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Reliability analysis of torpedo loading based on fractional-order optimization model

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Abstract: A fractional-order cumulative optimization GM(1,2) model based on grey theory is proposed to study the relationship between torpedo loading and working reliabilities. In this model, the average relative error function related to order and background value is established. Taking the average relative error function as the objective function, the optimal value of the two parameters is obtained through the optimization method, and the minimum value of the average relative error is determined. The calculation example shows that this method can greatly improve the accuracy of the model and more accurately reflect the relationship between torpedo loading and working reliabilities compared with the traditional GM(1,2) model.

Keywords: torpedo, loading reliability, working reliability, grey theory, fractional-order.

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1. Introduction

With the rapid development of science and technology, the performance of torpedo has become increasingly powerful with the application of various high and new technologies in the torpedo. At present, torpedo has become an offensive weapon that can automatically navigate underwater, automatic control, automatically find and track, and automatically explode when hitting the target. Torpedo has become the main combat weapon of modern naval warfare because of its strong aggression, good concealment, and high destructiveness [1–3]. With the intelligent improvement of its combat performance, the structure of torpedo is becoming more and more complex, the maintenance cost is greatly increased, and the requirement of reliability is becoming higher and higher, so the reliability index has become an important factor to evaluate the operational effectiveness of torpedo.

Torpedo reliability can be divided into torpedo storage reliability, loading reliability, and working reliability. Torpedo loading reliability is one of the important components of torpedo reliability, which mainly reflects the torpedo's ability to maintain the specified function under the specified ship loading conditions and within the specified loading time, which is usually measured by probability [4–6]. During loading period, the torpedo cannot be maintained and repaired, and the environment is worse than the cave warehouse, so the torpedo reliability will be much lower in this process. For this type of large and complex system of the torpedo, it is expensive to test and the test cycle is long, which results in very few loading tests. The scarcity of experimental data also brings difficulties in loading reliability evaluation. When torpedoes are equipped to the force, a rough estimate of the level of loading reliability would lead to difficulty for the force using torpedo and developing a maintenance support strategy. Therefore, it is very necessary to study the loading reliability of torpedo.

Torpedo loading reliability is of small sample, poor information, and uncertainty. An assessment method of it that is simple in application, in line with objective reality, and reflects the objective nature, is necessary to study. At present, researchers mainly study torpedo loading reliability from three aspects: loading experiment, loading reliability evaluation, and the relationship between loading reliability and working reliability. In the aspect of the loading reliability experiment, He et al. put forward the improved general idea of loading test as the main, accelerated test as the auxiliary, and took specific measures such as expanding loading information sources, increasing loading information amount, and formulating appropriate inspection methods [7]. Hou et al. proposed a test and comprehensive evaluation method based on Bayes theory and worked out a test scheme with feasible test technology, acceptable test time, and credible test results [8]. Liu et al. proposed an optimal design scheme of torpedo loading reliability tests based on analyzing the characteristics of the torpedo loading test and test data [9]. In terms of loading reliability evaluation, Yang et al. pro-

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posed an evaluation method based on test strategy and test information, which constructed a maximum likelihood function and combined it with the existing exponential distribution evaluation model [10]. Xing et al. adopted the comprehensive evaluation method of multi-source test information and proposed the comprehensive evaluation method of product reliability based on similar information and the environmental conversion coefficient [11]. Meng et al. put forward the Bayes evaluation method of comprehensive utilization of prior and posterior information based on analyzing the sources of torpedo reliability information [12]. For the research on the relationship between loading reliability and working reliability, Tian et al. proposed the use of fuzzy regression theory to establish the relationship between loading reliability and working reliability [13]. Shao et al. established the relationship between loading failure rate and work failure rate using the grey GM (1,2) model [14].

