the stage i.

   Calculate the average failure rate $\bar{\lambda}_{\text{Mini}} = (\int_{t_{i-1}}^{t_i} \lambda_{\min}(t)dt)/(t_i - t_{i-1})$ in the stage i without considering the impact of the $(i-1)$th detection.
   Calculate the actual increment $\Delta_{\lambda_{i-1}} = \bar{\lambda}_i - \bar{\lambda}_{Mini}$ of failure rate caused by the $(i-1)$th detection.

2) In the stage i, the failure rate is $\lambda_i(t) = \lambda_{\min}(t) + \Delta_{\lambda_{i-1}}$, the reliability is $R_{i2} = R(t_{i-1}{}^{+})e^{-\int_{t_{i-1}}^{t} \lambda_i(t)dt}$.
3) Calculate the increment $\lambda_b(i-1) - \lambda_0 = \lambda_0(i)^{\beta} - \lambda_0 = \sum_{k=1}^{i-1} \Delta_{\lambda_{k-1}}$ of failure rate caused by the $(i-1)$th detection relative to the initial failure rate, the new parameter values $\hat{\beta}$ is obtained by solving this equation.

4. Result and analysis

Assuming that the number of samples is n, the technical data of a batch of torpedo electronic components are initial reliability $R_0 = 0.9980$, failure threshold $R_{\text{out}} = 0.9250$, storage life $T_{\text{use}} = 15$ years and detection cycle $\tau = 1.5$ years.

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Table 3. *Service experience.*

Service experience	Stage1	Stage2	Stage3	Stage4	Stage5	Stage6
Environment category	Store on good ground G_B	Transportation and deployment G_{M1}	Store in submarine N_{SB}	Store in launch tube N_{SB1}	Transportation and deployment G_{M1}	Store on good ground G_B
Length of time / day	300	2	30	8	3	300
Detection results (n_i, r_i)	(20, 0)	(20, 0)	(20, 0)	(20, 0)	(20, 1)	(20, 0)

Table 4. *Evaluation results.*

Service Experience	Stage1	Stage2	Stage3	Stage4	Stage5	Stage6
Initial reliability	0.998000	0.996105	0.996083	0.995848	0.995809	0.995848
Prediction reliability at the detection moment	0.996105	0.996079	0.995837	0.995808	0.995784	0.991434
Evaluation reliability at the detection moment	0.996105	0.996083	0.995848	0.995809	0.995784	0.991490
Average failure rate	0.002311	0.002732	0.002887	0.002853	0.002991	0.003201

The inherent failure rate model was determined according to Equation (3.4) and 3.2.1 part, expressed as

$$\begin{aligned}\lambda(t) &= ab(a(T-t))^{b-1} + a(a(T-t))^{1/b-1}/\mathrm{b} \\ &= 0.04 * 26 * (0.04 * (17.157 - t))^{26-1} + 0.04(0.04(17.157 - t))^{1/26-1}/26,\ 0 \le t \le 15 \\ &= 1.04 * (0.68628 - 0.04t)^{25} + \frac{0.04}{26}(0.68628 - 0.04t)^{1/26-1}\end{aligned}$$

The range of detection parameter determined according to 3.2.2 part is $0 < \beta < \hat{\beta} = 0.0049$.

The model errors are shown in Table 2.

It can be seen from Table 2 that the reliability values, which calculated under the parameters determined in Section 3.2, are close to the assumed value of theory R_{out} at time T_{use}, regardless of performance degradation or detect degradation.

The data corresponds to Figure 7 that the horizontal axis is the service time and the vertical axis is failure rate.

It can be seen from Figure 7 that the overall change trend of the inherent failure rate model satisfies the random failures stage of the bathtub curve in Figure 2, and there is only 0·001 error between the average failure rate of the model and the theoretical value. Under the condition that the starting and ending reliability are basically the same between model and theory, the results in Figure 7 can prove the applicability of the model established and parameter determination methods in this paper to a certain extent.

Assuming that the service experience of the sample as shown in Table 3.

According to Section 3.3, the reliability of sample during service life is evaluated. The evaluation results are shown in Table 4 and the curves are shown in Figure 8.

Table 4 shows the initial reliability of the torpedo electronic components in each stage in the service environment of Table 3, the reliability prediction value at the end of the stage according to the service environment, the reliability evaluation value according to the detection data at the end of the stage and the average failure in the stage rate. It can be seen from the reliability data at the end of the stage that the predicted value is basically similar to the estimated value, showing a decreasing trend; from the failure rate data, it can be seen that the failure rate of electronic components increases with the service life without repair. And the range of changes has been increasing year by year, and with the restoration, the range of changes has slowed down.

