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Joint optimization of maintenance inspection and spare provisioning for aircraft deteriorating parts

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Abstract: With the wide application of condition based maintenance (CBM) in aircraft maintenance practice, the joint optimization of maintenance and inventory management, which can take full advantage of CBM and reduce the aircraft operational cost, is receiving increasing attention. In order to optimize the inspection interval, maintenance decision and spare provisioning together for aircraft deteriorating parts, firstly, a joint inventory management strategy is presented, then, a joint optimization of maintenance inspection and spare provisioning for aircraft parts subject to the Wiener degradation process is proposed based on the strategy. Secondly, a combination of the genetic algorithm (GA) and the Monte Carol method is developed to minimize the total cost rate. Finally, a case study is conducted and the proposed joint optimization model is compared with the existing optimization model and the airline real case. The results demonstrate that the proposed model is more beneficial and effective. In addition, the sensitivity analysis of the proposed model shows that the lead time has higher influence on the optimal results than the urgent order cost and the corrective maintenance cost, which is consistent with the actual situation of aircraft maintenance practices and inventory management.

Keywords: joint optimization, maintenance, spare provision, aircraft part, Wiener process.

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1. Introduction

According to the statistics, the aircraft maintenance cost accounts for more than 20 percent of the total operating cost of airlines, and the maintenance cost reveals much controllable margin compared with the cost of fuel, landing, navigation and crew [1]. Facing the fierce competition, it is vitally important for the airlines to minimize the aircraft maintenance cost without compromising safety. The maintenance cost consists of direct maintenance cost (DMC) and indirect maintenance cost (IMC), and IMC includes spares inventories, shipping and facilities. IMC is getting more and more attention, and the literature [2] shows that the spares inventories sum up above $50 billion in the airlines business. Therefore, reasonable inventory management is an important aspect of maintenance cost saving. In maintenance practice, maintenance and inventory have a mutual influence, and it is universally acknowledged that the joint optimization of inventory and maintenance is more beneficial than the separate optimization in many studies [3 – 9]. Thus a combination of maintenance schedule and inventory management would be an effective means of reducing aircraft maintenance cost.

Over the past years, increasing studies have focused on maintenance and inventory together, where inventory can be reviewed continuously or periodically. The (s, S) and (s, Q) policies are a classic continuous review policies, and the inventory levels are checked continuously and spares are ordered when a certain condition is met. The continuous review policy has been widely used in joint optimization [10 – 14]. In a periodic review policy such as (R, S), spares are ordered up to maximum inventory level S depending on the forecasted demand of the next R inspection intervals [15]. These two review policies are simultaneously studied in [16]. In the existing continuous review policy and periodic review policy, it is assumed that the demand for spare parts is basically stable, thus both maximum inventory level S and safety inventory level s keep unchanged throughout the whole life cycle. However, in reality, aircraft inventory management is classified into the initial provisioning phase and ongoing provisioning phase [17], and the demand for spare parts is intermittent [18] because the first several years in an aircraft's life is called a 'maintenance honeymoon' with limited demand for spare parts. The initial provisioning should differ from the ongoing provisioning in order to avoid long time occupation of much money. However, in many airlines, excessive spare parts are ordered in the initial provisioning

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phase, therefore the initial provisioning may exceeds 10% of the cost of purchasing an airplane.

With a wide application of condition based maintenance (CBM) in aircraft maintenance practice, monitoring information can be gradually integrated into the joint optimization. Due to technical limitations and expensive cost, the conditions of most aircraft parts are still identified through periodic inspections, rather than through continuous monitoring. Because performance degradation of the aircraft deteriorating part is a slow and gradual process widely described with the Wiener process [5,19], frequent inspections are not required at the beginning of putting into operation. Instead, the inspection interval should vary in the life cycle, i.e. the inspection should be separated into the threshold inspection and the repeated inspection. However, the existing studies in thresholds and repeated inspections are only for single-unit system [20], and cannot be directly used in a fleet consisting of many identical parts.