For the two methods of establishing the relationship between loading reliability and working reliability, the fuzzy model mainly considers the fuzziness of loading reliability and is suitable for modeling with large scale samples. The grey model mainly considers the ambiguity of the internal information of the system and is suitable for small sample modeling. The traditional grey GM(1,2) model has different processing ability for different data, and the fitting accuracy will also fluctuate greatly. Since most systems in real life are fractional order, the establishment of a continuous fractional-order grey model can better describe the complex rules in the process of small sample data change. The fractional-order accumulation grey model has been studied earlier and applied widely [11−14]. Wu et al. also applied the fractional-order grey model to the prediction of the number of high pollution days in a certain area of North China [15]. Sui et al. applied the fractional grey model to the prediction of wind power generation [16]. Zeng et al. used fractional-order to establish a dynamic grey model and applied it to the prediction of electricity consumption in Hong Kong, China [17]. These successful applications fully show the superiority of the fractional-order grey model. Based on the complex relationship between torpedo loading reliability and operational reliability, which is influenced by some random factors, the fractional-order grey model is suitable to establish the model. A fractional grey model is proposed in this paper to reflect the relationship between torpedo loading reliability and working reliability. The model uses the optimization method to find the optimal values of the model order and background value. Simulation results show that the accuracy of this method is greatly improved compared with the traditional GM(1,2) model.

This paper is organized as follows. In Section 2, the modeling method and optimization principle of the fractional-order accumulation optimization model are introduced. In Section 3, the actual torpedo loading reliability and working reliability test data are calculated and analyzed, and the results are compared with the traditional GM(1,2) model, the GM(1,2) model which only optimizes the background value and the fractional grey GM(1,2) model. In Section 4, conclusions are drawn.

2. Reliability analysis method of torpedo loading based on the fractional-order accumulation optimization GM (1,2) model

The modern torpedo is a complex underwater precision-guided weapon, which contains electronic, mechanical, electromechanical, chemical, rubber, and other parts and components. Obviously, the reliability distribution is different for each component, functional component, and system. However, according to the characteristics of torpedo equipment and engineering experience, the storage life of the torpedo is usually treated as the equivalent exponential distribution. The loading life actually refers to the life of the torpedo stored on the ship. In terms of the failure mechanism, the harsh storage environment on the ship does not change the failure mechanism, so the loading life of the torpedo can also be considered to obey an exponential distribution [18]. Then, the relationship between torpedo loading reliability and the loading failure rate is

$$R_c(t_c) = \mathrm{e}^{-\lambda_c t_c}$$

where R_c is the loading reliability of the torpedo, t_c is the loading time of the torpedo, and λ_c is the loading failure rate of the torpedo.

Since the torpedo loading life follows an exponential distribution, the torpedo loading failure rate can be considered as a constant during the loading period, which makes it possible to infer the torpedo loading failure rate by using other information. For the same torpedo, the loading failure rate and the working failure rate can be regarded as the torpedo failure rate in different environments. At the same time, the torpedo loading directly affects the torpedo work, and there must be a very close relationship between them. The loading failure rate can be inferred indirectly by studying the relationship between the torpedo loading failure rate and the torpedo working failure rate under the circumstance that the torpedo actual flight test information is relatively large. Due to the lack of torpedo loading test data and large greyscale, this paper will use fractional grey GM(1,2) to establish a more accurate relationship between them.

2.1 Modeling method

Definition 1 [19–23] The original non-negative sequence $X_1^{(0)}=(x_1^{(0)}(1),x_1^{(0)}(2),\cdots,x_1^{(0)}(n))$ is the characteristic sequence of the system, and the sequence of related factors is $X_2^{(0)}=(x_2^{(0)}(1),x_2^{(0)}(2),\cdots,x_2^{(0)}(n))$. Then, $X_i^{(r)}=(x_i^{(r)}(1),x_i^{(r)}(2),\cdots,x_i^{(r)}(n))$ is the r-order accumulated sequence of sequence $X_i^{(0)}=(x_i^{(0)}(1),x_i^{(0)}(2),\cdots,x_i^{(0)}(n))$, where

$$x_i^{(r)}(k)=\sum_{j=1}^{k}\frac{\Gamma(r+k-j)}{\Gamma(k-j+1)\Gamma(r)}x^{(0)}(j)=$$
$$\sum_{j=1}^{k}\frac{(r+k-j-1)(r+k-j-2)\cdots r}{(k-j)!}x^{(0)}(j),$$
$$k=1,2,\cdots,n;i=1,2.$$

