Reliability analyzes of unmanned engine cabin based on fault diagnosis and preventive under the maintenance cost

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Reliability analyzes of unmanned engine cabin based on fault diagnosis and preventive under the maintenance cost

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Abstract

The reliability and overall cost of unattended engine cabin are researched for two aspects: fault diagnosis and preventive maintenance in this paper. The ME-OWA algorithm is adopted to predict the fault diagnosis of per module in the unattended engine cabin and the cost of preventive maintenance is calculated, its costs are controlled by adopting the optimal number of preventive maintenances under the object of minimum reliability. The optimization of maintenance cost can be achieved by repairing modules with excessive fault diagnosis rates under the determining preventive maintenance times and reliability. The reliability model of the unattended engine cabin is founded to the series-parallel structure of per module, and its reliability is compared between the regular maintenance and the irregular maintenance. The calculations show that the reliability of the unattended engine cabin is more stable under the irregular maintenance.

Keywords unattended engine cabin, fault diagnosis, preventive maintenance, reliability, maintenance cost, maintenance period

1 Introduction

The mechanical fault diagnosis is to understand and master the state of the machine during operation. It is a technology that can determine the overall or local situation of the machine, and early failures and their causes are discovered, and predict the development trend of failures. The extending of equipment life and reducing failures can be achieved through preventive maintenance, and equipment fault diagnosis rates and depreciation rates are minimized. The unmanned engine cabin and machine tools have similarities in the mechanical control structure and they all have X, Y, Z axis motion modules and control system modules. Therefore, it has important reference significance for the reliability analysis of machine tools. The fault diagnosis and preventive maintenance of machines are studied based on various theories to improve the usability and reliability of the equipment in the life cycle.

Wang Jun et al.[1]have used the fault tree analysis method to establish a fault tree model of CNC machine tools. The classification and identification of features used the fault degree of the deep neural network model to achieve the purpose of deep fault diagnosis.

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He Xinxin et al.[2] have used an optimization algorithm based on discrete teaching and learning to solve the NP-hard problem. The maintenance start time of the parallel machine was determined by the failure mode auxiliary gated recursive unit life prediction method. Zhang Xiangyi and Chen Lu et al.[3] have studied the MPP scheduling problem of machine health and preventive maintenance. A general variable neighborhood search heuristic algorithm is proposed with the goal of minimizing the total delay and quality risk, and the algorithm is shown to be very efficient in parallel machine scheduling. Garg Divesh and Garg Reena et al.[4] have studied the preventive maintenance method, and the overlooked issues such as Overheating, abnormal sound, excessive vibration, etc., and other faults were analyzed.The optimization of system profit value is realized by artificial bee colony algorithm, and the availability, profit, and mean time of system failure are considered. Zhang Kaiyu et al. [5]have proposed a multi module generation countermeasure network enhanced by adaptive decoupling strategy, and the problem of Poor smart diagnosis is alleviated by adopting an adaptive learning method. Hou Bingchang et al.[6]have studied the integration of online monitoring data and fault transient cyclostationarity. The optimization model is constructed based on fault cyclostationarity and solved using the maximum logarithm. Naveen Venkatesh S and Sugumaran V et al.[7] have discussed the RGB image classification of PV module obtained by the fusion of deep learning and machine learning techniques. The visual failures of PV module performance and lifetime were distinguished by utilizing computer vision and a machine learning approach. An Youjun et al.[8] have studied the optimization problem of preventive maintenance and machining speed selection. The improved productivity is achieved by considering the dynamics of the machine, and the superiority of the strategy is verified. S A Kosarevskaia et al.[9] have proposed the equipment robotized maintenance algorithm and automatic control system scheme. The selection of changes to the failed unit is achieved through the analysis of technical summary conditions during the machine learning phase of the collected statistics. Pradipta Haris Salsabila Tyas and As'adi Muhammad et al.[10] have Designed preventive maintenance processing interval schedules with a reliability-centred maintenance approach. The reliability and cost savings of the working conditions before and after preventive maintenance are compared, and the effectiveness of the method has been proved. Liu Yu et al.[11] have proposed a new production synchronization evaluation model. The uncertainty caused by machine failures is quantified, and the solution is achieved by an improved CGA and heuristic initialization. Neto Anis Assad et al.[12] have developed a decision support system for preventive maintenance to minimize production penalties by exploiting supply shortages, idle machines or machine failures, etc. Guo Jinyan et al.[13] have studied a DT-based online forecast method of service life and preventive maintenance model. The best of preventive maintenance pian can be defined and feedback to the manufacturing shop, and the relevant parts are repaired. Sun Shilin and Lu Renxiang et al.[14] have proposed a fault diagnosis model adopting ACO algorithm to optimize SVM, and the accuracy of gearbox fault diagnosis is improved.is. Wang Hongfeng and Yan Qi and Zhang Shuzhu et al. [15]have proposed a flexible PM strategy to proactively deal with machine failures under the premise that PM intervals