To conclude, there are two problems in the joint optimization of aircraft maintenance and inventory management: i) the different spare provisioning phases need be considered, ii) the inspection interval should vary in the life cycle. In order to solve the two problems, the rest of this paper is organized as follows: a joint inventory management strategy is presented in Section 2. Section 3 estimates parameters of performance degradation for aircraft deteriorating parts. A joint optimal model of maintenance inspection and spare provisioning is developed in Section 4. A case study using real data is analyzed in Section 5. Finally, the conclusion is made in Section 6.

2. Joint inventory management strategy

In this study it is assumed that a new fleet consists of N identical critical parts that are subject to the Wiener degradation process, which can be used to describe a variety of performance degradation process of typical part and has been applied in many fields, such as corrosion, and mechanical vibration [19]. Based on the actual situation of aircraft inventory management, spare provisioning is divided into two phases: the initial provisioning and the ongoing provisioning. In order to minimize the total cost rate of maintenance and inventory management, the proposed joint inventory management strategy is comprised of two policies: the inspection and maintenance policy and the spare provisioning policy.

2.1 Inspection and maintenance policy

The inspection and maintenance policy can be described as Fig. 1 (FH in Fig. 1 represents flight hours) and explained as follows:

(i) For any new part put into operation, the threshold interval is k_1T ($k_1 \in \mathbf{N}$), and T is the repeated inspection interval. The true states X_i ($i = 1, 2, \ldots, N$) of the part are identified through inspections.

(ii) If X_i reaches the preventive state L_p but less than the functional failure state L_f, a preventive maintenance (PM) for part i would be held. If X_i is greater than L_f, a corrective maintenance (CM) would be held. Both PM and CM can restore the part i to be as good as a new state.

(iii) The part at the preventive state would keep operating in case of inventory shortage.

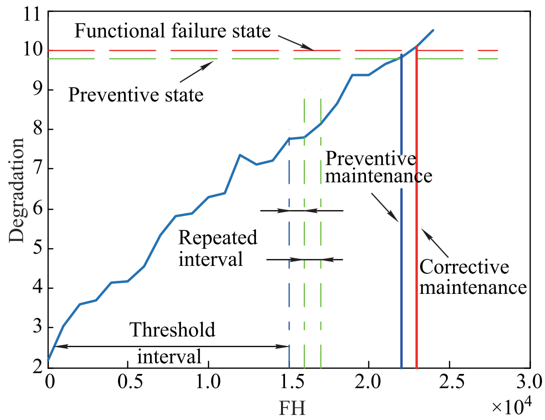


Fig. 1 Inspection and maintenance policy

2.2 Spare part provisioning policy

For a new aircraft, almost no maintenance is required at the beginning of putting into operation, with limited demand for spare parts. With time going on, the demand for spare parts gradually stabilizes to a certain level, which is called as the ongoing provisioning phase. Thus the spare part provisioning policy in this study can be described as Fig. 2.

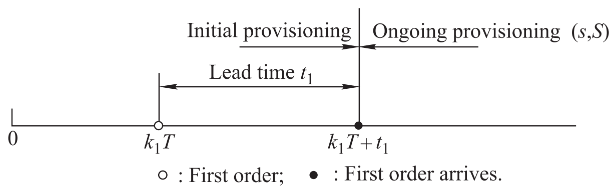


Fig. 2 Spare part provisioning policy

The spare part provisioning policy can be understood in this way:

(i) There is no spare part at the beginning, then at time k_2T ($k_2 \in \mathbf{N}$), the first order quantity S (maximum inventory level) is placed with lead time t_l, so the time $k_2T + t_l$ is taken as the start time of the ongoing provisioning phase.

(ii) In the ongoing provisioning phase, continuous review policy (s, S) is adopted.

(iii) In case of shortage, urgent orders would be placed immediately and the order quantity is equal to the number of failed parts.