Definition 2 [19–23] The definition of $X_i^{(0)}$, $X_i^{(r)}$ is as shown in Definition 1, and $Z_1^{(r)}=(z_1^{(r)}(1),z_1^{(r)}(2),\cdots,z_1^{(r)}(n))$ is the r-order nearest neighbor accumulation generating operator of $X_1^{(r)}$, where

$$z_1^{(r)}=\alpha z_1^{(r)}(k)+(1-\alpha)z_1^{(r)}(k-1),\ \ k=2,3,\cdots,n.$$

The equation $x_1^{(r)}(k)-x_1^{(r)}(k-1)+az_1^{(r)}(k)=bx_2^{(r)}(k)$ is called the r-order cumulative grey GM(1,2) model, and its parameter $\hat{\boldsymbol{a}}=[a,b]^{\mathrm{T}}$ can be estimated using the least square method.

$$\hat{\boldsymbol{a}}=(\boldsymbol{B}^{\mathrm{T}}\boldsymbol{B})^{-1}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{Y}$$

$\boldsymbol{B}$ and $\boldsymbol{Y}$ are

$$\boldsymbol{B}=\begin{bmatrix}-z_1^{(r)}(2) & x_2^{(r)}(2)\\ -z_1^{(r)}(3) & x_2^{(r)}(3)\\ \vdots & \vdots\\ -z_1^{(r)}(n) & x_2^{(r)}(n)\end{bmatrix},$$

$$\boldsymbol{Y}=\begin{bmatrix}x_1^{(r)}(2)-x_1^{(r)}(1)\\ x_1^{(r)}(3)-x_1^{(r)}(2)\\ \vdots\\ x_1^{(r)}(n)-x_1^{(r)}(n-1)\end{bmatrix}.$$

Definition 3 [19–23] If the parameters are shown in Definition 2, then

$$\frac{\mathrm{d}x_1^{(r)}(t)}{\mathrm{d}t}+az_1^{(r)}=bz_2^{(r)} \tag{1}$$

is called the whitening differential equation of r-order accumulated grey GM(1,2) model $x_1^{(r)}(k)-x_1^{(r)}(k-1)+az_1^{(r)}(k)=bx_2^{(r)}(k)$.

If $\boldsymbol{B}$, $\boldsymbol{Y}$, and $\hat{\boldsymbol{a}}$ are shown in Definition 2, then the time response sequence of $x_1^{(r)}(k)-x_1^{(r)}(k-1)+az_1^{(r)}(k)=bx_2^{(r)}(k)$ model can be obtained by solving differential (1).

$$\hat{x}_1^{(r)}(k+1)=[x_1^{(0)}(1)-\frac{b}{a}x_2^{(r)}(k+1)]\mathrm{e}^{-ak}+$$
$$\frac{b}{a}x_2^{(r)}(k+1),\ \ k=0,1,\cdots,n \tag{2}$$

Restore the time response sequence (2),

$$\hat{x}_1^{(0)}(k)=(\hat{x}_1^{(r)})^{-r}(k)=$$
$$\sum_{j=0}^{k-1}(-1)^j\frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)}\hat{x}^{(r)}(k-i),\ \ k=2,3,\cdots,n. \tag{3}$$

2.2 Basic principles of optimization

2.2.1 Constraint condition

In the conventional fractional-order accumulation model, the value of α in the background value $Z_1^{(r)}=\alpha x_1^{(r)}(k)+(1-\alpha)x_1^{(r)}(k-1)$ is usually taken as 0.5. However, the value can take any value from 0 to 1, so we can optimize this value [24].

Through the above analysis, the optimization method can be introduced into grey modeling. The order r should be optimized because the model is based on fractional accumulation. Therefore, α and r can be optimized simultaneously. The average relative error function related to these two parameters is established as the objective function. Furthermore, the optimal values of α and r are calculated through constrained nonlinear programming to determine the minimum value of the average relative error.