are relatively regular. Pires C.R and Lopes I.S et al.[16] have proposed a conceptual model for the definition of dynamic clusters and intervals. The reduction in the number of machine tool production downtimes is achieved by using group technology and the concept of clustering to group components and set preventive maintenance intervals. Makoto Fujishima et al. [17]have adopted the development of sensing interfaces and the technology of analyzing machine operating status to implement preventive maintenance and the machine downtime can be prevented by necessary maintenance work before the machine fails.

The above literature results show that the prediction of machine fault diagnosis rate based on the ME-OWA algorithm and the impact of preventive maintenance on machine reliability under different periods, it has not been used in unattended engine cabin. The reliability and cost optimization can be analyzed from two aspects: fault diagnosis and preventive maintenance. In this paper, the reliability analyzes of unattended engine cabin based on fault diagnosis and maintenance is proposed for the first time under the maintenance cost.

2 Design of unattended engine cabin

2.1 Structural Design of unattended engine cabin

The overall structure of the unattended engine cabin is designed by adopting the idea of modularization, it is mainly divided into five modules: the X axis module of the cabin door, the Z-axis module of the parking apron, the X,Y axis module of the positioning device, the power supply system module, and the control system module. The 3D modeling of the unattended engine cabin is shown in **Figure 1**.

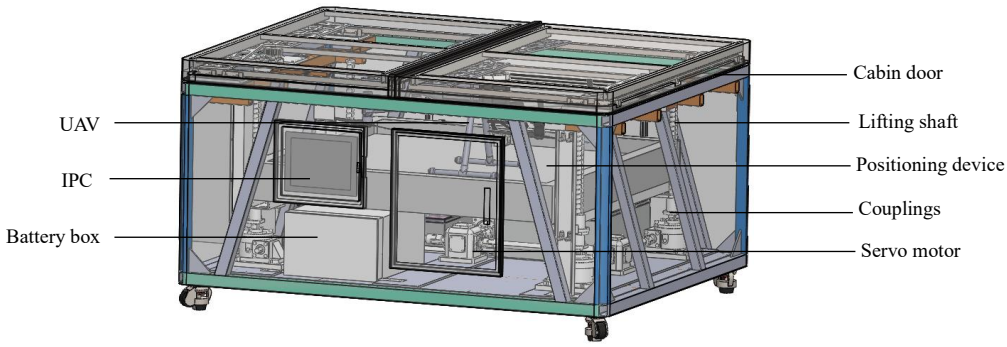

Figure 1. 3D modeling of the unattended engine cabin

The cabin door of the unattended engine cabin is driven by a stepping motor, the lift of the parking apron is driven by a servo motor, and the parking apron positioning device is driven by a stepping motor. There are a total of 7 controlled motors: two X axis opening and closing motors of cabin door, one Z axis lifting motor of the parking apron, two X axis positioning motors and two Y axis positioning motors of the parking apron. Two stepper motors are installed under the cabin door respectively, and the opening and closing of the cabin door is realized by transmission through gears and racks. The proximity switches are fixed on both sides of the cabin to control the opening and closing position of the cabin door. The lifting and landing of the parking apron are realized by the ball and screw driving the Z axis lifting motor. The positioning motor of parking apron is driven by four stepping motors, and the action of tightening the positioning is completed by driving the ball and screw. The unattended engine cabin is

shown in **Figure 2**.