Based on the above joint strategy, the inspection interval T, coefficient k_1 and k_2, and the preventive state L_p as well as s and S are derived as the optimization variables.

3. Parameter estimation

3.1 Basic model of Wiener process

The degradation of the interested aircraft part at time t is denoted as $X_i^{t_k}$, which can be characterized by the following expression:

$$X_i^{t_k} = X(0) + \mu t_k + \sigma W(t_k) \tag{1}$$

where $X(0)$ is the original state, μ and σ are the drift coefficient and diffusion coefficient respectively, and $W(t_k)$ is a standard Brownian motion, i.e. $W(t_k) \sim N(0, t_k)$. $\Delta X_i^{t_k}$ is subject to normal distribution and can be described as

$$\Delta X_i^{t_k} \sim N(\mu T, \sigma^2 T). \tag{2}$$

3.2 Parameter estimation

The likelihood function can be expressed by

$$L(\mu,\sigma) = \prod_{i=1}^{n}\prod_{k=1}^{m_i}\frac{1}{\sqrt{2\sigma^2\pi T}}\exp\left[-\frac{(\Delta X_i^{t_k}-\mu T)^2}{2\sigma^2 T}\right]. \tag{3}$$

μ and σ can be estimated using maximum likelihood estimate by solving the following equations:

$$\begin{cases} \dfrac{\partial \ln(L(\mu,\sigma))}{\partial \mu} = 0 \\ \dfrac{\partial \ln(L(\mu,\sigma))}{\partial \sigma} = 0 \end{cases}. \tag{4}$$

Based on (3) and (4), $\hat{\mu}$ and $\hat{\sigma}^2$ can be obtained as

$$\hat{\mu} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{m_i}\Delta X_i^{t_k}}{\sum_{i=1}^{n} m_i T} \tag{5}$$

$$\hat{\sigma}^2 = \frac{1}{\sum_{i=1}^{n} m_i}\left[\sum_{i=1}^{n}\sum_{k=1}^{m_i}\frac{(\Delta X_i^{t_k})^2}{T} - \frac{\left(\sum_{i=1}^{n}\sum_{k=1}^{m_i}\Delta X_i^{t_k}\right)^2}{\sum_{i=1}^{n} m_i T}\right]. \tag{6}$$

4. Joint optimal model

4.1 Establishment of joint optimal model

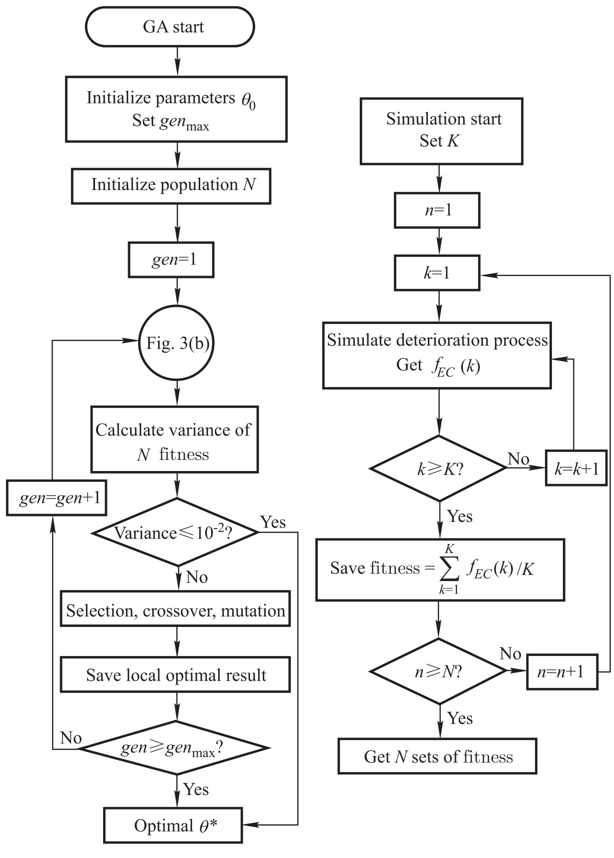
According to the proposed joint strategy, the function minimizing the total cost rate of maintenance and inventory management can be described as follows:

$$\begin{cases} EC_\infty = \min f_{EC}(T, k_1, k_2, S, s, L_p) \\ \text{ s.t. } S > s, L_f > L_p, \\ S \in [0, N]; \quad s \in [0, N-1]. \end{cases} \tag{7}$$

