Research Article

Reliability Evaluation of Cryogenic Shut-Off Valve Based on Weibull Segmented Model

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1. Introduction

With the development of deep-sea operations of naval equipment, there is extremely high demand for various equipments of naval ships in polar conditions.

As one of the main components, the cryogenic globe valve is mainly used to control ships and communicate with the outside sea or gas. Cryogenic valve has the characteristics of high working pressure, low-temperature resistance, and strong antivibration ability, whose reliability directly affects the performance of naval equipment. If a cryogenic valve fails, then the warplane will be missed, causing ship being destroyed. The failure change rule of low-temperature stop valve during the whole life cycle is typically a bathtub shape curve. According to the failure rate of low-temperature stop valve, the whole life cycle is divided into three different stages: the early failure stage, the accidental failure stage, and the depletion failure stage. Given that the shape of the failure rate curve of the cryogenic shut-off valve reveals a certain failure mechanism or a corresponding specific use stage, it is helpful to predict and control the failure of the low-temperature shut-off valve. Therefore, studying the change law of the failure rate curve of low-temperature shut-off valve has considerable theoretical relevance and practical value.

Long et al. [1] proposed the comprehensive application of the least square method and the mean rank method to estimate the parameters of the prediction model, and on this basis established the life prediction model of aviation equipment components. Based on three-parameter Weibull and the failure record data of an aircraft over the years, Sun et al. [2] conducted reliability modeling for several important equipments of the aircraft and verified it in fault prediction. By comparing with the failure data of the same sortie aircraft in the same period over the years, the feasibility of the model and the prediction method were verified. Zhang and Zhao [3] proposed the Weibull reliability analysis method based on least square support vector machine based on the graph estimation method and carried out reliability life analysis, indicating that this method can improve reliability analysis efficiency and accuracy. Dai and Wang [4] obtained the convergence maximum likelihood estimation by using the maximum likelihood estimation and confidence interval of the reliability of the generalized inverse Weibull distribution stress intensity model. Liu and Chen [5] combined the maximum likelihood method, constructed a likelihood function for the failure of the Weibull distribution product sample, and carried out reliability analysis. Shakhatreh et al. [6] used the estimation of differential entropy...
of Weibull distribution based on different noninformational prior distributions and used Monte Carlo simulation to evaluate Bayes estimation of partial entropy and root-mean-square error. Finally, the real data set was analyzed. Ullah et al. [7] used Weibull distribution to build a paired comparison model to evaluate social media applications and found that the developed model has the advantage of being suitable for standards. Wang Shao-hua used the lognormal distribution to calculate the fatigue reliability of construction machinery, which has a higher accuracy than other methods [8]. Wang Wen-yue introduced in detail the application of Weibull distribution in mechanical products and elaborated on the estimation method of parameters [9]. Keller et al. used the Duane reliability growth model to analyze the failure data of 35 machine tools and found that the time between failures obeyed the Weibull distribution [10]. Montoya proposed the correct likelihood of three-parameter Weibull distribution for the first time based on the original likelihood, aiming at the problem that the irregularity of three-parameter Weibull distribution and the singularity of density would lead to the inability to estimate when the likelihood function is not properly defined [11]. Flygareti proposed using interval data to estimate the maximum likelihood estimation of the failure time distribution and compared the interval data of the six Weibull distributions and the parameter estimation of the interval key [12]. Zheng Da-yong used a genetic algorithm based on D-test to study the reliability of deep-sea general sealing surfaces; compared with traditional mathematical methods, the fitting accuracy was remarkably better than various mathematical derivations [13]. Yang Ming established the corresponding EM solving algorithm to solve the parameters of finite mixed Weibull, deduced the selection of initial parameter values, and obtained a good accuracy [14].