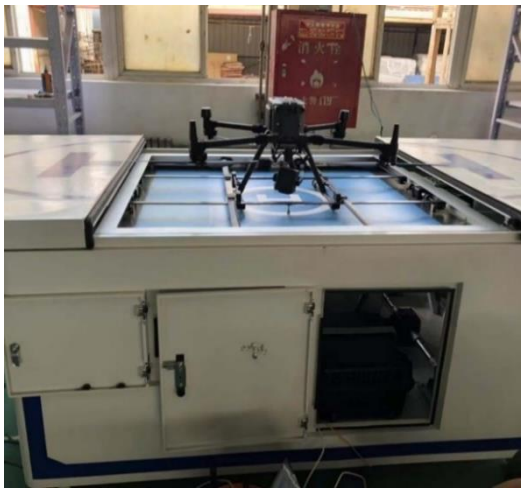

Figure 2. unattended engine cabin

2.2 Design of Control System for unattended engine cabin

The industrial computer is the upper computer in the unattended engine cabin, and the parameter settings, manual, automatic operation procedures and human-computer interaction are controlled. On the other hand, the CAN bus network communication with the lower embedded controller, it is mainly responsible for the debugging of the cabin, the opening and closing of the cabin door, the lifting and lowering of the parking apron, the tensioning and opening of the positioning device, and the control of the charging and power failure of the drone. The charging station is the parking apron of the unattended engine cabin, it includes positioning and tightening, charging, data transmission, etc., and is connected to the industrial computer through TTL. The charging device of the drone is realized by the battery box, and its power-on and power-

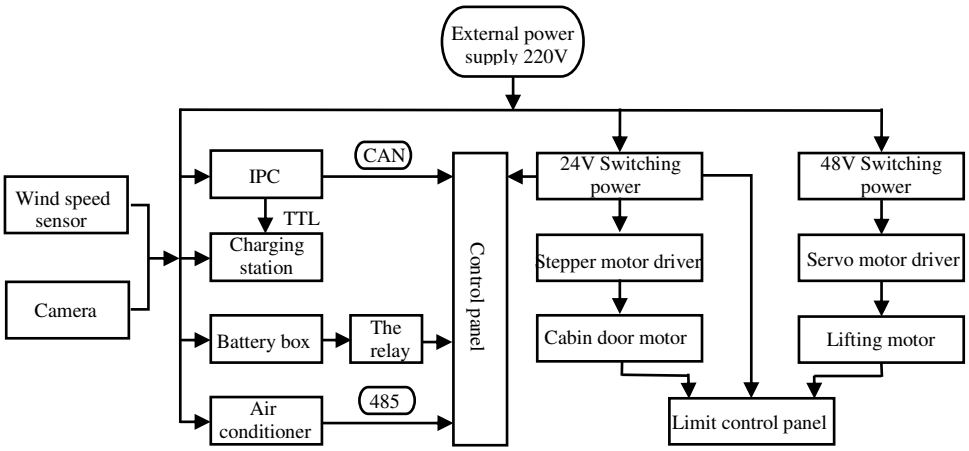

Figure 3. control system of the unattended engine cabin

off is determined by the embedded control panel through a relay and amplifier. The air conditioner is connected to the control panel through the RS-485 serial bus. The limit control panel is mainly responsible for the control of the lower motor in motion. The connection between the cabin body and the upper position is realized by the lower embedded control panel, which is also the core part of the control system. Additionally, the wind sensor and camera are on the outside of the cabin. The control system of the unattended engine cabin is shown in **Figure 3**.

The overall hardware scheme design of the unattended engine cabin control system is

shown in **Figure 4**. The STM32F4 was selected as the controller chip for the cabin, and the overall hardware scheme of the control system was designed. The overall scheme planning needs to take into account the complex functions involved in the lower embedded controller. The upper and lower computer system bus communication, the stepper motor control of multiple axes, the servo motor control, the power supply module and other functions need to be completed.