Average relative error function:

$$e(k)=\frac{1}{n}\sum_{k=1}^{n}\left(\frac{\hat{X}_1^{(r)}(k)-X_1^{(0)}(k)}{X_1^{(0)}(k)}\times 100\right).$$

The objective function is established by the average relative error function:

$$\begin{aligned}&\min F(\alpha,r)=e(k)\\ &\text{s.t. } 0<\alpha<1,\\ &\qquad 0<r<1.\end{aligned} \tag{4}$$

2.2.2 Optimization algorithm

Most nonlinear programming algorithms are solved by the gradient descent method, which has strong local searching capability, but weak global searching ability. The genetic algorithm is just the opposite. It uses selection, crossover, and mutation operators to search, which has strong global search ability and weak local search capability. Generally, it can only get the suboptimal solution of the problem, not the optimal solution. Therefore, this paper will combine the advantages of the two algorithms, first use the genetic algorithm for global search, and then use the nonlinear programming method for local search, so as to get the optimal solution needed by the problem [25–27]. The algorithm flow is shown in Fig. 1.

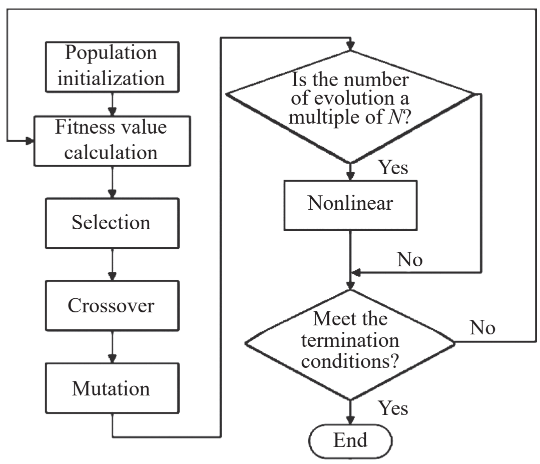

Fig. 1 Optimization algorithm flow chart

Firstly, the population initialization module is utilized to initialize the population according to the problem, and then the fitness value calculation module calculates the fitness value of chromosomes in the population according to the fitness function. Selection, crossover, and mutation are search operators. N is a fixed value. When the number of evolution is a multiple of N, the optimization method of nonlinear programming is used to speed up the evolution. The nonlinear optimization in this article will directly use the function fmincon in Matlab to find the local optimal value of the problem, and this local optimal value will be taken as a new individual chromosome to continue to evolve.

3. Calculation and analysis

The initial data are from [9]. The loading failure rate of torpedo is 599.528 9, 645.566 2, 645.268 3, 656.245 8, and 689.258 9, and the working failure rate is 6 564.566 6, 5 989.249 5, 6 400.256 6, 6 325.948 5, and 5 987.236 8. Considering the different dimensions of the two groups of data, the dimensionless processing of the data is carried out. That is,

$$x_i^{(0)}(k) = \frac{x_i^{(0)}(k)}{x_i^{(0)}(1)}, \quad k = 1, 2, \cdots, n; i = 1, 2.$$

Table 1 shows the results of dimensionless processing. $X_1^{(0)}$ is the loading failure rate, and $X_2^{(0)}$ is the working failure rate.

Table 1 Dimensionless processing data

Falilure rate	k				
	1	2	3	4	5
$X_1^{(0)}$	1.000 0	1.076 8	1.076 3	1.094 6	1.149 7
$X_2^{(0)}$	1.000 0	0.912 4	0.975 0	0.963 7	0.912 1

(i) Model A: conventional A modeling without optimization $\hat{\boldsymbol{a}} = [1.444\,1, 1.691\,8]^{\mathrm{T}}$. The time response sequence is

$$\hat{x}_1^{(1)}(k+1) = [1.000\,0 - 1.171\,5x_2^{(1)}(k+1)]\mathrm{e}^{-1.444\,1k} + 1.171\,5x_2^{(1)}(k+1). \tag{5}$$

(ii) Model B: optimization parameter α. The optimization results are $\alpha = 0.298\,2$ and $\hat{\boldsymbol{a}} = [1.992\,9, 2.341\,4]^{\mathrm{T}}$. The time response sequence is

$$\hat{x}_1^{(1)}(k+1) = [1.000\,0 - 1.174\,8x_2^{(1)}(k+1)]\mathrm{e}^{-1.992\,9k} + 1.174\,8x_2^{(1)}(k+1). \tag{6}$$