The application of segmentation models also involves machine learning and emotional issues. Aytug Onan presented a hybrid intelligent classification model for breast cancer diagnosis. The proposed classification model consists of three phases: instance selection, feature selection, and classification. In instance selection, the fuzzy-rough instance selection method based on weak gamma evaluator is utilized to remove useless or erroneous instances. In feature selection, the consistency-based feature selection method is used in conjunction with a reranking algorithm, owing to its efficiency in searching the possible enumerations in the search space. In the classification phase of the model, the fuzzy-rough nearest neighbor algorithm is utilized. This classifier does not require the optimal value for K neighbors and has richer class confidence values [15, 16]. The main challenge faced by Aytug Onan et al.’s machine learning-based approach to emotion classification is the large amount of data available. This amount makes training the learning algorithm in a feasible time and degrading the classification accuracy of the model difficult. An integrated feature selection method was proposed; it aggregates several separate feature lists obtained by different feature selection methods such that more robust feature subsets can be obtained. To aggregate the feature lists, genetic algorithms are used. Experimental evaluation shows that the proposed clustering model is effective and superior to the feature selection method based on a single filter [17]. Aytug Onan proposed a deep learning-based sentiment analysis method for product reviews obtained from Twitter. The presented architecture combines TF-IDF-weighted GloVe word embeddings using CNN-LSTM architecture. The empirical results show that the proposed deep learning architectures outperform traditional deep learning methods [18]. Aytug Onan proposed an efficient framework for social sarcasm recognition to acquire media data by pursuing the paradigm of neural language models and deep neural networks. It focuses on the word-weighted word embedding model and triples based on antigravity moment. A three-layer stacked bidirectional long short-term memory architecture was proposed to recognize satirical text documents. For the evaluation task, the proposed framework was evaluated on three sarcasm recognition corpora. For the sarcasm recognition task, the proposed model achieved promising results by classification with an accuracy of 95.30% [19]. Aytug Onan proposed a highly predictive and efficient sentiment classification scheme by pursuing an ensemble paradigm, performance learning, and deep learning in MOOC reviews. Empirical analysis shows that deep learning-based architectures outperform ensemble learning methods and supervised learning methods for sentiment analysis tasks in educational data mining. For all the compared configurations, the highest prediction performance was achieved with a long-term short-term memory network scheme-based representation incorporating GloVe word embeddings, with a classification accuracy of 95.80% [20]. Aytug Onan proposed instance selection and feature selection to achieve scalability in machine learning-based sentiment classification. The field of predictive performance for text classification was examined by examining 15 benchmark instance selection methods. The experimental results showed that the classification accuracy of the highest C4.5 algorithm is generally obtained through the model class selection method, whereas that of the radial basis function network is obtained through the nearest centroid neighbor version [21].