There are intricate relationships among the parameters T, k_1, k_2, S, s and L_p, and it is difficult to find the analytic solution. Therefore, a combination of the genetic algorithm (GA) and the Monte Carol method is developed to obtain an approximate optimization result, i.e. $\theta^* = (T^*, k_1^*, k_2^*, S^*, s^*, L_p^*)$.

4.2 Algorithm

The solution flow of the combination is shown in Fig. 3.



(a) Flow diagram for GA (b) Flow diagram for Monte Carol

Fig. 3 Solution flows

The fitness of GA $f_{EC}(T, k_1, k_2, S, s, L_p)$ is evaluated by the Monte Carol method, and Fig. 4 shows the stimulation diagram.

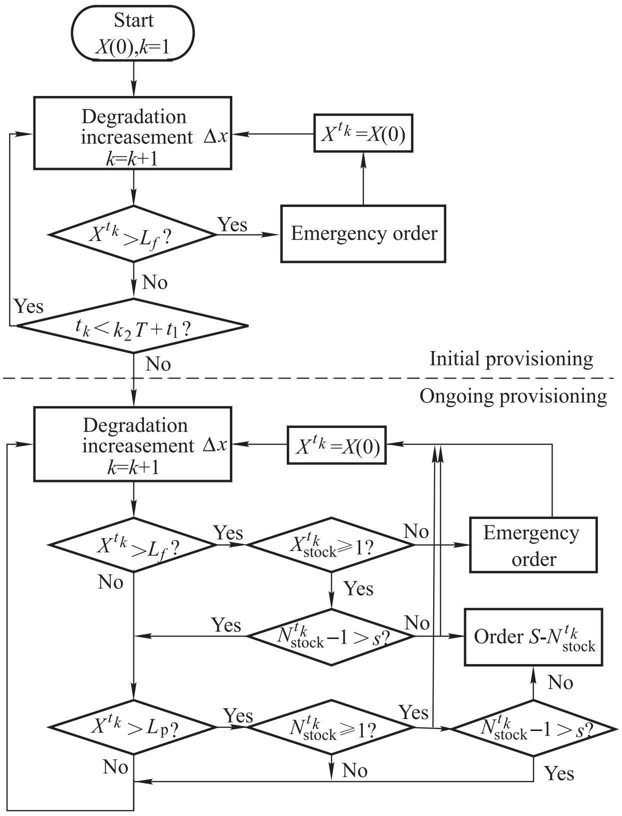


Fig. 4 Stimulation diagram

If the simulation time span t_m is long enough, $f_{EC}(T, k_1, k_2, S, s, L_p)$ can be expressed by

$$EC_\infty = \lim_{t_m \to \infty} \frac{C_{ins} \cdot N_{ins} + C_p \cdot N_p + C_c \cdot N_c}{t_m} + \frac{C_o \cdot N_o + C_e \cdot N_e + C_k \cdot \sum_{k=1}^{m} N_{\text{stock}}^{t_k}}{t_m} \tag{8}$$

where C_{ins} is each inspection cost; N_{ins} is the total number of inspections; C_p is the PM cost mainly including the purchasing cost of air cycle machine (ACM) and the labor cost; N_p is the total number of PM; C_c is the CM cost mainly including the purchasing cost of ACM and the downtime cost; N_c is the total number of CM; C_o is the spare order cost per time; N_o is the total number of order t_k; C_e is the urgent order cost per spare part; N_e is the total urgent order quantity; C_k is the holding cost and capital charge per T unit time per spare part; and $N_{\text{stock}}^{t_k}$ is the number of spare parts between t_{k-1} and t_k.