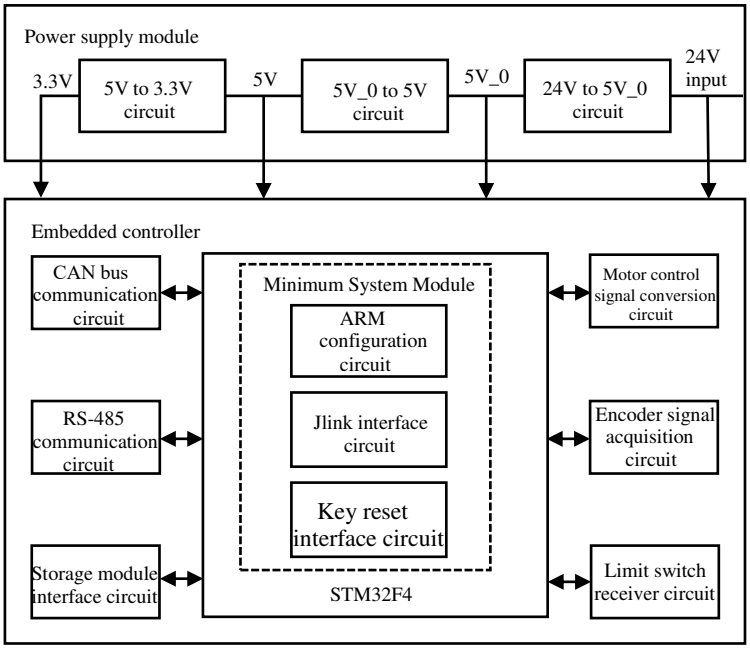

Figure 4. hardware scheme design of the unattended engine cabin control system

3 Fault diagnosis analysis of per module in unattended engine cabin based on ME-OWA

The fault diagnosis rate of per module in the unattended engine cabin under different measures is determined by the method of ME-OWA. And the sophistication (I), processing standard (s), work hours (T) and runtime environment (E) of per module are assigned weight.

The total fault diagnosis rate of the unattended engine cabin system is determined by evaluating its overall structure, and the reliability and the working hours are obtained. The total fault diagnosis rate of the system is calculated by formula (1):

$$\lambda_s = \frac{-\ln R}{T}$$

(1)

Where, R is reliability, T is working hours, λ_s is total fault diagnosis rate. The assigned value w_k' of per module in the unattended engine cabin is calculated by formula (2):

$$w_k' = r_{Ik} \cdot w_1 + r_{Sk} \cdot w_2 + r_{Tk} \cdot w_3 + r_{Ek} \cdot w_4$$

(2)

Where, r_{Ik} , r_{Sk} , r_{Tk} , r_{Ek} —ISTE value of per module in unattended engine cabin,w_1,w_2,w_3,w_4—Assignment weight of ISTE.The complexity C_k of per module in the unattended engine cabin is calculated by formula (3):

$$C_k = \frac{w_k{}'}{\sum_{i=1}^{n} w_i'}, (k = 1,2, \dots ,5) \quad (3)$$

The fault diagnosis rate λ_k of per module in the unattended engine cabin is calculated by formula (4):

$$\lambda_k = C_k \lambda_s, (k = 1,2, \dots ,5)$$

(4)

The weight value of the OWA is obtained by the method of ME-OWA under the Orness measure level is adopted. The solution of the OWA polynomial is calculated by using the Lagrangian algorithm, and the analysis of the weight vector function is obtained.[18-19]

（a）when α is 0,w=[0,0, ... 1]^T,when α is 1,w=[1,0, ... 0]^T

（b）when n=2,w_1=α, w_2=$1-\alpha$

（c）when $n \gg 3, 0 < \alpha < 1$, the weight value function is calculated by formula (5)-(7):

$$w_1 \cdot [(n-1) \cdot \alpha + 1 - nw_1]^n$$
$$= [(n-1) \cdot \alpha]^{n-1} \cdot \left[\left((n-1) \cdot \alpha - n\right) \cdot w_1 + 1\right] \quad (5)$$

$$w_i = \left(w_1^{n-i} w_n^{i-1}\right)^{\frac{1}{n-1}}$$

(6)

$$w_n = \frac{\left((n-1) \cdot \alpha - n\right) w_1 + 1}{(n-1) \cdot \alpha + 1 - nw_1}$$

(7)

Where,w is weight value,α is measure,n is number of factors. The reliability of the unattended engine cabin is calculated according to the selection of different measurements, and various optimal weight value are obtained. The measure values were selected for calculation as shown in **Table 1**. The degree of machine reliability is predicted to be determined by the measure from low to high. The number of factors n is 4, the optimal weight value is calculated based on formulas (5)-(7).

Table 1. weight value in different α

	w_1	w_2	w_3	w_4
$\alpha = 0.5$	0. 25000	0. 25000	0. 25000	0. 25000
$\alpha = 0.6$	0. 41666	0. 23334	0. 13086	0. 07355
$\alpha = 0.7$	0. 49381	0. 23731	0. 11377	0. 05492
$\alpha = 0.8$	0. 59647	0. 25195	0. 10645	0. 04502
$\alpha = 0.9$	0. 76410	0. 18213	0. 04346	0. 01036
$\alpha = 1.0$	1. 00000	0. 00000	0. 00000	0. 00000

As shown in **Table 2**. The sophistication (I), processing standard (S), work hours (T) and runtime environment (E) of per module in the unattended engine cabin are hdetermined according to the Delphi method.

