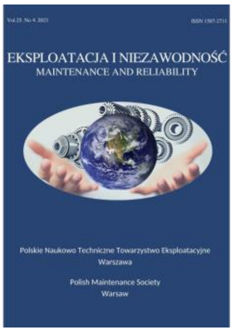

Eksploatacja i Niezawodnosc – Maintenance and Reliability
Volume 26 (2024), Issue 2
journal homepage: http://www.ein.org.pl

Article citation info:
Wang W, Liu W, Fang Y, Zheng Y, Lin C, Jiang Y, Liu D, Reliability analysis of subway sliding plug doors based on improved FMECA and Weibull distribution, Eksploatacja i Niezawodnosc – Maintenance and Reliability 2024: 26(2) http://doi.org/10.17531/ein/178275

Reliability analysis of subway sliding plug doors based on improved FMECA and Weibull distribution

Indexed by: Web of Science Group

Weibo Wang[a,*], Wenxiu Liu[a], Yu Fang[a], Yongkang Zheng[b], Chuan Lin[c], Yonghua Jiang[d], Dong Liu[c,*]

[a] The School of Electrical Engineering and Electronic Information, Xihua University, China
[b] The State Grid Sichuan Electric Power Research Institute, China
[c] The School of Electrical Engineering, Southwest Jiaotong University, China
[d] China Broadnet Pengzhou Branch, Chengdu 611930, China

Highlights

- An improved FMECA method is proposed that can effectively consider the effect of the repetitive values, expert weights, and evaluation factors' weights on hazard analysis.
- Researching different reliability evaluation indexes, MTBF and component fault rates.
- Testing the service life of the subway sliding plug door by Weibull distribution and predicting its remaining useful life.

Abstract

Using traditional failure mode effects and criticality analysis (FMECA) to analyze the hazard of subway sliding plug door system, there are problems such as easy-to-take repetitive values, irrational allocation of expert's weights, and failure to consider the weights of evaluation factors. To address the above problems, this paper proposes an improved FMECA by using linear interpolation to increase the differentiation of the same fault probability occurrence among various fault modes. Apply the dependent uncertain ordered weighted averaging (DUOWA) algorithm to assign weights to different experts dynamically. The analytic hierarchy process (AHP) is used to endow weights to diverse evaluation factors to make them more suitable for engineering needs. We collected 1,836 days of metro train operation records from the Shanghai subway manufacturing plant and studied 17 common faults. Next, use a reliability-centered maintenance (RCM) strategy to determine maintenance periods for different fault modes. Finally, through the Weibull distribution fitting test, the fault rate function of the door is obtained, and the remaining useful life (RUL) of the door is predicted. The consistency between the vulnerable parts obtained by our proposed method and the statistics of the maintenance records of the subway sliding plug door verifies the effectiveness and reliability of our improved FMECA.

Keywords
subway sliding plug door, improved FMECA, DUOWA operator, AHP, Weibull distribution

1. Introduction

With the rapid development of China's economy and the deepening of urbanization, the subway is gradually expanding from the central urban area to the city's edge. According to the fault data statistics of subway operating companies, door faults account for more than 30% of the total number of train faults, ranking first among train subsystems [29]. As a subsystem in direct contact with passengers, the safety and reliability of subway doors have always been a critical concern for rail transit

(*) Corresponding author.
E-mail addresses: W. Wang (ORCID: 0000-0003-1865-4689) wangweibo@mail.xhu.edu.cn, W. Liu (ORCID: 0000-0003-2533-910X) liuwx1121@foxmail.com, Y. Fang (ORCID: 0000-0002-0262-3872) yfang_123@163.com, Y. Zheng, zyk555@sina.com, C Lin. lin_langai@163.com, Y Jiang, 342044638@qq.com, D. Liu (ORCID: 0000-0001-8683-453X) liudong@swjtu.edu.cn

operators. In our team's previous research, we first proposed using motor currents to detect the subway sliding plug door faults, studied three faults and extracted 24 features with a classification accuracy of 93.6% [19]. To detect more fault types and improve the classification accuracy, we proposed the adaptive empirical mode decomposition and recursive feature elimination based on the cross-validation (AEMD-RFECV) method to diagnose 12 sliding plug door faults with 98.96% accuracy [36]. Therefore, based on the above study, we further analyze the reliability of subway sliding plug doors.

Reliability analysis predicts current product performance, saves maintenance costs, and informs subsequent product improvements. Literature [16] developed a neuro-fuzzy-based machine learning method to predict the multiaxial fatigue life of various metallic materials, and the results show that the proposed model has better predictive performance and extrapolation capability than six classical machine learning models. Literature [17] considers the combined effects of performance degradation and effective stress growth, proposes a pair of composite fatigue reliability models, and compares the results with strength and stiffness-based composite reliability analysis. An improved multiaxial low-cycle fatigue life prediction model based on the equivalent strain method was developed in the literature [45]. The validity of the established model was verified using experimental data for five metals. Literature [35] proposes a Discrete Event Simulation (DES) model for estimating system reliability considering increased failure and repair rates. Also, a genetic algorithm is utilized to find the optimal repairable system. It is experimentally verified that the optimal design of the repairable system is to obtain higher reliability at a lower cost when considering failures and repairs.

FMECA is a common method for performing system reliability analysis [24]. Grumman Aircraft of the United States, in 1950, for the first time applied it to the fault analysis of the main system of the aircraft. FMECA is gradually involved in mechanical maintenance, military, aviation, electronics, transportation and firefighting. Deng Y et al. [10] proposed a new fault analysis framework for metro equipment using FMECA and influence diagram theory. This study provides recommendations for designing, operating and maintaining subway equipment. Wang L et al. [37] proposed an extended FMECA method for optimizing equipment maintenance, using metro vehicles as an example, and demonstrated that the proposed method could quantitatively measure reliability, availability, and maintenance cost risk. Cheng X et al. [6] applied FMECA to the reliability analysis of the subway sliding plug door system. They optimized the design and maintenance of the door system based on the analysis results. However, the above studies did not consider the effect of uncertainty and ambiguity of fault description languages and rubrics on analysis results. In response to the above problems, many scholars have improved the traditional FMECA method. Ciani L et al. [7] proposed using fuzzy linguistic terminology to evaluate the parameters and applying fuzzy weights to assess the difference in importance of each parameter. A reliability study of the protection system of the railroad train was carried out using this method, and the results showed the effectiveness of the improved method. Hlinka J et al. [20] used FMECA, Fuzzy logic and multiple-criteria decision analysis to discuss the safety and reliability assessment of the development process for modern aviation products. Lv J et al. [28]combined fuzzy comprehensive evaluation and FMECA to propose a fuzzy FMECA method and applied it to the safety analysis of subway turnouts. Wang X et al. [38] used group decision theory and hierarchical analysis to improve the traditional FMECA and combined the decision-making and experimental evaluation laboratory methods to find out the weak part of the door. F. Fang et al. [15] proposed a fuzzy FMECA method based on fuzzy comprehensive judgment and AHP to analyze the reliability of components with high fault rates in subway doors. Meanwhile, they introduced the RCM strategy to calculate the maintenance periods. However, the above methods are improved by giving the same weight to different experts or fixing different weights without considering the subjective differences between experts. Aiming at the above problems, Cheng et al. [8] proposed a new multi-criteria decision aggregation model, which assigns dynamic weights based on the reliability of the ordered weighted averaging (OWA) operator and uses it to assess the airlines' service quality.

The Weibull distribution was first proposed in the 1920s and applied in the 1930s to characterize the distribution of debris. It is widely used in probability distribution description, reliability assessment, life prediction, and maintenance program development. J. Wang et al. [39] established a new fault rate prediction model for substation equipment based on Weibull distribution and time series analysis. The model's effectiveness is verified by comparing it with the traditional fault rate prediction methods. Bai W et al. [3] proposed a stochastic model based on the Weibull distribution for estimating the renewal cycle of sharply curved subway rails based on analyzing rail wear characteristics. Jiang D et al. [25] proposed an improved Weibull distribution by linking two failure models in series to explore and fit the reliability of the aircraft door locking mechanism. The results showed that the enhanced model fits better. Kundu P et al. [26] combined a clustered change point detection algorithm with a general log-linear Weibull distribution to construct an RUL prediction model. Validation was carried out using roller-bearing life data. Herp J et al. [21] proposed a RUL estimation model for wind turbine main bearing faults based on the Weibull distribution to avoid the increase in O&M costs due to subjective human involvement and overly conservative control strategies. Ghomghaleh A. et al. [18] used the Weibull vulnerability model to determine the RUL under reliability analysis of excavators and compared it with the classical exponential model. Yao B et al. [41] proposed a multi-timescale capacitor reliability assessment method. Taking subway DC capacitors as an example, the method estimates the lifetime of DC link capacitor banks with different control methods. Qin Y et al. [30], to quantitatively analyze the reliability status of subway door systems, using the Weibull distribution model as a fault distribution model for the door system. The reliability characteristic parameters such as reliability, unreliability and Mean time between failure (MTBF) are calculated, which is helpful to help arrange the vehicle overhaul plan and reduce accidents.