$N_{ins}, N_p, N_c, N_o, N_e$ and $N_{\text{stock}}^{t_k}$ can be captured by statistics according to the stimulation diagram.

5. Case study

ACM is an important refrigeration part of the environmental composite system used in pressurized gas turbine-powered aircraft. The outlet temperature of ACM will increase with its performance degradation, and the temperature would be inspected every 1 000 FH, i.e. T=1 000 FH. If the outlet temperature is higher than a certain value (generally $L_f = 10°$), ACM must be removed and overhauled. In this study, ACMs in one of the Chinese airlines are selected as an example to illustrate the application of the proposed model.

5.1 Estimation of degradation parameter

The collected historical outlet temperatures of 20 ACMs data are plotted in Fig. 5.

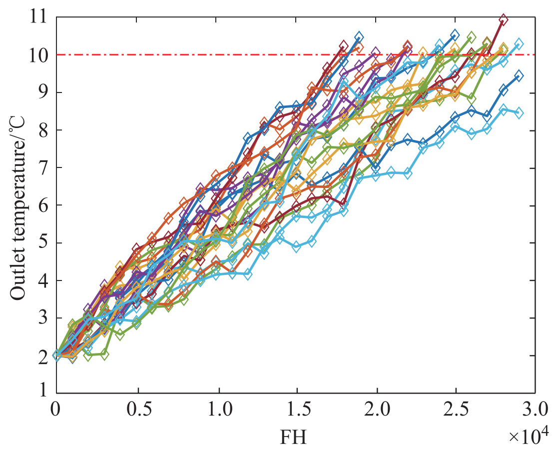


Fig. 5 Outlet temperature data of the ACM

Based on the approach introduced in Section 3, the degradation parameters are estimated as follows:

$$\hat{\mu} = 3.33 \times 10^{-4}, \quad \hat{\sigma} = 0.009\,9.$$

Since the initial outlet temperature $X(0)$ is 2°C, the outlet temperatures can be expressed as

$$X(t) = 2 + 0.000\,333t + 0.009\,9W(t). \tag{9}$$

5.2 Joint optimization simulation

According to statistics, the related inputs required for the joint optimal model are given by

$$C_{ins} = ¥1\,000, C_p = ¥100\,000, C_c = ¥400\,000,$$
$$C_o = ¥5\,000, C_k = ¥10/\text{FH}, C_e = ¥400\,000,$$
$$t_l = 2\,000 \text{ FH}.$$

In GA, the population is 80, the iteration time is 500, the crossover probability is 0.8, and the mutation probability is 0.05. In order to eliminate the randomness of simulation, we set t_m=100 000 FH and take the mean value of 200 simulation results as the fitness. The process of iteration is shown as the green-solid line in Fig. 6, and the optimal result $[k_1^*, k_2^*, S^*, s^*, L_p^*]$ is $[14, 17, 4, 0, 8.1]$, and the $f_{EC}(14, 17, 4, 0, 8.1)$ is equal to ¥107.42.