Table 2. ISTE of per module

	（I）	（S）	(T)	(E)
control System	6	7	6	2
cabin door X axis	3	3	6	3

park apron Z axis	4	5	6	2
position X,Y axis	5	5	6	2
power supply	4	5	6	2

The reliability of the unattended engine cabin is 0.785, and the working time is 1000h. The total fault diagnosis rate of the system is calculated according to formula (1):

$$\lambda_s = \frac{-\ln 0.785}{1000} = 2.42072 \times 10^{-4}$$

As shown in **Table 3**. The fault diagnosis rate (every 10^5 hours) of per module in unattended engine cabin is calculated according to formulas (2)-(4). The reliability analysis of the unattended engine cabin is determined under the premise of reliability by predicting the fault diagnosis rate of per module.

Table 3. fault diagnosis rate of per module in different α

	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 1.0$
control System	2.67553	3.05783	3.12957	3.17799	3.29759	3.30098
cabin door X axis	1.91100	1.78426	1.75690	1.73735	1.68103	1.65049
park apron Z axis	2.16591	2.27309	2.28471	2.28978	2.28137	2.20066
position X,Y axis	2.29331	2.52460	2.57003	2.60110	2.69168	2.75082
power supply	2.16591	2.27309	2.28471	2.28978	2.28137	2.20066

4 Reliability analysis of unmanned engine cabin based on preventive under the maintenance cost

The service life of unmanned engine cabin is determined by the reliability and maintenance cost of per modules. The equally of preventive maintenance period is adopted to prevent repeatedly machine shutdowns for the maintenance of individual modules. Therefore, the preventive maintenance period is properly planned for the optimization of the maintenance scheme. The cost of corrective maintenance is predicted according to different measures, so that maintenance cost and reliability of the system are considered in the life cycle.[20-21]

4.1 Mathematical model based on reliability and maintenance cost of unmanned engine cabin

The cost optimization is determined by the best (N, T) in finite lifetime, it is to ensure the service life of the system under the premise of reliability. N is preventive maintenance times for unmanned engine cabin and T is the optimal maintenance period. The maintenance cost of unmanned engine cabin is made up of preventive maintenance cost and corrective maintenance cost. It is taken N times preventive maintenance, and corrective maintenance for system failure is carried out during the preventive maintenance period. The mathematical model of unmanned engine cabin reliability is established under the index of overall cost, and two basic assumptions are required:

(a) The modules cannot be restored to their original state after preventive maintenance. Therefore, the device is maintained and its initial fault is 0.

(b) The corrective maintenance measures are taken for system faults, and the device status is the same as before the failure after maintenance.

The overall cost of the unmanned engine cabin is calculated by formula (8):

$$c_{total}(\mathrm{N},\mathrm{T}) = Nc_p + c_e$$

(8)

Where, $c_{total}(\mathrm{N},\mathrm{T})$ is maintenance cost,c_p is the cost of preventive maintenance,c_e is the cost of corrective maintenance. The corrective maintenance costs of unmanned engine cabin are calculated by formula (9):

$$c_e = \sum_{i=1}^{n} c_i h_{itotal} \tag{9}$$

Where, c_i is Corrective maintenance cost of per module,h_{itotal} is fault diagnosis time of the i-th module. The reliability of the unmanned engine cabin is affected by the optimization of maintenance cost, therefore, the minimum of reliability is regarded as the constraint objection of settling the model. The model for maintenance is calculated by formula (10):

$$c_{total}(\mathrm{N},\mathrm{T}) = Nc_p + \sum_{i=1}^{n} c_i h_{itotal}$$
$$R_k \gg R_{min}$$

(10)

Where,R_k is the reliability of unmanned engine cabin after k-th of maintenance,R_{min} is minimum reliability of unmanned engine cabin. The reliability of the unmanned engine cabin was determined by Weibull distribution analysis, and the modeling of fault diagnosis rates and lifespans was determined by this method. The components are calculated using Weibull's algorithm for convenience. It is calculated by formula (11):

$$\lambda_i(t) = \frac{m_i t^{m_i - 1}}{\mu_i^{m_i}} \tag{11}$$

Where,$\lambda_i(t)$ is fault diagnosis rate of the module,m_i is Shape parameter, μ_i is Scale parameter. The research of shape factors and scale factors on fault diagnosis rate is considered, and the model of fault diagnosis rate variation after preventive maintenance is constructioned. The fault diagnosis rate function before and after maintenance is calculated by formula (12):

When $0 < t < T_{k+1}$,

$$\lambda_{i,k+1}(t) = b_{i,k}\lambda_{i,k}\left(t + a_{i,k} \cdot T_k\right)$$

(12)