It can be seen from Figure 8(d) that in the whole stage 1~6, as the service time of the sample increases, the reliability gradually decreases. It is affected by external factors and its value is lower than the inherent reliability. Among them, in stage 1 to stage 4, the torpedo samples have no failures, the failure rate of the corresponding torpedoes increases with the increase of the number of detections, and the trend of changes in each stage gradually increases. When detection in stage 5, the fault is found and repaired. After the repair, the sample reliability is improved and the impact of performance degradation

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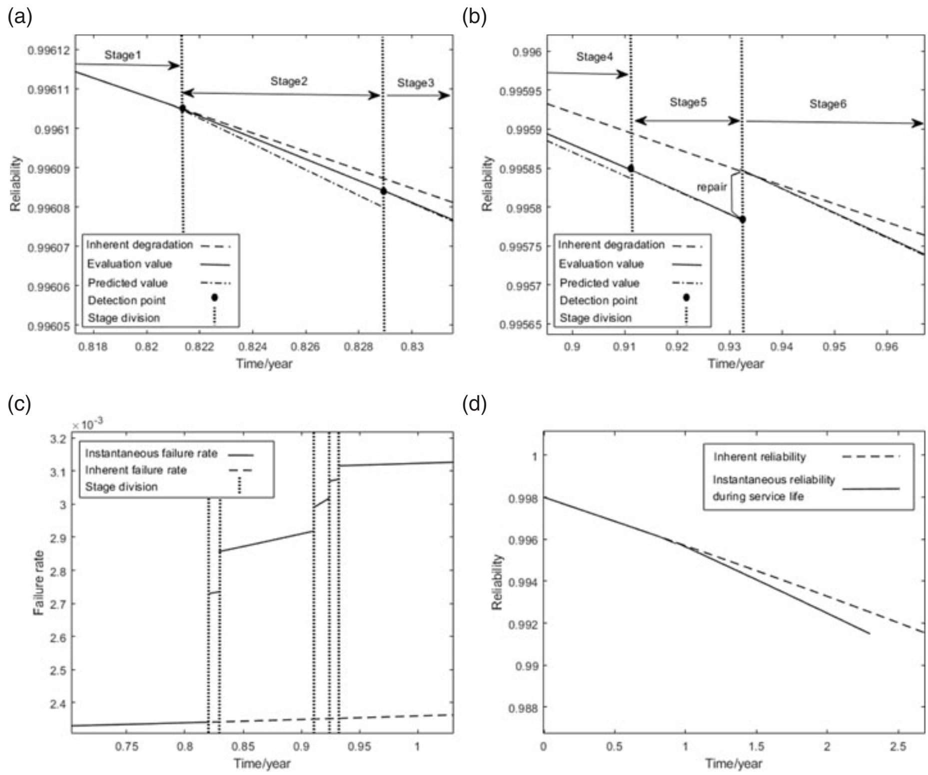

Figure 8. *Evaluation curves.*

on failure rate reduce. They correspond to the beginning of the stage 6 in Figure 8(b) and the failure rate of the stage 6 in Figure 8(c). The failure rate slope is reduced compared with the previous stage, the reliability change is slower and the life span is increased.

After the service environment of the next stage is known, the reliability of torpedo electronic components in the next stage can be predicted by repeating the above work. The purpose is to repair the components in time when the reliability is low, slow down the aging of the components and improve the life.

5. Conclusion

According to the service experience of general electronic components, this study analyses the changing trend of reliability in the service life by technical parameter data recursively. Then the influences of performance degradation and detection are used for modeling and parameter determination. Afterwards, the pieces of information for every stage are predicted. Finally, Bayes prediction is used to estimate the reliability of the detection moment through the detection results at the end of the stage. On the one hand, the evaluation results could correct the failure rate and reliability in this stage and make predictions for the next stage. In addition, the increment of failure rate caused by the detection can be used to reestimate the degradation parameters. This work provides a basis for studying the overall reliability of the torpedo. This study can also be used as a tool to evaluate the reliability of multi-electronic component systems. The shortcoming of this study is that the reliability is influenced by a single factor when the parameters are estimated, which will lead to conservative evaluation results. This part will be further studied and improved in the future. And in future work, by studying how the failure of multiple components affects the reliability of the system, how the performance of other systems affects

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the system being checked, etc., it can also predict the overall reliability of the torpedo to help personnel better understand the quality of torpedoes.

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