Aytug Onan presented a machine learning-based approach to sentiment analysis on students’ evaluation of higher educational institutions. We analyze a corpus containing approximately 700 student reviews written in Turkish, with the use of conventional text representation schemes and machine learning classifiers. In the experimental analysis, three conventional text representation schemes (i.e., term-presence, term-frequency, and TF-IDF scheme) and three N-gram models (1-gram, 2-gram, and 3-gram) were considered in conjunction with four classifiers (i.e., support vector machines, Naïve Bayes, logistic regression, and random forest algorithm). The predictive performance of four ensemble learners (i.e., AdaBoost, bagging, random subspace, and voting algorithm) was also evaluated. The empirical results indicated that the machine learning-based approach yields promising results on students’ evaluation of higher educational institutions [22]. Aytug Onan proposed a method for sarcasm recognition based on deep learning. In this regard, the predictive performance compares topic-rich word embedding
schemes with traditional word embedding schemes. Experimental analysis showed that topic-rich word embedding schemes used in conjunction with traditional feature sets can yield promising results for sarcasm recognition [23]. Aytuğ Onan examined the predictive performance of five statistical keyword extraction methods (most common measurement-based keyword extraction, word frequency inverse sentence frequency-based keyword extraction, co-occurrence statistics-based keyword extraction, eccentricity-based keyword extraction rate keyword extraction, and TextRank Algorithms). Integrated methods are used in classification algorithms and classification (classification) of scientific text documents. Experimental analysis showed that the bagging ensemble of random forests produced promising results for text classification based on the most common keyword extraction methods. For the ACM document collection, the utilization rate achieved the highest average prediction performance (93.80%) based on the most frequent keyword extraction method using the bagging ensemble of random forest algorithms. In general, bagging and random subspace ensembles of random forests yielded promising results. Empirical analysis showed that utilizing keyword-based text document representation combined with ensemble learning can enhance the predictive performance and scalable classification scheme of text, which has practical importance in the field of text classification applications [24]. Aytuğ Onan’s analysis of different feature engineering schemes (naïve Bayesian, support vector machines, logistic regression, k-Nearest neighbors, and random forests) and five different base learners are combined with an ensemble learning approach such as boosting, bagging, and random subspaces. Based on empirical analysis, an ensemble classification scheme for ensemble of random subspace ensembles of ensemble random forests was proposed with four types of features (author attribution, character n-grams, part-of-speech n-grams, and most frequently discriminatory words). In the LFA corpus, get the highest average [25]. An ensemble scheme based on hybrid supervised clustering was presented for text classification. In the presented scheme, supervised hybrid clustering, which is based on cuckoo search algorithm and k-means, is introduced to partition the data samples of each class into clusters such that training subsets with higher diversities can be provided. Each classifier is trained on the diversified training subsets, and the predictions of individual classifiers are combined by the majority voting rule. The predictive performance of the proposed classifier ensemble is compared with conventional classification algorithms (such as Naïve Bayes, logistic regression, support vector machines, and C4.5 algorithm) and ensemble learning methods (such as AdaBoost, bagging, and random subspace) using 11 text benchmarks [26]. Aytuğ Onan built an effective emotional classification program by pursuing holistic pruning paradigms. Global pruning is a key method of building classifier integrations with high predictive accuracy and efficiency. Tradeoffs exist when selecting an integrated pruning method. In this respect, hybrid integrated pruning schemes can be more promising. In this study, a text sentiment classification based on clustering and random search is proposed. The results show that consensus clustering and elitist Pareto-based multiobjective evolutionary algorithm can be effectively used for ensemble pruning. The conventional experimental analysis integration method and pruning algorithm demonstrate the proposed scheme [27].

In this study, on the basis of collecting cryogenic globe valve failure data, combined with the two-parameter Weibull segmentation model, least square sum-based solving algorithm is set up to determine the position of section point, estimate the parameter, and compared with the Weibull probability plot (WPP) figure income fitting curve method. Finally, compliance with the reliability model of the distribution of low-temperature cut-off valve life is confirmed.

2. Failure Data Collection and Preliminary Analysis

To obtain the failure data of the low-temperature stop valve, we cooperated with the Henan Boiler and Pressure Vessel Inspection and Research Institute to track and collect 1,114 low-temperature stop valves from 2018 to 2019. A total of 60 low-temperature stop valve failure data were obtained, including disc wear and scratches: 57 units, 2 units with valve stem transmission failure, and 1 unit with loose packing. Figure 1 shows that according to the method of mathematical statistics, the valve is operated once when it is opened and closed once, and the operation times of the valve before failure are arranged in order from small to large, as shown in Table 1.

According to the probability theory, in a single distribution, the probability density function curve of normal distribution and logarithmic normal distribution shows a single peak, the probability density function curve of exponential distribution shows a monotonic descending form, and the probability density function curve of Weibull distribution may show a single peak or a monotonic descending form according to the different shape parameters. Therefore, according to the shape of the curve fitted by the observations, which distribution a certain random variable obeys can be preliminarily judged. According to the mathematical statistic method, the number of operating times of the collected cryogenic valves when they fail is taken as the observation value, the number of operating times, 300 times, is the interval, and the number of valve failures in each interval is observed, followed by the middle of the number of failures of each group, as shown in Table 2. The value is taken as the abscissa, the observed value \( f(t) \) and the frequency of each group of probability density are taken as the ordinate, and the data points are fitted by interpolation. The probability density function graph is obtained, as shown in Figure 2. \( f(t) \) is calculated by the following formula:

\[
f(t) = \frac{n_i}{n\Delta t_i},
\]

where \( n \) is the failure frequency of each failure time.
Figure 2 shows that the failure rate of the cryogenic valve varies widely and does not follow a certain rule. According to the statistical distribution, the probability density of the exponential distribution shows a monotonically decreasing trend, whereas the normal distribution and the lognormal distribution exhibit the rule of a single convexity, but the probability density function value becomes smaller as the distance from the center of symmetry increases on both sides of a single peak. Therefore, the above three types of distributions do not match the failure rate curve. At present, a large number of studies have shown that the Weibull distribution can be widely used in the reliability modeling of various failure phenomena of mechanical or electromechanical products, such as corrosion, fatigue, and wear life, and all obey the Weibull distribution. Therefore, the Weibull distribution is selected for reliability modeling. Figure 3 shows the comparison of the failure rate curve of the failure data with the Weibull distribution probability density curve.

Figure 3 shows that after the valve is opened and closed about 2,100 times, the trend of the probability density curve of the failure data is the same as the trend when the shape parameter is greater than 1; in the stage before the number of opening and closing times 2,100, the probability density function curve is the same as the trend when the Weibull distribution shape parameter is around 1. At the same time, the failure rate of mechanical products conforms to the characteristics of the bathtub curve according to the failure law of mechanical products, that is, the failure rate of mechanical products in the initial stage of use is relatively large, but as the working time continues to extend, the failure rate drops sharply to a certain stable value and reaches the working life of the product. Later, the failure rate rises sharply, and the failure rate trends of Weibull distribution parameters are less than 1, equal to 1, and greater than 1. However, for the failure data of sealing face in the whole life cycle, if a single Weibull distribution is adopted, hidden fault features in the data may be ignored, resulting in large parameter estimation errors. In summary, this paper uses the dual Weibull segmentation model with \( m \leq 1 \) and \( m > 1 \) to model the reliability of the failure data according to the characteristics of the failure data of the weak link.

| Serial number | Number of runs | Serial number | Number of runs | Serial number | Number of runs |
|---------------|----------------|---------------|----------------|---------------|----------------|
| 1             | 74             | 21            | 2793           | 41            | 3077           |
| 2             | 256            | 22            | 2806           | 42            | 3089           |
| 3             | 482            | 23            | 2827           | 43            | 3107           |
| 4             | 905            | 24            | 2843           | 44            | 3129           |
| 5             | 1437           | 25            | 2848           | 45            | 3146           |
| 6             | 1804           | 26            | 2858           | 46            | 3159           |
| 7             | 2332           | 27            | 2876           | 47            | 3177           |
| 8             | 2502           | 28            | 2900           | 48            | 3189           |
| 9             | 2552           | 29            | 2916           | 49            | 3209           |
| 10            | 2595           | 30            | 2918           | 50            | 3227           |
| 11            | 2631           | 31            | 2937           | 51            | 3246           |
| 12            | 2633           | 32            | 2952           | 52            | 3255           |
| 13            | 2649           | 33            | 2960           | 53            | 3265           |
| 14            | 2680           | 34            | 2971           | 54            | 3281           |
| 15            | 2702           | 35            | 2988           | 55            | 3292           |
| 16            | 2716           | 36            | 3012           | 56            | 3302           |
| 17            | 2734           | 37            | 3030           | 57            | 3314           |
| 18            | 2750           | 38            | 3044           | 58            | 3326           |
| 19            | 2762           | 39            | 3048           | 59            | 3337           |
| 20            | 2777           | 40            | 3064           | 60            | 3345           |
Table 2: Number of valve failures corresponding to the intervals.

| Interval     | 0–300 | 300–600 | 600–900 | 900–1200 | 1200–1500 | 1500–1800 | 1800–2100 | 2100–2400 | 2400–2700 | 2700–3000 | 3000–3300 | 3300–3600 |
|--------------|-------|---------|---------|----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Number of failures | 2     | 1       | 0       | 1        | 1         | 0         | 1         | 1         | 7         | 21        | 27        | 5         |
3. Establishment of Two-Parameter Weibull Segmented Model

The two-parameter Weibull segmented model is used to establish the fault distribution model of the cryogenic shut-off valve. The physical background is that the fault data of the cryogenic valve belongs to early faults, accidental faults, and loss faults. Different distribution models are in different fault periods; thus, two simple models were fitted separately.