Where,$a_{i,k}$is life reduction factor,$b_{i,k}$is risk increase factor. In formula (12), the initial value of fault diagnosis rate is $b_{i,k}(\alpha_{i,k}, T_k)$ after maintenance. The life reduction factor and the risk increase factor are assumed constant as follows:

$$a_{i,0} = a_{i,1} = \cdots = a_{i,N} < 1$$
$$b_{i,0} = b_{i,1} = \cdots = b_{i,N} > 1$$

The fault diagnosis rate of the per module in the unmanned engine cabin after k maintenance periods is calculated by formula (13):

$$\lambda_{i,k+1}(t) = b_i^{k+1}\lambda_{i,0}\left(t + a_i \sum_{\eta=0}^{k} T_\eta\right) \tag{13}$$

Where, $\lambda_{i,0}$ is Initial fault diagnosis value. The number of corrective maintenances for the i-th module in the k-th maintenance period is calculated by formula (14):

$$h_{i,k} = \int_0^{T_k} \lambda_{i,k}(t)\, dt = \int_0^{T_k}\left(t + a_i \sum_{\eta=0}^{k-1} T_\eta\right)$$

$$= \frac{b_{i,k}}{\mu_i^{m_i}}\left[\left(T_k + a_i\sum_{\eta=0}^{k-1} T_\eta\right)^{m_i} - \left(a_i\sum_{\eta=0}^{k-1} T_\eta\right)^{m_i}\right] \quad (14)$$

The reliability of the unmanned engine cabin can be determined by the key modules, and the reliability of the modules are calculated by formula (15):

$$R_i(t) = e^{-\int_0^t \lambda_i(t)dt}$$

(15)

The reliability of the per module after maintenance is calculated by formula (16):

$$R_{i,k} = e^{-h_{i,k}}$$

(16)

The reliability of the unmanned engine cabin is determined by the reliability of per module. The reliability is calculated by formula (17) after k preventive maintenance:

$$R_k(t) = f(e^{-h_{1,k}}, e^{-h_{2,k}}, \dots e^{-h_{n,k}})$$

(17)

The cost optimization is constrained by the minimum reliability of the unmanned engine cabin. The $\mathrm{Min}c_{\mathrm{total}}(\mathrm{N},\mathrm{T})$ is objective function, and decision variables are N and T. The constraint function is shown in formula (18):

$$R_k \geq R_{min}$$
$$\sum_{k=1}^{N} t_k + \sum_{k=0}^{N} T_k = L$$

(18)

Where,t_k is Preventive maintenance hours. The maintenance costs and reliability of unmanned engine cabin are analyzed through five modules (the X axis module of the cabin door, the Z axis module of the parking apron, the X,Y axis module of the positioning device, the power supply system module, and the control system module). The lifespan of the unmanned engine cabin is 10 years, the cost of preventive maintenance is 800 and the minimum of reliability is 0.785. The other factors are in Table 4

Table 4. The factors of per module in the unmanned engine cabin

	h_{itotal}	$b_{i,k}$	$a_{i,k}$	m_i	μ_i	c_i	t_k
control System	2.74150	1.2	0.2	3	8	2500	0.004
cabin door X axis	1.53904	1.1	0.2	3	7	1000	0.004
park apron Z axis	2.00141	1.1	0.2	3	6	2000	0.004
position X,Y axis	2.25135	1.1	0.2	3	6	1500	0.004
power supply	2.00141	1.2	0.2	3	8	2000	0.004

The fault diagnosis time of per module in the unmanned engine cabin is within 10 years, which is determined by $\alpha = 0.7$ in **Table 3**. The reliability of per module after k-th preventive maintenance is calculated by taking the parameters in **Table 4** into formulas (14)-(16). Therefore, the formula (19) is obtained:

$$R_{1,k}(t) = e^{-h_{1,k}} = e^{\left\{-\frac{1.2^k}{8^3}\left[\left(T_k + 0.2\sum_{\eta=0}^{k-1} T_\eta\right)^3 - \left(0.2\sum_{\eta=0}^{k-1} T_\eta\right)^3\right]\right\}}$$

$$R_{2,k}(t) = e^{-h_{1,k}} = e^{\left\{-\frac{1.1^k}{7^3}\left[\left(T_k+0.2\sum_{\eta=0}^{k-1}T_\eta\right)^3-\left(0.2\sum_{\eta=0}^{k-1}T_\eta\right)^3\right]\right\}}$$