To summarize, there are current papers applying FMECA and Weibull distribution to subway sliding plug door systems for reliability analysis, and good results have been achieved, but there is still room for improvement. This paper uses the following methods to improve the traditional FMECA: (1) The linear interpolation is used to distinguish the fault occurrence probability of the same level in different fault modes. (2) The DUOWA operator dynamically assigns weights to different experts. (3) AHP is applied to endow weights to different evaluation factors to make them meet the needs of engineering. Secondly, the results obtained from the improved FMECA are combined to determine the maintenance pattern and calculate the maintenance periods. Finally, the RUL of the doors is predicted by a two-parameter Weibull distribution. Taking the historical fault data of a metro manufacturing plant in Shanghai as the research object, the improved FMECA is utilized to calculate the fault hazard, and the results before and after the improvement are compared to verify the effectiveness of the improved FMECA. A comprehensive reliability analysis of the subway sliding plug door system is performed by considering the derived maintenance periods and predicting the RUL.

This paper is divided into four parts. The first part briefly introduces the current status of domestic and foreign research on the reliability of subway sliding plug doors. The second part presents the hazard analysis method based on improved FMECA, the maintenance periods calculation method based on RCM strategy and the RUL prediction method based on Weibull distribution. The third part shows the experimental results and discussion. Finally, the fourth part gives the conclusion.

2. Methods

When using traditional FMECA to analyze the hazard level of subway sliding plug doors, there are problems of not distinguishing the occurrence probability of different fault modes of the same level and not considering the weights of various experts and evaluation factors. Therefore, firstly, the traditional FMECA is improved using linear interpolation, the DUOWA operator and the AHP method. Secondly, the maintenance period of each fault is calculated by combining the hazard analysis results and based on the RCM strategy. The door fault rate function is derived, and the Weibull distribution fitting test predicts the door RUL. Fig. 1. shows the flowchart of the subway sliding plug door reliability analysis.

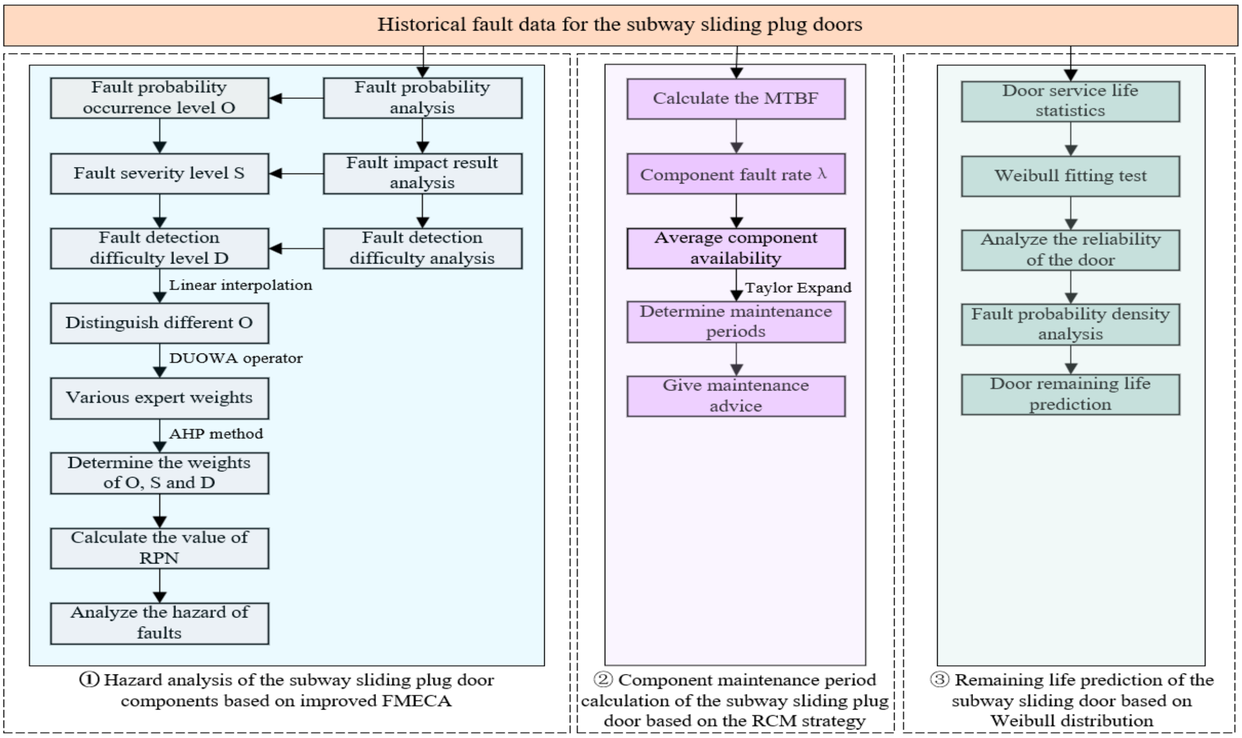

Fig. 1. Flowchart for reliability analysis of subway sliding doors.

2.1. Hazard analysis method based on improved FMECA

FMECA combines failure mode effect analysis (FMEA) and criticality analysis (CA), an essential method for analyzing the system's reliability. Literature [11] studied the system reliability of 4 diesel generators using Dynamic Fault Tree, FMECA, and Bayesian Belief Network. The analysis results helped to provide insights into the importance of faults and components for ship maintenance and availability. Literature [31] used Ishikawa diagrams and FMECA to determine the probable causes of woodchip pump system failures. It combined them with an artificial network to predict the monitored variables with an error of less than 10%, proving the effectiveness of the proposed method. In the literature [46], the Type-I fuzzy inference system is used as an alternative method to improve the failure modes' risk level computation in the classic FMECA analysis and applied to the networked power grids. A method of optimizing the process parameters of mechanical parts manufacturing technology based on the FMECA method is proposed in the literature [27]. Through the reliability analysis of metal cutting machine tools, it verified its effectiveness. FMECA is mainly used to analyze the possible fault modes of the components in a system and their impacts on the system. And categorize and comprehensively assess the occurrence probability of each fault mode, the severity level of the hazards, and the detection difficulty level of the faults [9].

A risk priority number (RPN) is commonly used in FMECA analysis to calculate the fault mode hazard. The fault mode's occurrence probability level, severity level, and fault detection difficulty level are denoted by O, S, and D, respectively. The RPN for a given fault mode is equal to the product of O, S, and D, i.e.

$$RPN = O \times S \times D \tag{1}$$

According to the Chinese standard GB/T 21562 [32], and practical experience and comprehensively considering the characteristics of urban rail transportation, the experts divided the occurrence probability, severity and detection difficulty of each fault mode of the subway sliding plug door into five levels, as shown in Table 1, Table 2 and Table 3.

Table 1. Classification of fault occurrence probability

Fault occurrence probability level	Occurrences of fault modes (%)	Rating level O
I	≥20	10
	15~20	9
II	10~15	8
	5~10	7
III	2~5	6
	0.5~2	5
IV	0.1~0.5	4
	0.05~0.1	3
V	0.01~0.05	2
	≤0.01	1

Table 2. Classification of fault severity.

Fault severity level	The definition of fault severity level	Rating level S
I	A door fault injured the passenger's safety during the train operation.	9
II	Unable to troubleshoot door faults, the passengers must be cleared and shut down the train.	7
III	The door faults cannot be solved quickly, and the faulty door must be removed before the train can continue to operate.	5
IV	Train door malfunction, resulting in a late stop on the main line, with short delays	3
V	It does not affect train operations. It can be repaired after returning to the depot.	1
	somewhere in between	(2,4,6,8)

2.1.1. Distinguish the probability of different faults

The evaluation factors ratings are taken as integers when using traditional FMECA to analyze the subway sliding plug doors hazard. When the fault modes are different, and the fault probability differs by a factor of several, both the fault probability ratings O may yet be categorized as the same. To solve this problem, we consider using interpolation to improve the fault occurrence probability differentiation of various fault modes. Linear interpolation is characterized by simplicity and convenience compared with other interpolation methods. Therefore, O^l can be achieved by linear interpolation to distinguish different fault occurrence probabilities, and the specific interpolation process is shown in the Eq. (2).

$$O^l = Rank^l + \frac{r^l - r_{Rank^l}}{r_{Rank^l+1} - r_{Rank^l}} \tag{2}$$

where: $r^l$is the probability occurrence of fault mode *l*; $Rank^l$is the corresponding O level of r^l.r_{Rank^l} is the minimum of the probabilities range of fault corresponding to $Rank^l$.r_{Rank^l+1} is the minimum of the probabilities range of fault corresponding to $Rank^l + 1$.

Table 3. Classification of fault detection difficulty.