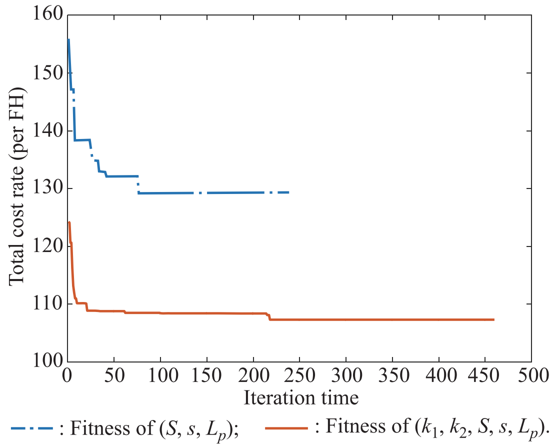


Fig. 6 Change of the fitness with iteration

(i) Comparison with the existing optimization model

In the existing optimization model [11], different spare provisioning phases have not been considered, and the threshold is equal to the repeated interval. Thus k_1 and k_2 do not need to be optimized in the existing optimization model and the process of iteration is shown as the blue-point line in Fig. 6, the optimal result $[S^*, s^*, L_p^*]$ is $[4, 0, 8.1]$, and $f_{EC}(4, 0, 8.1)$ is equal to ¥129.51/FH, that is 20.56% higher than $f_{EC}(14, 17, 4, 0, 8.1)$.

Based on the above analysis, it can be found that the coefficients k_1 and k_2 have much impact on the total cost rate, as shown in Fig. 7.

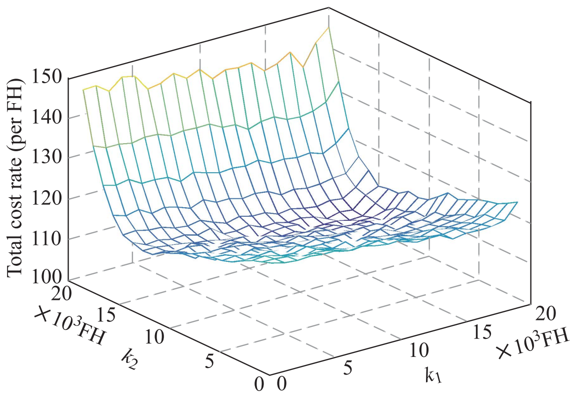


Fig. 7 Different total cost rates under different k_1 and k_2

It can be concluded from Fig. 7 that a bigger (or smaller) k_1 and k_2 would result in a bigger total cost rate, and the reason is that a bigger k_1 and k_2 means higher failure frequency, which results in more CM cost and urgent order cost. On the other hand, a smaller k_1 and k_2 means higher inspection frequency and inventory level, which results in more inspection cost and spare holding cost. Furthermore, Fig. 7 shows that k_2 has a higher impact on the total cost rate than k_1, and the reason is that k_2 and k_1 mainly influence the numbers of the urgent order and inspection respectively, and the urgent order cost is far higher than the inspection cost.

Similarly, maximum inventory level S and safety inventory level s also have impact on the total cost rate as shown in Fig. 8. Fig. 8 shows that a bigger (or smaller) S and s would result in a bigger total cost rate, which is consistent with the actual situation.

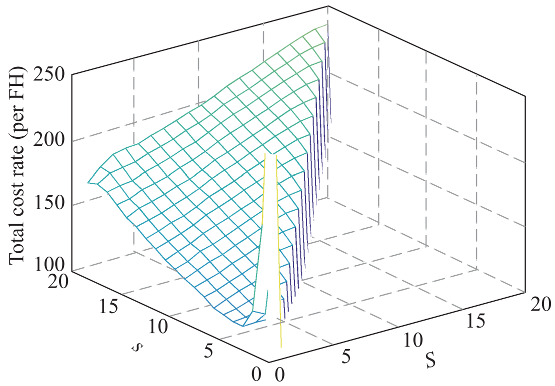


Fig. 8 Different total cost rates under different inventory levels

With the optimal result $[14, 17, 4, 0, 8.1]$, the change of the inventory level with FH is shown in Fig. 9, and the corresponding change of the order number with FH is shown in Fig. 10.