$$R_{3,k}(t) = R_{4,k}(t) = e^{-h_{3,k}} = e^{-h_{4,k}}$$

$$= e^{\left\{-\frac{1.1^k}{6^3}\left[\left(T_k+0.2\sum_{\eta=0}^{k-1}T_\eta\right)^3-\left(0.2\sum_{\eta=0}^{k-1}T_\eta\right)^3\right]\right\}}$$

$$R_{5,k}(t) = e^{-h_{1,k}} = e^{\left\{-\frac{1.2^k}{8^3}\left[\left(T_k+0.2\sum_{\eta=0}^{k-1}T_\eta\right)^3-\left(0.2\sum_{\eta=0}^{k-1}T_\eta\right)^3\right]\right\}} \quad (19)$$

The series-parallel of the five modules in the unmanned engine cabin is shown in **Figure 5**.

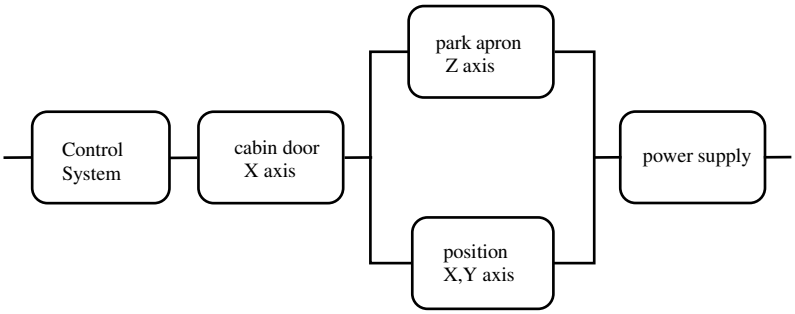

Figure 5. series-parallel of per module in the unmanned engine cabin

The reliability of the unmanned engine cabin is calculated according to formula (17), as shown in formula (20):

$$R_k(t) = e^{-h_{1,k}} \cdot e^{-h_{2,k}} \cdot (e^{-h_{3,k}} + e^{-h_{4,k}} - e^{-h_{3,k}} \cdot e^{-h_{4,k}}) \cdot e^{-h_{5,k}} \quad (20)$$

4.2 The optimum maintenance hours for unmanned engine cabin

The maintenance costs for unmanned engine cabin are calculated by Equation (10). The optimal maintenance times are obtained from the relationship between the average reliability of the unmanned engine cabin and the cost of maintenance. The maintenance times, maintenance costs, and average reliability of unmanned engine cabin are shown in **Table 5**.

Table 5. Maintenance hours, Maintenance costs, average reliability of the system

N	$c_{total}(N,T)$	R_{aver}
3	22175.455	0.8650
4	22975.455	0.9125
5	23775.455	0.9376
6	24575.455	0.9523
7	25375.455	0.9615
8	26175.455	0.9676
9	26975.455	0.9717
10	27775.455	0.9748
11	28575.455	0.9774
12	29375.455	0.9778
13	30175.455	0.9783

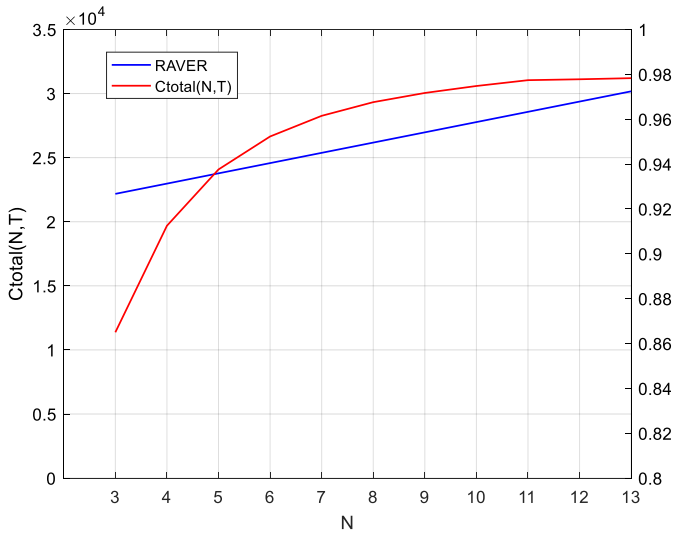

Figure 6. The average reliability of the system and maintenance cost

As shown in **Figure 6**, the minimum of reliability is satisfied when N=3, but the average reliability is very low. Its average reliability is improved by selecting more maintenance times, and the cost of maintenance will increase. Therefore, the reliability after each maintenance of the unmanned engine cabin is calculated by selecting N=5.