Fault detection difficulty level	The definition of fault detection difficulty level	Rating level D
I	Very difficult	9
II	harder	7
III	moderate	5
IV	easy	3
V	Very easy	1
	somewhere in between	(2,4,6,8)

2.1.2. Calculate the weights of different experts

Due to experts having their own specializations, assigning fixed weight to experts before analysis is not reasonable. OWA operator was proposed by Yager in 1988 and is an important multi-attribute comprehensive decision-making method [42]. The DUOWA operator is an extension of the OWA operator based on the deviation measure, and the associated weights depend only on the aggregate independent variables, which can reduce the influence of unfair independent variables on the aggregate results [40]. It has been widely used in engineering, neural networks, data mining, decision-making, image processing, and expert systems. Therefore, this paper chooses the DUOWA operator to empower the experts, and the specific steps of the DUOWA operator are as follows.

Assuming that a review panel of *K* experts evaluates a fault mode, the RPN of the kth expert is denoted by the set $Z_k = \{O_k, S_k, D_k\}$.

(1) Calculate the mean of O, S, and D as $Z_a = \{O_a, S_a, D_a\}$.

$$O_a = \frac{1}{K}\sum_{k=1}^{K} O_k\,, k = 1,2,\cdots,K \tag{3}$$

$$S_a = \frac{1}{K}\sum_{k=1}^{K} S_k\,, k = 1,2,\cdots,K \tag{4}$$

$$D_a = \frac{1}{K}\sum_{k=1}^{K} D_k\,, k = 1,2,\cdots,K \tag{5}$$

(2) Calculate the measured distance between Z_k and Z_a.

$$d(Z_k, Z_a) = \frac{1}{3}(|O_k - O_a| + |S_k - S_a| + |D_k - D_a|) \tag{6}$$

(3) Compute the similarity between Z_k and Z_a. For a set of K risk-prioritized numbers $Z_k = \{O_k, S_k, D_k\}, k = 1,2,\cdots,K$, the similarity between the risk-priority number and its mean is:

$$s(Z_k, Z_a) = 1 - \frac{d(Z_k,Z_a)}{\sum_{k=1}^{K} d(Z_k,Z_a)} \tag{7}$$

(4) Use the DUOWA operator to obtain the aggregation formula.

$$Z = (O, S, D) = \sum_{k=1}^{K} \omega_k Z_k \tag{8}$$

$$\omega_k = \frac{s(Z_k,Z_a)}{\sum_{k=1}^{K} s(Z_k,Z_a)} \tag{9}$$

2.1.3 Determine the weight of evaluation factors

The traditional FMECA needs to allocate the weights between different evaluation factors rationally. AHP is a comprehensive evaluation method for system analysis and decision-making created by T.L. Saaty in the 1970s, which rationally solves the quantification of qualitative problems [1]. AHP has been widely used in decision-making, evaluation and analysis of problems in engineering [43], agriculture, environment, talent, medicine and transportation [2]. Therefore, in this paper, AHP is used to calculate the weights of different evaluation factors, and the AHP method is briefly introduced in conjunction with the subway sliding plug door system in the following steps:

(1) Determine the set of factors U that influence the subway sliding plug door system, with different elements representing different evaluation factors.

$$U = \{U_1, U_2, U_3\} = \{\text{occurance probability, severity, detection difficulty}\} \tag{10}$$

(2) Decompose the factors and construct a factor comparison matrix.

$$H^l = \begin{bmatrix} h_{11}^l & h_{12}^l & \cdots & h_{1N}^l \\ h_{21}^l & h_{22}^l & \cdots & h_{2N}^l \\ \vdots & \vdots & \ddots & \vdots \\ h_{N1}^L & h_{N2}^l & \cdots & h_{NN}^l \end{bmatrix} \tag{11}$$

where: H^l represents the nine-scaled judgment matrix for the FM^l fault mode. h_{ij}^l represents the relative importance of the evaluation factors U_i to U_j when FM^l is used as the judgment criterion.The size is classified by the judgment scale.

The nine-scaled and three-scaled scales are the most commonly used judgment scale criteria for the AHP method. The nine-scaled scale has better accuracy than the three-scaled scale, so this paper adopts the nine-scaled scale as the judgment matrix calculation standard. The nine-scale judgment scale is shown in Table 4.

Table 4. Nine-scaled judgement scale table

Scale	Definition
1	For FM^l, U_i and U_j are equally important
3	For FM^l, U_i is slightly more important than U_j
5	For FM^l, U_i is significantly more important than U_j
7	For FM^l, U_i is strongly more important than U_j
9	For FM^l, U_i is extremely more important than U_j
2，4，6，8	Denote the intermediate value of the above-neighbouring judgments
reciprocal	If the ratio importance of U_i to U_j is h_{ij}, then the ratio importance of U_j to U_i is $1/h_{ij}$

(3) Determine the weight vector of the FM^l fault mode's evaluation factors. Let $B^l = \{b_1^l, b_2^l, \cdots, b_N^l\}^T$ be the weights, then:

$$\begin{cases} \sum b_i^l = 1 \\ b_i^l > 0 \end{cases} \tag{12}$$

where: b_i^l is the weight of the i evaluation factor for the FM^l fault mode.

According to the obtained nine-scaled judgment scale matrix H^l, determine the relative weight of each factor. This paper adopts the square root method to determine the relative weights. The specific calculation steps are as follows:

① Calculate the N power of the product of each row element of the matrix H^l:

$$M_i^l = \left(\prod_{j=1}^N h_{ij}^{\,l}\right)^{\frac{1}{N}}, i = 1,2,\cdots,N \tag{13}$$

Normalize M_i:

$$b_i^l = \frac{M_i^l}{\sum_{i=1}^N M_i^l}, i = 1,2,\cdots,N \tag{14}$$

Then the weight vector is $B^l = \{b_1^l, b_2^l, \cdots, b_N^l\}^T$.

② Compute the maximum eigenvalue of the matrix H^l:

$$\delta_{max} = \frac{1}{N}\sum_{i=1}^N \frac{(H^l B^l)_i}{b_i^l} \tag{15}$$

③ After calculating the maximum eigenvalue δ_{max} of the matrix H^l and its corresponding eigenvector, the consistency test is carried out and calculate the consistency ratio R_c.

$$I_c = \frac{(\delta_{max} - N)}{N-1} \tag{16}$$

$$R_c = \frac{I_c}{I_R} \tag{17}$$

where: I_c is the consistency index. I_R is the average random consistency index of the judgment matrix. When N=3, i.e., the system has three evaluation factors, I_R=0.58, the values of, I_R are shown in Table 5 [4]. When R_c<0.1, the consistency of the matrix is considered acceptable. Otherwise, the matrix should be corrected appropriately

Table 5. The values of I_R.

N	1	2	3	4	5	6	7	8	9	10
I_R	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

In summary, it can be seen that this paper uses linear interpolation to differentiate the fault occurrence probability O of different fault modes of the same level, adopts the DUOWA operator to dynamically assign weights to various experts, and utilizes AHP to endow weights to different evaluation factors, and improves the traditional FMECA through the above methods. Take the subway sliding plug door system as an example. The RPN of each fault mode is calculated according to the improved FMECA. The hazard ranking is carried out to find the critical components of the door system that need to be repaired.

2.2. Calculate the maintenance period based on the RCM strategy

The RCM strategy was first proposed by Stan Nowlan and Howard Heap of United Airlines in 1978. It is a famous systems engineering approach for identifying equipment preventive maintenance work and optimizing maintenance regimes [5]. Literature [44] based on RCM and quality stochastic flow networks proposed mission reliability–centered maintenance quality evaluation method for multistage manufacturing systems. Take the flow receiver of a subway as an example and verify the effectiveness of the proposed method. Literature [22] used the RCM strategy to optimize the maintenance of complex systems in subway trains, determine the maintenance periods of components under reliability constraints, and improve the availability of subway trains. Therefore, this paper applies the RCM strategy to the subway sliding plug door system and briefly introduces it.

Reliability is the probability that a product will perform a specific function under specific conditions, at a particular time, and at a specific capacity [34]. It is usually denoted by $D(t)$. Assuming that the lifetime of each component of a subway sliding plug door system follows an exponential distribution, it can be described as:

$$D(t) = e^{-\lambda t} \tag{18}$$

where $\lambda$is the component fault rate and $D(t)$is the component reliability at time t, 0<$D(t)$<1.

For repairable systems, the operation time between two adjacent faults is represented by MTBF. The MTBF is calculated using the point estimation method by counting the fault interval data based on operation and maintenance records:

$$MTBF = \frac{\sum_{i=1}^{N_1} \Delta t}{N_1} \tag{19}$$

where Δtdenotes the fault interval, N_1 represents the occurrence times of fault.

The link between MTBF and λ can be described as:

$$MTBF = \frac{1}{\lambda} \tag{20}$$

For complex systems such as the subway sliding plug doors, it is not accurate to determine the maintenance periods of door components only through experience and qualitative analysis. Therefore, periodic maintenance models are selected for calculating the maintenance period. Standard periodic maintenance models are based on task reliability. However, calculation models based on maximum availability and minimum maintenance cost are not applicable for exponentially distributed systems. Therefore, we choose the average availability model to compute the maintenance periods.