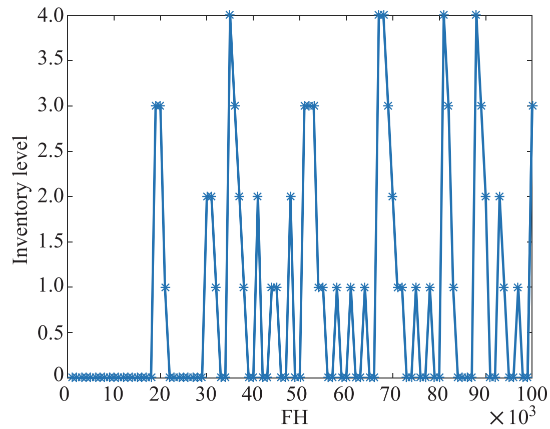


Fig. 9 Change of inventory level with FH

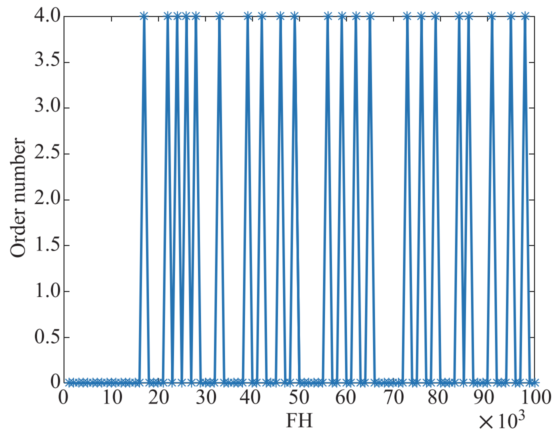


Fig. 10 Change of order number with FH

(ii) Comparison with the airline real case

According to the statistics of the real case in the airline, in the past 15 years, $N_{ins} = 900$, $N_p = 30$, $N_c = 2$, $N_o = 11$, $N_e = 0$. In reality, the period of the initial provisioning of civil aircraft is five years, and during the period, only one spare ACM is needed. And ACM operates about 3 000 FH each year, so

$$\sum_{k=1}^{15} N_{\text{stock}}^{t_k} = 15\,000 \text{ FH}.$$

According to the data in Fig. 9 or the actual statistics, the required average of spare parts per 1 000 FH in the ongoing provisioning phase is about 1, so the annual required average D of spare parts is about 3. In airlines, D is seen as subject to some distribution such as Poisson, exponential, or equal to the reciprocal of mean time between unscheduled repairs or mean time between failures. In this study, the Chinese airline assumes that D of ACM is subject to Poisson distribution according to the method recommended by Boeing, and the required shortage rate FR of ACM is less than 1%, therefore S and s can be obtained in accordance with the airline traditional method as below:

$$FR = \sum_{s} \frac{D^{(D+s)} \cdot \mathrm{e}^{-D}}{(D+s)!}. \tag{10}$$

Substituting $FR = 1\%$ and $D = 3$ into (10), it can be obtained that s is approximately equal to 4, and then the maximum inventory S is equal to $4 + 3 = 7$. Therefore, the mean of the inventory level during the ongoing spare provisioning phase is $\dfrac{7+3}{2} = 5$ and $\sum_{k=16}^{45} N_{\text{stock}}^{t_k}$ can be obtained as follows:

$$\sum_{k=16}^{45} N_{\text{stock}}^{t_k} = 10 \times 5 \times 3\,000 = 150\,000 \text{ FH}.$$

Therefore,

$$\sum_{k=1}^{45} N_{\text{stock}}^{t_k} = 165\,000 \text{ FH}.$$

According to (8), the total cost rate $EC_{45\ 000}$ in the past 15 years ($t_m = 45\,000$ FH) can be obtained as follows:

$$EC_{45\ 000} = \frac{1\,000 \times 900 + 100\,000 \times 30}{45\,000} + \frac{400\,000 \times 2 + 5\,000 \times 11 + 10 \times 165\,000}{45\,000} = ¥142.33/\text{FH}.$$

$EC_{45\ 000}$ is 32.50% higher than $f_{EC}(14, 17, 4, 0, 8.1)$. Obviously, the total cost rate is increasing with the extending of the ongoing provisioning phase.