4.3 The reliability of unattended engine cabin under the regular maintenance and irregular maintenance

The reliability of the unmanned engine cabin is calculated by formula (19)-(20) under the regular maintenance and the regular maintenance. The calculation results are shown in Tables 6 and 7.

Table 6. $R_{i,k}$ in the regular maintenance

k	T_k	$R_{i,k}$
1	1.663	96.39%
2	1.663	94.37%
3	1.663	90.38%
4	1.663	86.19%
5	1.663	81.31%
6	1.663	71.12%

Table 7. $R_{i,k}$ in the irregular maintenance

k	T_k	$R_{i,k}$
1	2.115	92.60%
2	1.935	89.85%
3	1.785	86.89%
4	1.555	85.66%
5	1.375	84.59%
6	1.215	84.05%

As shown in **Figure 7**, the reliability of the unmanned engine cabin is compared under the regular maintenance and the irregular maintenance. Its reliability declines rapidly with increasing maintenance times under the regular maintenance, and the reliability is not satisfied requirement after 5 maintenances. Its reliability decreases slowly with the increase in the number of maintenances, under the irregular maintenance, and the reliability is satisfied requirement after 5 maintenances.

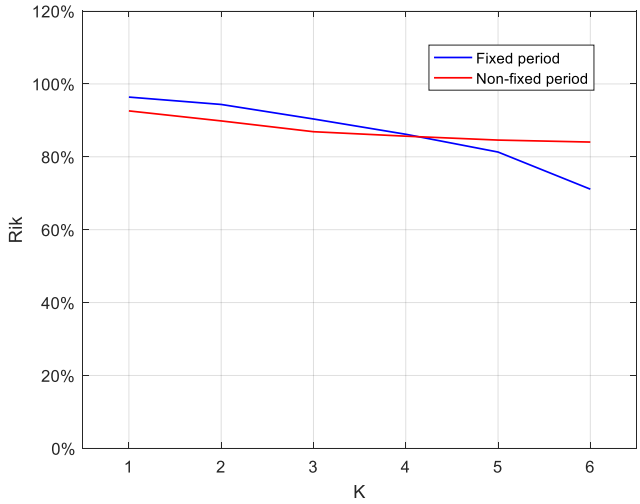

Figure 7. $R_{i,k}$ under the regular maintenance and the irregular maintenance

4.4 Maintenance costs of unmanned engine cabin under different α

The cost optimization is finished by repairing modules with a high fault diagnosis rate under the object of minimum reliability and number of maintenances. The maintenance cost of the unmanned engine cabin is 23775.455 RMB when a is estimated to be 0.7. The module with high failure in the unmanned engine cabin has been praised by experts through improvement, the maintenance cost of the unmanned engine cabin is 18136.195 RMB when a is estimated to be 0.5. It is maintenance cost was saved by 5638.66 RMB.

5 Conclusions

The fault diagnosis rate of per module in the unmanned engine cabin is predicted by the ME-OWA, and the cost of corrective maintenance for per module is obtained by it. The cost of preventive maintenance in the unmanned engine cabin is related to the optimal maintenance times. Its maintenance cost is estimated, the reliability is predicted in the non-fixed maintenance and fixed maintenance periods. Theoretically, unmanned engine cabin is maintained five times in 10 years, its reliability is reduced by 26.22% under the regular maintenance and the reliability is reduced by 9.23% under the irregular maintenance. The computational verification shows that the reliability of the unmanned engine cabin is more stable during the irregular maintenance, and the maintenance cost is reduced by 23.72% under the premise of reliability and 5 maintenances. Therefore, the index of overall cost and reliability of the unmanned engine cabin can be optimized through the ME-OWA algorithm combined with the maintenance cost model.

Author contribution

Minggang Xu and Hao Fu: validation, analysis, investigation,writing of the original draft.
Wang Tian and Binbin lyu: Data calculation, analysis, investigation, writing review.
Honglin Jiao and Yang Liu: investigation, analysis, writing review.

Availability of data and materials The datasets used or analyzed during the current studyare available from the corresponding author on reasonable request.

Code availability Not applicable

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Declarations

Ethics approval This paper is our original unpublished work, and it has not been submitted to any other journal for reviews.

Consent to participate All authors were fully involved in the study and preparation of the manuscript; each of the authors has read and concurs with the content in the final manuscript.

Consent for publication All authors consent to publish the content in the final manuscript.

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