Average life is defined as the time of continuous fault-free operation of the equipment under specified conditions and can be written as:

$$E(t) = \int_0^\infty t f(t)\, dt \tag{21}$$

$$f(t) = \lambda e^{-\lambda t} \tag{22}$$

The average availability of the device is:

$$A(t) = \frac{E(t)}{t} = \frac{1-e^{-\lambda t}}{\lambda t} \tag{23}$$

According to Taylor's formula, one can expand $e^{-\lambda t}$ as:

$$e^{-\lambda t} = 1 - \lambda t + \frac{(\lambda t)^2}{2!} - \frac{(\lambda t)^3}{3!} + \frac{(\lambda t)^4}{4!} + \cdots + \frac{(\lambda t)^{N_2}}{(N_2)!} \tag{24}$$

Substituting Eq.(24) into Eq.(23) and taking N_2 = 4, then $A(t) = 1 - \frac{(\lambda t)^2}{2!} + \frac{(\lambda t)^3}{3!}$ and calculate the maintenance period t:

$$t = \frac{1.5-\sqrt{6A-3.75}}{\lambda} \tag{25}$$

2.3. Door remaining life prediction method based on Weibull distribution

The Weibull distribution was proposed in the 1920s and first applied to characterize debris distribution in the 1930s [33]. Since its development, it has been widely used in the fields of probability distribution description [13], lifetime prediction [39], reliability assessment [25], and maintenance program development [15]. Meanwhile, literature [23] points out that the service life of the subway sliding plug door system obeys the Weibull distribution, so this paper chooses the Weibull distribution to predict the door's remaining life and the Weibull distribution function is shown as follows:

A set of non-negative variables, G, is said to conform a Weibull distribution if it satisfies the Weibull probability distribution function shown in Eq.(26) [14].

$$f(g) = \frac{\beta}{\eta}\left(\frac{g-\gamma}{\eta}\right)^{\beta-1} exp\left[-\left(\frac{g-\gamma}{\eta}\right)^{\beta}\right], g \le \gamma \tag{26}$$

where β is a shape parameter that can affect the curve's overall trend, and η is a scale parameter that can impact the curve's position. γ is a location parameter that is a response to the service life, indicating that the device fails after this time. γ does not change the shape of the probability density curve but only shifts the curve.

Due to the difficulty of parameter estimation of the three-parameter Weibull distribution, it is not widely used in practical engineering problems. Therefore, this paper uses the two-parameter Weibull distribution model to analyze the subway sliding plug doors' reliability.

The fault rate, fault probability density function, reliability and probability distribution function of the two-parameter Weibull distribution are shown below:

$$\lambda(g) = \frac{\beta}{\eta}\left(\frac{g}{\eta}\right)^{\beta-1}, g \geq 0 \tag{27}$$

$$f(g) = \frac{\beta}{\eta}\left(\frac{g}{\eta}\right)^{\beta-1} exp\left[-\left(\frac{g}{\eta}\right)^{\beta}\right], g \geq 0 \tag{28}$$

$$R(g) = exp\left[-\left(\frac{g}{\eta}\right)^{\beta}\right], g \geq 0 \tag{29}$$

$$F(g) = 1 - exp\left[-\left(\frac{g}{\eta}\right)^{\beta}\right], g \geq 0 \tag{30}$$

Before prediction, the data should be fitted to the Weibull distribution. If the fitting is good, the data obeys the Weibull distribution and can be reliably predicted by the Weibull distribution model. Otherwise, we should find other well-fitting distribution types to make the prediction. Therefore, this section will briefly introduce the fitting test method of two-parameter Weibull distribution. Taking two logarithmic treatments on both sides of Eq. (30) can be obtained:

$$ln\left(\frac{1}{1-F(g)}\right) = \left(\frac{g}{\eta}\right)^{\beta} \tag{31}$$

$$lnln\left(\frac{1}{1-F(g)}\right) = \beta\, ln\, g - \beta\, ln\, \eta \tag{32}$$

If we let

$$x_i = ln\, g_i \tag{33}$$

$$y_i = lnln\left(\frac{1}{1-F(g)}\right) \tag{34}$$

Then Eq. (34) can be simplified as:

$$y_i = -\beta\, ln\, \eta + \beta x_i \tag{35}$$

The data is substituted into the above equation for fit test and analysis. If the data are distributed along a straight line with a slope greater than zero, it is considered that the data obeys a Weibull distribution. Also, let $b = -\beta\, ln\, \eta, e = \beta$, the roughly estimated shape and scale parameters can be obtained.

$$\begin{cases} \eta_0 = exp\left(-\frac{b}{\beta}\right) \\ \beta_0 = e \end{cases} \tag{36}$$

The results of Eq. (36) are used as the initial values of the parameters, and the great likelihood estimation method is utilized to compute β and η.

where, e, b are the regression coefficients, and the linear equation obtained from the fitting is the data observations regression equation. A quantitative indicator of the closeness of two linear correlations is called the correlation coefficient, denoted by C, then

Table 6. Statistics of door system fault components.

Components	No of faults	Fault mode	Times
EDCU	FM^1	Safety relay fault	24
	FM^2	Software fault	15
	FM^3	Other functional fault	198
Close travel switch S4	FM^4	Plug loose	27
	FM^5	Functional fault	23
Motor	FM^6	Functional fault	2
	FM^7	Line breakage	6
	FM^8	Plug loose	5
Locked travel switch S1	FM^9	Functional fault	9
Upper guideway	FM^{10}	Exist cracks	6
Electromagnetic brake	FM^{11}	Circlip breakage	6
Door leaf	FM^{12}	The glass is broken	2
	FM^{13}	Deformation and peeling of sealing tape	4
	FM^{14}	Fractured hinges	4
Cutting out the travel switch S2	FM^{15}	Functional fault	6
Screw	FM^{16}	Poor lubrication	3
Isolation locking device	FM^{17}	Functional fault	7

$$\tilde{x} = \frac{\sum_{m=1}^{M} x_i}{M} \tag{37}$$

$$\tilde{y} = \frac{\sum_{m=1}^{M} y_i}{M} \tag{38}$$

$$C = \frac{\sum_{m=1}^{M}(x_i-\tilde{x})(y_i-\tilde{y})}{\sqrt{\sum_{m=1}^{M}(x_i-\tilde{x})^2(y_i-\tilde{y})^2}} \tag{39}$$

C takes values between 0 and ±1, with the closer C to ±1 indicating a more intimate linear relationship between the variables.

3. Presentation of experimental results

3.1. Hazard analysis

3.1.1. Description of the data

The data studied in this paper is the door fault data of a subway manufacturing plant in Shanghai from January 5, 2016, to January 16, 2021, totalling 484 times. The 347 faults that occurred in the ten components with many faults are taken as the research object, and the fault statistics are shown in Table 6.

3.1.2. Risk priority number calculation

Table 7. The score table of fault mode evaluation factors.

No of faults	Expert 1			Expert 2			Expert 3			Expert 4		
	O_1	S_1	D_1	O_2	S_2	D_2	O_3	S_3	D_3	O_4	S_4	D_4
FM^1	5	5	5	5	5	6	4	6	5	5	5	5
FM^2	5	7	5	4	8	5	5	8	5	5	7	5
FM^3	8	7	6	7	7	7	8	8	7	8	7	6
FM^4	5	5	5	5	5	6	5	6	6	5	5	5
FM^5	5	5	5	5	4	4	6	5	5	5	6	5
FM^6	4	6	7	4	5	7	4	4	6	4	6	7
FM^7	4	6	5	3	6	5	4	5	3	4	6	4
FM^8	4	5	4	4	6	3	3	6	3	4	4	4
FM^9	4	4	5	4	5	4	4	5	5	5	5	5
FM^{10}	4	6	6	4	5	5	4	5	5	4	6	6
FM^{11}	4	6	7	4	4	7	4	4	5	4	5	7
FM^{12}	4	6	4	4	6	4	4	7	5	4	6	4
FM^{13}	4	5	3	4	4	5	4	3	4	5	4	4
FM^{14}	4	5	4	5	4	2	4	5	3	4	5	4
FM^{15}	4	4	4	4	5	3	4	6	4	4	6	4
FM^{16}	4	3	6	5	2	7	4	2	6	3	3	6
FM^{17}	4	3	4	4	3	2	4	2	3	4	2	4

Table 8. Analysis results of the traditional FMECA.

No of faults	O	S	D	RPN	Rank
FM^1	4.75	5.25	5.25	130.92	5
FM^2	4.75	7.50	5.00	178.13	2
FM^3	7.75	7.25	6.50	365.22	1
FM^4	5.00	5.25	5.50	144.38	3
FM^5	5.25	5.00	4.75	124.69	6
FM^6	4.00	5.25	6.75	141.75	4
FM^7	3.75	5.75	4.25	91.64	11
FM^8	3.75	5.25	3.50	68.91	13
FM^9	4.25	4.75	4.75	95.89	10
FM^{10}	4.00	5.50	5.50	121.00	8
FM^{11}	4.00	4.75	6.50	123.50	7
FM^{12}	4.00	6.25	4.25	106.25	9
FM^{13}	4.25	4.00	4.00	68.00	14
FM^{14}	4.25	4.75	3.25	65.61	15
FM^{15}	4.00	5.25	3.75	78.75	12
FM^{16}	4.00	2.50	6.25	62.50	16
FM^{17}	4.00	2.50	3.25	32.50	17

Table 9. The analysis results based on LI-FMECA.