3.1. Two-Parameter Weibull Segmented Model Analysis.

According to the model definition of the Weibull segmentation model, failure data time \( t \geq 0 \) is divided into two intervals with \( t_0 \) as the segment point, namely \( t_1 \) and \( t_2 \), where \( t_1 = [0, t_0] \) and \( t_2 = [t_0, +\infty) \). To make the two Weibull distribution curves continuous at \( t_0 \), parameter \( k \) is introduced for adjustment. The reliability function of the model is 

\[
R(t) = k_1 R_1(t), \quad 0 < t \leq t_0,
\]

where \( R_1(t) = e^{-t/m_1}, \quad 0 < t \leq t_0 \),

and

\[
R(t) = k_2 R_2(t), \quad t_0 < t.
\]

Failure rate indicates the probability that each system of the cryogenic valve has not failed at a certain time and the failure of each system after that time. The failure rate function can describe the failure rules of various stages of cryogenic valves. Failure rate function is used to segment the failure rules of the valve system, and then the Weibull distribution model to be used is determined according to the segmentation situation. The failure rate is calculated as follows:

\[
\lambda(t) = \frac{f(t)}{R(t)},
\]

where \( f(t) \) is the failure probability density of the fault, and \( R(t) \) is the reliability.

If \( m_1 = m_2 \), the model will degenerate to a simple Weibull distribution, so we limit \( m_1 \neq m_2 \), then the reliability relationship of the two-parameter Weibull segmented model is as follows:

\[
R(t) = \begin{cases} 
  e^{-(t/t_0)^{m_1}}, & 0 < t \leq t_0, \\
  k_2 e^{-(t/t_2)^{m_2}}, & t_0 < t.
\end{cases}
\]

The logarithm of the above formula is taken to obtain the following:
By solving the above equations, the following can be obtained:

\[
t_0 = \left( \frac{m_1 \eta_2^{m_2}}{m_2 \eta_1^{m_1}} \right)^{1/(m_2 - m_1)},
\]

\[
k = \exp \left( \frac{1 - m_2}{m_1} \left( \frac{t_0}{\eta_1} \right)^{m_2} \right),
\]

where \( k \) is the adjustment parameter, and \( t_0 \) is the running times of the segmentation point.

### 3.2. WPP Method Parameter Estimation of Two-parameter Weibull Segmented Model Micromachne

At present, the commonly used method for solving the parameters of the dual Weibull segmented model is the Weibull graph estimation method (abbreviated as WPP). This method uses graphs on graph paper to estimate the unknown parameters in the model, which has the advantages of simplicity and intuition. However, the parameter estimation results are affected by the mapping accuracy. It may cause large errors in the parameter estimation results, or the calculated segment point \( t_0 \) is not within the assumed range of the initial segment point before the solution, resulting in solution contradiction.

The Weibull probability diagram can be used to test the distribution type, obtain parameter estimates, and obtain reliability index values on the diagram [28]. For the two-parameter Weibull distribution, the sample points can be approximated to a line by transformation. The formula is transformed into the following:

\[
e^{-\left(\frac{t_0}{\eta_1}\right)^m} = 1 - F(t).
\]

Taking the natural logarithm twice on both sides of (6),

\[
\ln \ln \left( \frac{1}{1 - F(t)} \right) = m \ln(t) - m \ln(\eta).
\]

Make

\[
y = \ln \ln \left( \frac{1}{1 - F(t)} \right),
\]

\[
x = \ln t,
\]

\[
b = -m \ln(\eta).
\]