(iii) Model C: optimization parameter r. The optimization results are $r = 0.092\,2$ and $\hat{\boldsymbol{a}} = [0.160\,1, 0.261\,6]^{\mathrm{T}}$. The time response sequence is

$$\hat{x}_1^{(0.092\,2)}(k+1) = [1.000\,0 - 1.633\,7x_2^{(0.092\,2)}(k+1)]\mathrm{e}^{-0.160\,1k} + 1.634\,4x_2^{(0.092\,2)}(k+1). \tag{7}$$

(iii) Model D: optimization parameters α and r. The optimization results are $\alpha = 0.999\,9, r = 0.010\,5$ and $\hat{\boldsymbol{a}} = [-0.090\,6, -0.057\,4]^{\mathrm{T}}$. The time response sequence is

$$\hat{x}_1^{(0.010\,5)}(k+1) = [1.000\,0 - 0.633\,2x_2^{(0.010\,5)}(k+1)]\mathrm{e}^{0.090\,6k} + 0.633\,2x_2^{(0.010\,5)}(k+1). \tag{8}$$

The torpedo loading failure rate is fitted by (5)–(8), and Table 2 shows the specific results.

Table 2 Fitting results

Number	Original value	Model			
		A	B	C	D
2	645.566 2	568.144 5	645.551 1	601.129 5	616.867 5
3	645.268 3	780.689 5	761.936 9	622.317 5	631.212 1
4	656.245 8	728.674 2	700.026 8	656.260 9	655.018 3
5	689.258 9	659.712 4	646.792 8	666.105 8	689.238 4

Table 3 shows the residual error.

Table 3 Residual error

Number	Residual			
	A	B	C	D
2	−77.4217	−0.0151	−44.4367	−28.6987
3	135.4212	116.6686	−22.9508	−14.0562
4	72.4284	43.7810	0.0151	−1.2275
5	−29.5465	−42.4661	−23.1531	−0.0205

The average relative error of the data fitted in Table 3 is calculated as follows:

$$\Delta = \frac{|X_1^{(0)} - \hat{X}_1^{(r)}|}{X_1^{(0)}} \times 100.$$

Table 4 Fitting error %

Number	Model			
	A	B	C	D
2	11.9928	0.0023	6.8834	4.4455
3	20.9868	18.0806	3.5568	2.1783
4	11.0368	6.6714	0.0023	0.1871
5	4.2867	6.1611	3.3591	0.0030
Average relative error	12.0758	7.7289	3.4504	1.7035

Table 5 shows the corresponding relationship between average relative error and fitting accuracy [10].

Table 5 Reference table for precision inspection

Accuracy class	Relative error
First-order accuracy	0.01
Second-order accuracy	0.05
Third-order accuracy	0.10
Fourth-order accuracy	0.20

Because the initial value of the model uses the first data of the torpedo loading failure rate data, and the error of the first data of all fitting models is zero, the fitting accuracy of the first data will no longer be considered in the error analysis. According to the fitting error, the simulation accuracy of traditional Model A belongs to the fourth-order accuracy. When a single parameter optimization is carried out, the precision of Model B changes to third-order accuracy after optimizing the background value parameters α. Average relative error of Model C is 3.4504% when order r is optimized, and the accuracy reaches the second level. When α and r are optimized simultaneously, average relative error of Model D is 1.7043%. Compared with optimizing one parameter, its single error reaches the second-order accuracy, and the average relative error is evidently reduced, reaching the second-order accuracy and approaching the first-order accuracy. Therefore, compared with the traditional GM(1,2) model, the simulation accuracy of the model for parameter optimization has been significantly improved. Thus, this model can be well applied to the relationship modeling between torpedo loading and working reliabilities.

4. Conclusions

Grey theory is used to establish the relationship between torpedo loading and working reliabilities, which can effectively reduce experimental samples of torpedo loading reliability. However, the accuracy of the traditional grey model needs to be improved through the optimization method. The average relative error is only 1.7043%, which can accurately represent the relationship between torpedo loading and working reliabilities particularly when the two parameters are optimized. The optimization model has a high engineering application value.

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