No of faults	O	S	D	RPN	Rank
FM^1	5.91	5.25	5.25	162.93	4
FM^2	5.36	7.50	5.00	201.00	2
FM^3	8.16	7.25	6.50	384.35	1
FM^4	5.65	5.25	5.50	163.05	3
FM^5	5.56	5.00	4.75	132.11	9
FM^6	4.03	5.25	6.75	142.64	5
FM^7	5.58	5.75	4.25	136.39	8
FM^8	5.17	5.25	3.50	94.98	12
FM^9	4.98	4.75	4.75	112.35	10
FM^{10}	4.57	5.50	5.50	138.39	7
FM^{11}	4.58	4.75	6.50	141.25	6
FM^{12}	4.03	6.25	4.25	106.91	11
FM^{13}	4.43	4.00	4.00	70.85	15
FM^{14}	4.43	4.75	3.25	68.36	16
FM^{15}	4.58	5.25	3.75	90.07	13
FM^{16}	4.57	2.50	6.25	71.38	14
FM^{17}	4.70	2.50	3.25	38.19	17

In the improved FMECA, N=3 represents that there are three evaluation factors in the factors set U, i.e., the fault probability O, the fault severity S, and the fault detection difficulty D. K=4 represents that

Table 10. Assembly results of the DUOWA operator.

No of faults	Expert 1	Expert 2	Expert 3	Expert 4
FM^1	0.2778	0.2407	0.2037	0.2778
FM^2	0.2619	0.2143	0.2619	0.2619
FM^3	0.2667	0.2333	0.2333	0.2667
FM^4	0.2619	0.2619	0.2143	0.2619
FM^5	0.3000	0.2000	0.2667	0.2333
FM^6	0.2593	0.2963	0.1852	0.2593
FM^7	0.2639	0.2361	0.2083	0.2917
FM^8	0.2821	0.2564	0.2308	0.2308
FM^9	0.2407	0.2407	0.2778	0.2407
FM^{10}	0.2500	0.2500	0.2500	0.2500
FM^{11}	0.2361	0.2639	0.2083	0.2917
FM^{12}	0.2778	0.2778	0.1667	0.2778
FM^{13}	0.1970	0.2576	0.2576	0.2879
FM^{14}	0.2639	0.1806	0.2917	0.2639
FM^{15}	0.2222	0.2593	0.2593	0.2593
FM^{16}	0.2879	0.1970	0.2879	0.2273
FM^{17}	0.2500	0.2167	0.2833	0.2500

Table 11. The analysis results based on DUOWA-FMECA.

No of fault	O	S	D	RPN	Rank
FM^1	4.796	5.204	5.241	130.801	5
FM^2	4.786	7.476	5.000	178.895	2
FM^3	7.767	7.233	6.467	363.290	1
FM^4	5.000	5.214	5.476	142.772	4
FM^5	5.267	5.033	4.800	127.243	6
FM^6	4.000	5.333	6.815	145.383	3
FM^7	3.764	5.792	4.292	93.555	11
FM^8	3.769	5.256	3.513	69.598	13
FM^9	4.240	4.759	4.759	96.055	10
FM^{10}	4.000	5.500	5.500	121.000	8
FM^{11}	4.000	4.764	6.583	125.449	7
FM^{12}	4.000	6.167	4.167	102.778	9
FM^{13}	4.288	3.939	4.061	68.590	14
FM^{14}	4.181	4.819	3.347	67.440	15
FM^{15}	4.000	5.297	3.741	79.249	12
FM^{16}	3.970	2.515	6.197	61.873	16
FM^{17}	4.000	2.467	3.283	32.396	17

Table 12 The analysis results based on LI-DUOWA-FMECA.

No of faults	O	S	D	RPN	Rank
FM^1	5.843	5.204	5.241	159.332	4
FM^2	5.339	7.476	5.000	199.579	2
FM^3	8.156	7.233	6.467	381.501	1
FM^4	5.647	5.214	5.476	161.237	3
FM^5	5.567	5.033	4.800	134.491	9
FM^6	4.025	5.333	6.815	146.291	5
FM^7	5.525	5.792	4.292	137.337	8
FM^8	5.111	5.256	3.513	94.384	12
FM^9	4.979	4.759	4.759	112.786	10
FM^{10}	4.575	5.500	5.500	138.394	7
FM^{11}	4.575	4.764	6.583	143.482	6
FM^{12}	4.025	6.167	4.167	103.420	11
FM^{13}	4.448	3.939	4.061	71.148	14
FM^{14}	4.393	4.819	3.347	70.862	15
FM^{15}	4.575	5.297	3.741	90.640	13
FM^{16}	4.511	2.515	6.197	70.316	16
FM^{17}	4.700	2.467	3.283	38.065	17

the review panel consists of four experts familiar with the design and maintenance of subway sliding plug doors, and the kth expert's risk priority number is denoted by the set $Z_k = \{O_k, S_k, D_k\}$. Based on Table 1, Table 2 and Table 3,experts rated the factors affecting the 17 fault modes, and the evaluation set is shown in Table 7.

When all the evaluation factors and expert weights are the same, and the factor levels are taken as the mean value, the RPN of each fault mode in Table 7 is calculated according to Eq. (1), and the calculation results are shown in Table 8.

Considering the differences in the occurrence probability of various fault modes at the same level, the fault occurrence probability O is redefined using linear interpolation. In contrast, the RPN value of each fault mode is calculated according to Eq.(1), and the calculation and ranking results are shown in Table 9.

Because experts have differences in engineering experience, education level and other aspects, to objectively and scientifically describe experts' views, this paper unifies and aggregates the experts' views according to the DUOWA operator. Calculate the weight of each expert under different fault modes, as shown in Table 10.The different weights derived from the DUOWA operators are assigned to the experts.

Table 13. Weights of evaluation factors for FM1.

Evaluation factors	O	S	D	B^1
O	1	1/9	1/9	0.0526
S	9	1	1	0.4737
D	9	1	1	0.4737

Table 14. Weights of each fault evaluation factor for subway sliding plug doors.

No of faults	B
FM^1	$[0.0526,0.4737,0.4737]^T$
FM^2	$[0.0909,0.8182,0.0909]^T$
FM^3	$[0.4737,0.4737,0.0526]^T$

No of faults	B
FM^4	$[0.0909,0.8182,0.0909]^T$
FM^5	$[0.7352,0.0581,0.2067]^T$
FM^6	$[0.0526,0.4737,0.4737]^T$
FM^7	$[0.0909,0.8182,0.0909]^T$
FM^8	$[0.0909,0.8182,0.0909]^T$
FM^9	$[0.0909,0.0909,0.8182]^T$
FM^{10}	$[0.0526,0.4737,0.4737]^T$
FM^{11}	$[0.0581,0.2067,0.7352]^T$
FM^{12}	$[0.0909,0.8182,0.0909]^T$
FM^{13}	$[0.0909,0.8182,0.0909]^T$
FM^{14}	$[0.4737,0.4737,0.0526]^T$
FM^{15}	$[0.0909,0.8182,0.0909]^T$
FM^{16}	$[0.0581,0.2067,0.7352]^T$
FM^{17}	$[0.4737,0.0526,0.4737]^T$

Table 15. The analytical result based on AHP-FMECA.

No of faults	O	S	D	RPN	Rank
FM^1	0.2499	2.4869	2.4869	1.5453	3
FM^2	0.4318	6.1365	0.4545	1.2042	5
FM^3	3.6712	3.4343	0.3419	4.3107	1
FM^4	0.4545	4.2956	0.5000	0.9761	8
FM^5	3.8598	0.2905	0.9818	1.1009	6
FM^6	0.2104	2.4869	3.1975	1.6731	2
FM^7	0.3409	4.7047	0.3863	0.6195	13
FM^8	0.3409	4.2956	0.3182	0.4658	15
FM^9	0.3863	0.4318	3.8865	0.6483	12
FM^{10}	0.2104	2.6054	2.6054	1.4282	4
FM^{11}	0.2324	0.9818	4.7788	1.0904	7
FM^{12}	0.3636	5.1138	0.3863	0.7183	11
FM^{13}	0.3863	3.2728	0.3636	0.4597	16
FM^{14}	2.0132	2.2501	0.1710	0.7744	10
FM^{15}	0.3636	4.2956	0.3409	0.5324	15
FM^{16}	0.2324	0.5168	4.5950	0.5518	14
FM^{17}	1.8948	0.1315	1.5395	0.3836	17

The calculation and ranking results are shown in Table 11.The traditional FMECA method is also improved using linear interpolation and the DUOWA operator to calculate the RPN and ranking results for different fault modes, as shown in Table 12.

Table 16. The analytical results based on LI-AHP-FMECA.