Then

\[
y = mx + b.
\]

Equation (9) is a straight line equation in a rectangular coordinate system of equal division plane, with a slope of \( m \) and an intercept of \( b \), which is called a fitted straight line. The coordinates on the same graph paper are plotted to form a Weibull probability distribution diagram. The reliability estimation formula is obtained from the median rank calculation formula:

\[
R(t_i) = 1 - \frac{1 - 0.3}{n + 0.4} (t_i - t_{i-1}).
\]

According to \( F(t_i) = 1 - R(t_i) \), the data points on the Weibull probability chart are drawn: \((t_1, F(t_1)), (t_2, F(t_2)), \ldots, (t_n, F(t_n))\).

The fitting curve is drawn to make the middle part of the line close to the data points, and the data points are staggered and evenly distributed on both sides of the line. Shape parameters and scale parameters can be calculated according to the slope and the intercept of the line [29, 30].

The WPP graph obtained from the collected data through Weibull transformation can obtain the following characteristics: (1) for \( x < x_0 \), it is a straight line, namely the WPP graph of child 1, denoted as \( L_1 \); (2) For \( x > x_0 \), it is a curve with an asymptote as \( x \) goes to infinity: \( y = m_2 (x - \ln \eta_2) \), which is denoted as \( L_2 \). The characteristics are shown in Figure 4.

According to the definition of the two-dimensional Weibull segmented model probability map, the data on the left side of it can be fitted into a straight line \( L_1 \), then the slope of the straight line is \( m_1 \), the intercept of the straight line on the X-axis leads to the \( t \)-axis, and the vertical line intersects with \( t \). The scale of the vertical foot is recorded as the estimated value of \( \eta_1 \). Similarly, the fitted asymptotic line \( L_2 \) at the right end of the data adopts the same processing method as \( L_1 \) to obtain the estimated values of \( m_2 \) and \( \eta_2 \). In summary, the estimated values of the available parameters are shown in Table 3.

It is fitted with MATLAB program, as shown in Figure 5.

### 4. Parameter Solving Algorithm Based on Minimum Sum of Squares

Aiming at the shortcomings of the WPP parameter estimation method, this article is based on the WPP graph analysis method, combined with a simple and general genetic algorithm to design a two-parameter Weibull distribution parameter solving algorithm with higher precision to replace the graph analysis method, that is, the least square method is used to solve the parameters for the first section of the approximate straight line model, and the optimization algorithm is used for the second section of failure data. The solving steps are shown in Figure 6. The implementation of
4.1. Determination of Parameter Solution Space. The solution space of any intelligent optimization algorithm needs to have a certain range limit; otherwise, the algorithm may be unable to find the optimal solution quickly and effectively. This article improves the maximum likelihood interval estimation method and calculates the solution interval of the two-fold Weibull distribution. $n$ products are to be tested, and the test cut-off time is $t_0$. Among them, $r$ products have failed. Assuming that the point estimates $\hat{m}$ and $\hat{\eta}\sqrt{\hat{\alpha}^2 + \hat{b}^2}$ have been given by the maximum likelihood estimation, parameter $m$ has a confidence level of $1 - \alpha$. The confidence interval of $\alpha$ is $[W_1 \hat{m}, W_2 \hat{m}]$, where $W_1$ and $W_2$ are coefficients, which are calculated by the following formulas:

\[
\begin{align*}
W_1 &= \left( \frac{K_1}{r c} \right)^{1/\eta^2}, \\
W_2 &= \left( \frac{K_2}{r c} \right)^{1/\eta^2},
\end{align*}
\]

where $q = r/n$, $c = 2.14628 - 1.36119q$, $K_1 = \chi_{n/2}^2 [c(r - 1)]$, and $K_2 = \chi_{n/2}^2 [c(r - 1)]$. When the degree of freedom is large, looking up the $\chi^2$-distribution table is inconvenient. It can be approximated by the normal distribution, and the points of the $\chi^2$-distribution can be calculated according to the following formula:

\[
\chi_0^2 \approx \sqrt{\frac{1 - 2}{9\sigma}} + u_0 \sqrt{\frac{2}{9\sigma}}^3.
\]