No of faults	O	S	D	RPN	Rank
FM^1	0.3109	2.4869	2.4869	1.9230	2
FM^2	0.4872	6.1365	0.4545	1.3589	5
FM^3	3.8635	3.4343	0.3419	4.5365	1
FM^4	0.5133	4.2956	0.4999	1.1023	8
FM^5	4.0896	0.2905	0.9818	1.1664	7
FM^6	0.2117	2.4869	3.1975	1.6835	3
FM^7	0.5073	4.7047	0.3863	0.9221	9
FM^8	0.4698	4.2956	0.3182	0.6421	13
FM^9	0.4526	0.4318	3.8865	0.7596	11
FM^{10}	0.2406	2.6054	2.6054	1.6334	4
FM^{11}	0.2658	0.9818	4.7788	1.2472	6
FM^{12}	0.3659	5.1138	0.3863	0.7228	12
FM^{13}	0.4025	3.2728	0.3636	0.4790	16
FM^{14}	2.0977	2.2501	0.1710	0.8069	10
FM^{15}	0.4159	4.2956	0.3409	0.6089	15
FM^{16}	0.2654	0.5168	4.5950	0.6302	14
FM^{17}	2.2264	0.1315	1.5395	0.4507	17

Table 17. The analytical results based on DUOWA-AHP-FMECA.

No of faults	O	S	D	RPN	Rank
FM^1	0.2523	2.4650	2.4825	1.5438	3
FM^2	0.4350	6.1170	0.4545	1.2094	5
FM^3	3.6791	3.4264	0.3401	4.2879	1
FM^4	0.4545	4.2663	0.4978	0.9652	8
FM^5	3.8721	0.2924	0.9922	1.1235	6
FM^6	0.2104	2.5264	3.2282	1.7160	2
FM^7	0.3421	4.7387	0.3901	0.6325	12
FM^8	0.3426	4.3008	0.3193	0.4705	15
FM^9	0.3855	0.4326	3.8940	0.6494	11
FM^{10}	0.2104	2.6054	2.6054	1.4282	4
FM^{11}	0.2324	0.9847	4.8401	1.1076	7
FM^{12}	0.3636	5.0456	0.3788	0.6948	10
FM^{13}	0.3898	3.2232	0.3691	0.4637	16
FM^{14}	1.9803	2.28230	0.1761	0.7960	9
FM^{15}	0.3636	4.3334	0.3400	0.5358	14
FM^{16}	0.2306	0.5199	4.5560	0.5463	13
FM^{17}	1.8948	0.1297	1.5553	0.3824	17

A panel of experts evaluates each fault mode of the subway sliding plug door system. Every expert selects one level for each factor in the evaluation factors set U, thus determining the evaluation set for the fault mode FM^l. Taking FM^1 as an example, the panel's evaluation steps are as follows:

(1) Determine the evaluation factor set U.

$$U = \{U_1, U_2, U_3\} = \{O, S, D\}$$

(2) The nine-scaled scale for FM^1 is obtained, and its consistency is checked with Eq.(17). Obtain the weight vector B^1 of the evaluation factors. The specific calculation results are shown in Table 13. Similarly, the weight vectors of the remaining fault modes are calculated, and the results are shown in Table 14.

Table 18. The analytical results of improved FMECA based on LI-DUOWA-AHP.

No of faults	O	S	D	RPN	Rank
FM^1	0.3073	2.4650	2.4825	1.8806	2
FM^2	0.4853	6.1170	0.4545	1.3493	5
FM^3	3.8635	3.4264	0.3401	4.5029	1

No of faults	O	S	D	RPN	Rank
FM^4	0.5133	4.2663	0.4978	1.0901	8
FM^5	4.0926	0.2924	0.9922	1.1874	7
FM^6	0.2117	2.5264	3.2282	1.7267	3
FM^7	0.5023	4.7387	0.3901	0.9285	9
FM^8	0.4646	4.3008	0.3193	0.6381	13
FM^9	0.4526	0.4326	3.8940	0.7625	11
FM^{10}	0.2406	2.6054	2.6054	1.6335	4
FM^{11}	0.2658	0.9847	4.8401	1.2668	6
FM^{12}	0.3659	5.0456	0.3788	0.6992	12
FM^{13}	0.4043	3.2232	0.3691	0.4810	16
FM^{14}	2.0808	2.2830	0.1761	0.8364	10
FM^{15}	0.4159	4.3334	0.3400	0.6128	15
FM^{16}	0.2621	0.5199	4.5560	0.6208	14
FM^{17}	2.2264	0.1297	1.5553	0.4493	17

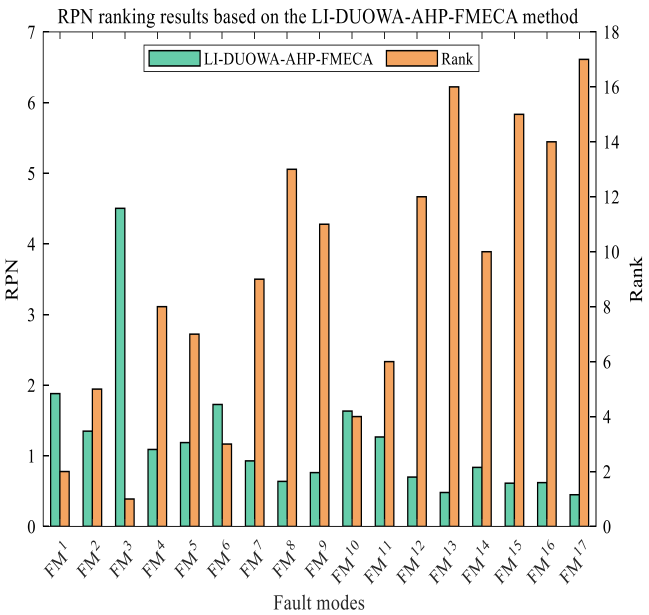

Fig. 2. RPN ranking results of improved FMECA based on LI-DUOWA-AHP.

The AHP method is used to derive the different evaluation factors' weights and combined with linear interpolation and DUOWA operator in turn to calculate the RPN of each fault mode. The results are shown in Table 15, Table 16, Table 17 and Table 18.

The RPN ranking results based on the LI-DUOWA-AHP-FMECA method are shown in Fig. 2.The RPN ranking results derived from the traditional FMECA and those obtained from the improved FMECA based on the different methods are compared. The comparison results are shown in Fig. 3.

Fig. 3 shows that the RPN ranking results derived from the LI-FMECA, DUOWA-FMECA, and AHP-FMECA methods differ from those obtained from the traditional FMECA method. The RPN ranking results based on the LI-DUOWA-FMECA method vary slightly from those derived from the LI-FMECA ranking results. Using the LI-AHP-FMECA method to rank the RPN results yields rankings that differ from those obtained with the LI-FMECA method.

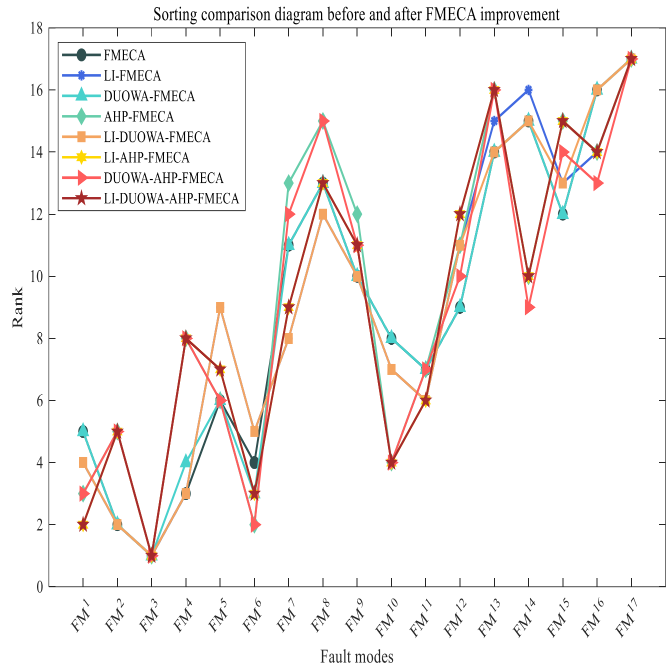

Fig. 3. Comparison of ranking results before and after FMECA improvement.

Therefore, we consider simultaneously using linear interpolation, DUOWA operator and AHP method for improving the traditional FMECA, and the RPN ranking results are shown in LI-DUOWA-AHP-FMECA. The specific computational results are shown in Fig. 2.