When the confidence is $1 - \alpha$, the confidence interval of the parameter $\eta$ is $[A_1 \eta, A_2 \eta]$. For the case of a complete sample, when $r = n$, the coefficients $A_1$ and $A_2$ are calculated as follows:

\[
\begin{align*}
A_1 &= e^{-1.053d_3/\hat{m}\sqrt{n-1}}, \\
A_2 &= e^{-1.053d_3/\hat{m}\sqrt{n-1}},
\end{align*}
\]

where $d_3 = t_{1-\alpha/2} (n - 1)$.

4.2. Determination of Segmentation Points. The failure interval of $t_0 \in [t_i, t_{i+1}]$ is not accurate because segment point $t_0$ is observed through graph analysis. Actual $t_0 \notin [t_i, t_{i+1}]$, which contradicts the known conditions, is possible. Therefore, the $t_0$ judgment condition shown in Figure 7 must be designed in the optimization, and the failure data around the initial
interval \([t_i, t_{i+1}]\) must be segmented as the failure interval until the solution meets the conditions \(t_0\).

4.3. Determination of Convergence Direction. The purpose of introducing the algorithm is to solve the unknown parameters \(m\) and \(\eta\) of the Weibull distribution with a better fitting effect and a higher accuracy. The usual approach in judging the accuracy of the fitting is to compare the distance between the fitted curve and the failure data point. If the distance is smaller, the fitting accuracy is higher; thus, it is determined to minimize the fitness function shown in (13). The convergence direction of the parameter solving algorithm is carried out according to the maximum value of the \(D\) value. The calculation formula is as follows:

\[
D = \max_{1 \leq i \leq n} \left| F_n(t_i) - F(t_i) \right| = \max_{1 \leq i \leq n} \delta_{i,0}
\]  

where \(F_n(t_i)\) is the cumulative failure probability value of the fitted distribution model, and \(F(t_i)\) is the value of the empirical distribution function.

Therefore, the fitness function is selected as \(D = \max_{1 \leq i \leq n} \left| F_n(t_i) - F(t_i) \right|\), and optimization direction \(D\) takes the minimum value. First, the segmentation of the Weibull model of the cryogenic shut-off valve is determined according to the distribution of the failure rate, as shown in Figure 8.

Figure 8 shows that the failure rate of the cryogenic valve is relatively flat when the number of operations is less than 2500, indicating that its shape parameter is around \(m = 1\). It shows that after the number of operations exceeding 2500, the failure rate suddenly changes. The shape parameter \(m\) is greater than 1; thus, the segmentation point of the segmentation model should be before 2500 runs.

According to the above formula, using MATLAB to solve the two parameters, the 90% two-sided confidence interval of the shape parameter \(m\) is \(m^* = [11.0219, 15.5594]\), and the 90% two-sided confidence interval of the scale parameter \(\eta\) is \(\eta^* = [3044.2527, 3149.8569]\). The obtained shape parameters and scale parameters are shown in Table 4.

The specific fitting curve is shown in Figure 9.
5. Model Test Analysis

Hypothesis testing is a statistical inference method used to determine whether the difference between the collected data sample and the population is caused by the essential difference caused by the improper model. The commonly used test methods are $\chi^2$ test and K-S test. However, due to the shortcomings of $\chi^2$ test, which requires a large sample size and is susceptible to human factors when dividing subsets, the K-S test is adopted in this paper to test the two-factor Weibull model to demonstrate the effectiveness and accuracy of the improved mean rank method more effectively.

The principle is to compare the empirical distribution function $F(t_i)$ with the cumulative distribution function $F(t)$ of the model obtained by analysis. The original hypothesis $H_0$ is that the number of failures obeys the specified distribution, and the alternative hypothesis $H_1$ is that the number of failures does not obey the specified distribution. The significance level of 0.05 is taken, and the K-S test critical value table is passed to obtain $D_{\alpha} = 0.18$. If $D < D_{\alpha}$, the null hypothesis $H_0$ is accepted, that is, the number of failures obeys the specified distribution. The smaller the $D$ value is, the better the fitting effect. If $D > D_{\alpha}$, then the alternative hypothesis $H_1$ is accepted, that is, the number of failures does not obey the specified distribution, and considering whether the data conform to other distributions is necessary. The fitting effect is shown in Figure 10.

Figure 10 shows that the minimum value of $D$ obtained by the WPP method is 0.0006, and the minimum value of $D$ obtained by the $D$ genetic algorithm is 0.0001. According to the principle of the K-S test method, the fitting effect of the genetic algorithm is better.

According to the above parameters, the reliability function $R(t)$ and the failure rate function $\lambda(t)$ of the weak link of the low-temperature globe valve are obtained as follows:

\[
R(t) = \begin{cases} 
\exp\left(-\left(\frac{t}{191982}\right)^{0.5964}\right), & 0 < t < 2500, \\
0.9396\exp\left(-\left(\frac{t}{3439.2}\right)^{10.4623}\right), & 2500 < t < \infty,
\end{cases}
\]

\[
\lambda(t) = \begin{cases} 
\left(\frac{m_1}{\eta_1}\right)\left(\frac{t}{\eta_1}\right)^{m_1-1} = 3.11 \times 10^{-6} \times \left(\frac{t}{191982}\right)^{-0.4036}, & 0 < t < 2500, \\
\left(\frac{m_2}{\eta_2}\right)\left(\frac{t}{\eta_2}\right)^{m_2-1} = 3.04 \times 10^{-3} \times \left(\frac{t}{3439.2}\right)^{9.4623}, & 2500 < t < \infty.
\end{cases}
\]

According to the above function, MATLAB is used to draw the function curve, as shown in the figure below.

Figures 11 and 12 show that the failure rate curve of the weak link of the low-temperature stop valve includes early
failure, accidental failure, and loss failure, which conform to the bathtub curve. However, the early failure rate curve is not apparent because the amount of failure data collected is not sufficient; thus, early failure rate is not sufficiently accurate. However, Figure 11 can clearly reflect the change rule of early failure reliability. Figure 12 shows that after the opening and closing life is approximately 3500 times, the reliability drops to approximately 91%, which has a decisive effect on the overall reliability of the valve. Therefore, controlling the sealing surface in future design or use is necessary. The material or size is optimized to reduce the early failure rate.

6. Conclusion

In this paper, combining the characteristics of Weibull distribution, using the segmented model of Weibull distribution, and based on the operating data of 60 cryogenic shut-off valves, a solution model based on the least square sum is established. The conclusions are as follows.

(1) The reliability modeling method is analyzed, the regular trend of the failure data of the weak link of the cryogenic shut-off valve is combined, and a two-stage Weibull reliability evaluation model is established to analyze the failure data and obtains its shape parameters and scales. Considering the confidence interval of the parameter, the Weibull model is segmented, and the accurate value of the segmentation point is obtained.

(2) The parameter estimation method of the two-dimensional Weibull segmented model is investigated. Aiming at the shortcomings of the accuracy of WPP graph analysis method that varies from person to person, a parameter solving algorithm based on the least square sum is proposed. In-depth analysis of the optimization direction and solution space and determination of segmentation points involved in the algorithm are carried out. Finally, the K-S test proves that the optimization algorithm can be effectively used in the reliability parameter estimation of this kind of data.

(3) The optimization algorithm is used to process the failure data of the weak link of the cryogenic shut-off valve and obtains the change law of the relationship between the life and the reliability model. The effective prediction of reliability and early warning of the failure of the low-temperature stop valve are realized.

Data Availability

The data used in this paper is obtained by investigating relevant experts from Pressure Vessel Safety Inspection Institute of He nan Province, Zhengzhou, China.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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