Comparing the ranking results of the FMECA method in the subway sliding plug door fault mode before and after the improvement, it can be found that (1) the ranking results of the two faults, FM^3 and FM^{17}, are unchanged before and after the improvement. The EDCU faults hazard caused by the other parts' functional faults is the greatest, with an RPN 4.5029, much larger than other fault modes. It is a crucial fault that jeopardizes the regular operation of the door system. This is because when Metro's vehicle sections meet EDCU faults, the probability is that they will directly replace the EDCU without disassembling and repairing the EDCU. As a result, it is difficult to count the specific causes of internal EDCU faults in detail, leading to a higher O level of FM^3 than the EDCU's other fault modes. Thus making FM^3 the most hazardous and should be focused on in the vehicle operation and maintenance process. (2) The rankings of the remaining fault modes all change, and those of a few fault modes change significantly. Taking two fault modes, FM^4 and FM^{10}, for example, the RPN values calculated by FM^4 using traditional FMECA are ranked 3, and FM^{10} is ranked 8. When the effects of fault probability and expert weights are considered separately, the hazard rankings of FM^4 and FM^{10} are less changed. However, the detection difficulty of crack faults in the upper guideway in daily life is greater than the influence of the other two factors on the RPN, so we use the AHP method to give different weights to the three evaluation factors of O, S, and D. The RPN value of the FM^{10} becomes 1.6335, and the ranking rises to 4. The ranking results are more satisfied with the actual situation. Similarly, the detection difficulty of EDCU faults caused by loose plugs in daily life is lower than the influence of the remaining two factors on the RPN value. The AHP method assigns a smaller weight to D. The RPN value of FM^4 is 1.0901, and the ranking declines to 8. The ranking result is more conformed to the actual situation.

In summary, the improved FMECA method can consider the differences in the occurrence probability of different fault modes of the same level, weaken the occasional judgmental errors of some experts, and consider the impact of other factors on the weight of various fault modes. Thus, the analysis results are more suitable for practical engineering applications.

3.2. Calculation of maintenance periods

According to the Shanghai metro manufacturing plant's door operation and maintenance records from January 5, 2016, to January 16, 2021, the time and number of the 17 fault modes listed above are counted, respectively. The reliability evaluation indexes MTBF and λ, calculated according to Eq. (19) and (20), are shown in Table 19.

Table 19. Reliability evaluation indicators.

No of faults	MTBF/day	$\lambda\ /h^{-1}$
FM^1	62.875	6.6269E-04
FM^2	48.667	8.5616E-04
FM^3	9.116	4.5707E-03
FM^4	68.000	6.1275 E-04
FM^5	70.913	5.8757E-04
FM^6	184.500	2.2584E-04
FM^7	232.667	1.7908E-04
FM^8	115.400	3.6106E-04
FM^9	195.556	2.1307E-04
FM^{10}	119.833	3.4771E-04
FM^{11}	275.333	1.5133E-04
FM^{12}	318.000	1.3103E-04
FM^{13}	173.350	2.4036E-04
FM^{14}	165.250	2.5214E-04
FM^{15}	100.830	4.1324E-04
FM^{16}	173.323	2.4040E-04
FM^{17}	98.429	4.2332E-04

Substituting the calculated λin Table 19 into Eq. (25), while taking A=0.8[12] as the reference availability, the maintenance periods of the listed components are calculated as shown in Table 20 and Figure 4.

From Table 20 and, Figure 4 it can be found that the maintenance periods of various components are different. The maintenance period of door leaf glass is the longest, about 3627.4136 hours. The maintenance period of EDCU faults due to other reasons is the shortest, about 103.9884 hours. Meanwhile, taking EDCU as an example, it can be found that the maintenance periods of the same component due to different fault causes are also different. Therefore, in daily life, the uniform "daily repair" or "monthly repair" of subway sliding plug doors is easy to cause "over-repair" or "under-repair". It is helpful to rank the door components' hazards and calculate the different parts' maintenance periods of the door to formulate a more reasonable maintenance plan, which can significantly reduce the running time of the train and save the maintenance cost.

Table 20. Maintenance periods for different fault modes.

Components	Faults num	Fault modes	Maintenance modes	Maintenance period/h
EDCU	FM^1	Safety relay fault	Regular replacement of EDCU	717.2283
	FM^2	Software fault	Regular upgrade the version of software	555.1532
	FM^3	Functional fault	Regular replacement of EDCU	103.9884
	FM^4	Plug loose	Check and tighten connections	775.6834

Close travel switch S4	FM^5	Functional fault	Adjust or replace	808.9249
Motor	FM^6	Functional fault	Regular replacement	2104.5873
	FM^7	Circuit damage	Regular monitoring and replacement	2654.1211
	FM^8	Plug loose	Tighten or improve connections	1316.4017
Locked travel switch S1	FM^9	Functional fault	Regular replacement	2230.7223
Upper guideway	FM^{10}	Exist cracks	Regular replacement	1366.9437
Electromagnetic brake	FM^{11}	Circlip breakage	Regular replacement	3140.8181
Door leaf	FM^{12}	Glass breakage	Regular monitoring and replacement	3627.4136
	FM^{13}	Deformation and peeling of sealing tape	Regular monitoring and replacement	1977.4505
	FM^{14}	Fractured hinges	Replacement	1855.0639
Cutting out travel switch S2	FM^{15}	Functional fault	Replacement	1150.1791
Screw	FM^{16}	Poor lubrication	Regular monitoring and lubrication	1977.1215
Isolation locking device	FM^{17}	Functional fault	Replacement of worn parts and lubrication	1122.7913

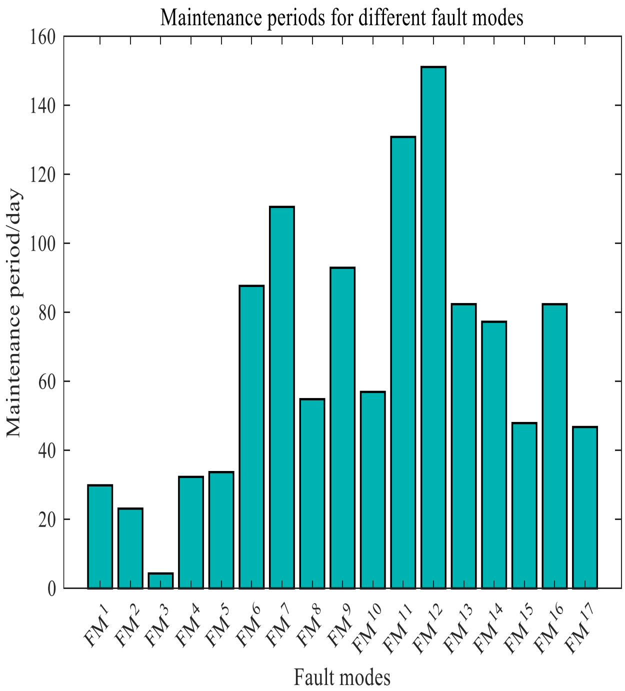

Fig. 4. The maintenance period of different faults.

3.3. Prediction of the remaining life

3.3.1. Description of the data

The data studied in this paper are the door fault data of a metro manufacturing plant in Shanghai from January 5, 2016, to January 16, 2021, with the service life data of 50 doors, as shown inTable 21.

Table 21. Door historical data service life/day

Door	Service life	Door	Service life	Door	Service life	Door	Service life	Door	Service life
1	101	11	133	21	173	31	195	41	357
2	101	12	138	22	174	32	338	42	357
3	180	13	173	23	175	33	343	43	364
4	181	14	147	24	178	34	242	44	367
5	105	15	161	25	103	35	250	45	354
6	109	16	153	26	104	36	257	46	410
7	112	17	147	27	182	37	288	47	401
8	120	18	165	28	184	38	334	48	396
9	118	19	171	29	194	39	195	49	414
10	113	20	140	30	187	40	202	50	422

3.3.2. Prediction of the remaining life

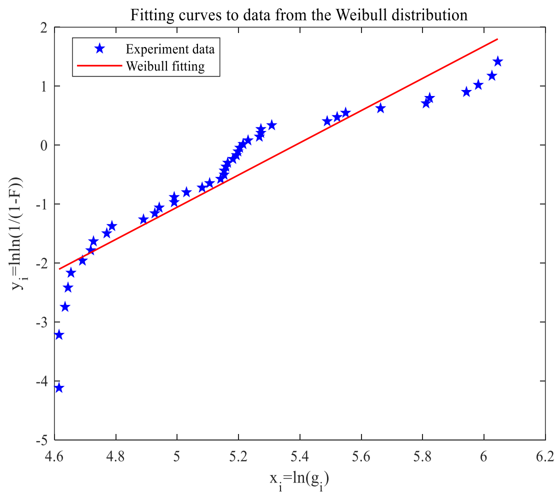

Fig. 5. The data fitting test using the Weibull distribution.

The statistical data of The data studied in this paper are the door fault data of a metro manufacturing plant in Shanghai from January 5, 2016, to January 16, 2021, with the service life data of 50 doors, as shown in Table 21. The data studied in this paper are the door fault data of a metro manufacturing plant in Shanghai from January 5, 2016, to January 16, 2021, with the service life data of 50 doors, as shown in Table 21.

Table 18, Table 21 are substituted into Eq. (37) and (38) to calculate the corresponding x_i and y_i values, and the fitting curve is drawn. As shown in Figure 5, it can be seen that the historical service life data samples are distributed along a straight line with a slope greater than zero, indicating that the sample distribution obeys the Weibull distribution. To verify that the data in this group conformed to the Weibull distribution, we tested the fit of normal and exponential distributions, and the fit results are shown in Fig. 6. Fitting test results for different distributions. At the same time, we also calculated the fitness of normal, exponential and Weibull distributions. The corresponding p-values were 0.0487, 0.0038 and 0.0516, respectively. We set the significance level as 0.05, thus rejecting exponential and normal distributions and accepting the Weibull distribution.

The corresponding p-values were 0.0487, 0.0038 and 0.0516, respectively. We set the significance level as 0.05, thus rejecting exponential and normal distributions and accepting the Weibull distribution. According to Eq. (39), the correlation coefficient C is 0.9972, indicating that the two-parameter Weibull distribution fits the service life data well. At the same time, according to the slope of the fitting curve, $e = 3.3187$, $b = -17.5353$, the shape parameter $\beta = 2.3254$, and the scale parameter $\eta = 247.6361$ can be calculated. Substituting β and η into Eq. (28), the fault probability density function of the two-parameter Weibull distribution model is obtained:

$$f(g) = \frac{2.3254}{247.6361}\left(\frac{g}{247.6361}\right)^{2.3254} exp\left[-\left(\frac{g}{247.6361}\right)^{2.3254}\right], g \geq 0 \quad (40)$$

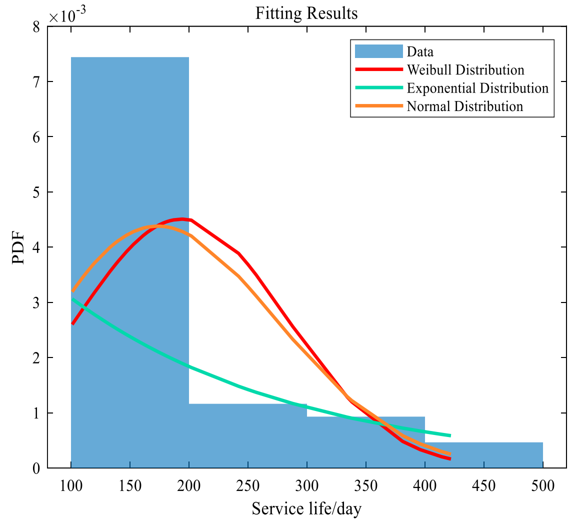

Fig. 6. Fitting test results for different distributions.

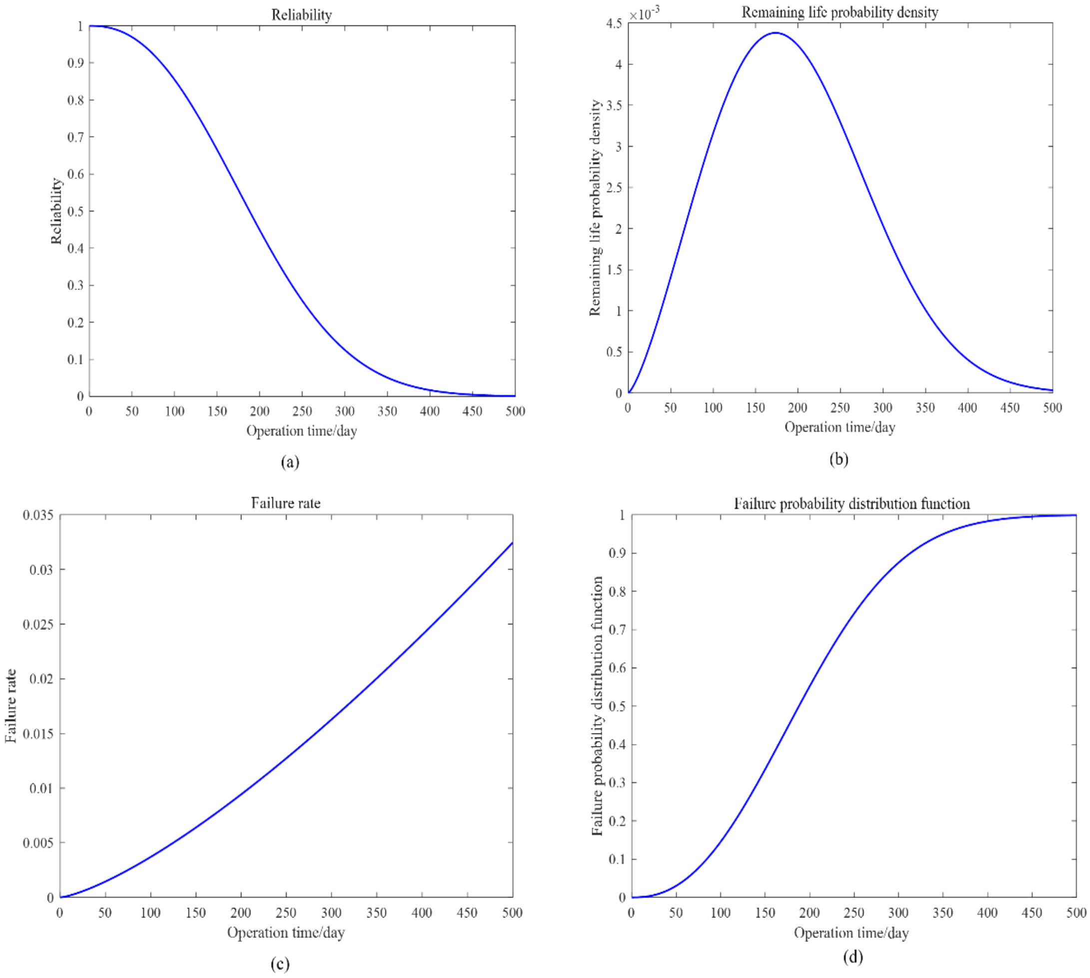

Fig. 7. The prediction results using the two-parameter Weibull distribution.

The relevant statistics of the subway sliding plug door system based on the two-parameter Weibull distribution are shown in Fig. 7, respectively. Among them, Figure 7 (a) shows the reliability trend of the sliding plug door system with the operation time, which shows that the system's reliability gradually decreases with the operation time. The system's reliability remains above 0.9 until the operation time g = 84 days. It starts to decrease sharply when operated to about g= 113 days, and the system's reliability is 50% at g = 188 days. Figure (b) shows the fault probability density trend of the subway sliding plug door system concerning the operation time. When g = 171 days, the system fault probability is maximum, so it is recommended to strengthen the monitoring and maintenance of the subway sliding plug door system around that time. Figure (c) shows the remaining life density trend of the subway sliding plug door system with operating time at g = 80. Figure (d) shows the fault probability distribution trend of the subway sliding plug door system with time.In Fig. 7(c) the running time $g = 80$ is an example to show the probability density changing trend of the remaining life with the running time. In the $g \in [10,80]$, a prediction point is taken every 10 periods, and the remaining life probability density of the subway sliding plug door system is predicted at 8 different time points.

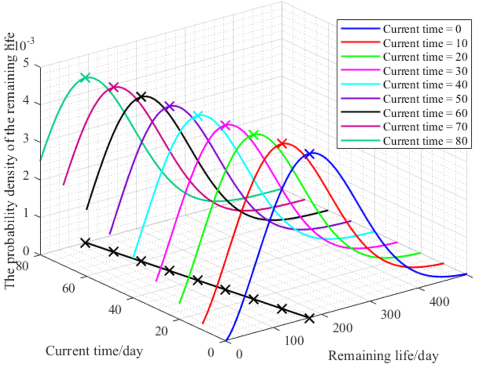

Fig.8. The probability density of remaining life using a two-parameter Weibull model.

It can be observed from Fig.8 that as the running time goes on, the remaining life corresponding to the maximum probability density of the remaining life of the system gradually decreases from $g = 171$ to $g = 91$. The curve on the x-y plane is formed by the projection of the maximum point of the remaining life probability density at 9 different moments, which can be regarded as the relationship between the remaining life prediction value and the running time.

4. Conclusion and discussion

In this paper, based on the historical fault maintenance data of subway sliding plug doors from the Shanghai metro manufacturing plant, reliability analysis was performed using the improved FMECA method and the Weibull distribution. First, the following improvements are made to address the shortcomings of the traditional FMECA method: (1) Make the same fault occurrence probability have a reasonable differentiation under different fault modes by linear interpolation. (2) Assign dynamic weights to different experts by introducing the DUOWA operator. (3) Endow different weights to various evaluation factors by using the AHP, which is more suitable for the needs of the actual engineering. The comparison shows that the improved method makes up for the shortcomings of the traditional method, and its hazard ranking results are more suitable for reality. Secondly, the maintenance periods of different components are calculated based on the RCM strategy, and the combination of the hazard ranking results provides a reference for developing door maintenance plans. Lastly, the two-parameter Weibull distribution predicts the doors' remaining life. In the future, when predicting the remaining life of the doors, it is necessary to monitor the operation of the sliding plug doors in real time, considering the unexpected situation and the differences between various doors.

Acknowledgement

The project was supported by Chunhui Plan of the Ministry of Education of China (No. 202201500).

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