Fifteen years is not long enough, and only one real case may not fully show the advantage of the proposed optimal model, so an optimized simulation model would be adopted. Because the preventive state $L_p = 9.5$ is adopted in airlines, and the initial provisioning of civil aircraft is five years, so the parameters $[15, 17, 7, 3, 9.5]$ would be taken as an input into the simulation model and the corresponding total cost rate is ¥150.42/FH, which is 40.03% higher than $f_{EC}(14, 17, 4, 0, 8.1)$, and the corresponding inventory difference with time is shown in Fig. 11.

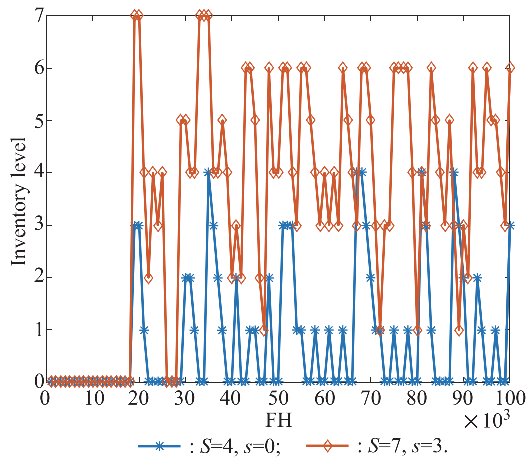


Fig. 11 Change of order number with FH

5.3 Sensitivity analysis

Urgent order cost C_e, PM cost C_c and lead time t_l are difficult to be estimated accurately in aircraft maintenance practice, therefore, it is necessary to analyze the sensitivity of these three parameters to the optimal results. Tables 1 – 3 show different optimal results under different C_e, C_c and t_l respectively.

Table 1 Different optimal results under different C_e

C_e/¥	k_1	k_2	S	s	L_p	EC_∞
400 000	14	17	4	0	8.1	106.50
500 000	14	17	4	0	8.1	106.96
600 000	14	17	4	0	8.1	107.42
800 000	14	17	4	0	8.1	108.35
1 000 000	14	17	4	1	8.3	108.94
1 200 000	14	17	4	1	8.3	109.51
1 400 000	13	16	4	1	8.3	110.08

Table 2 Different optimal results under different C_c

C_c/¥	k_1	k_2	S	s	L_p	EC_∞
100 000	14	17	4	0	8.4	101.97
200 000	14	17	4	0	8.2	104.34
300 000	14	17	4	0	8.1	105.99
400 000	14	17	4	0	8.1	107.42
500 000	14	17	4	1	8.1	109.30
600 000	14	17	4	1	8.0	110.59

Table 3 Different optimal results under different t_l

t_l/FH	k_1	k_2	S	s	L_p	EC_∞
1 000	14	18	3	0	8.7	101.77
2 000	14	17	4	0	8.1	107.42
3 000	14	16	5	1	7.8	113.56
4 000	13	15	7	1	7.8	115.62
5 000	13	14	8	2	8.0	123.31

First, from Tables 1 – 3, it can be found that the values of k_1 and k_2+t_l remain basically unchanged, which means C_e and C_c have slight impact on the threshold interval and the start time of the ongoing provisioning because k_1 and $k_2 + t_l$ mainly depend on the change rate of degradation.

Second, it can be found that C_e has little impact on S, s and L_p in Table 1, which indicates that shortage has basically been avoided, i.e. the probability of shortage is very small. However, when C_e becomes very large, the small probability events cannot be ignored. Therefore, the safety inventory level s changes from 0 to 1 in order to further decrease the probability of shortage. Obviously, C_c and C_e have similar influence on the optimal results by comparing Table 1 and Table 2, and when C_c becomes close to C_e (¥6 000), the safety inventory level s changes from 0 to 1, in order to decrease the probability of functional failure.

Finally, it can be seen from Table 3 that spare parts can be provided immediately if the lead time is short, and the safety inventory level s is equal to 0 especially when the lead time is 1 000 FH or 2 000 FH. As the lead time increases, both S and s would be increased to avoid the occurrence of shortage. Therefore, t_l has more impact on the optimal results than C_e and C_c.

To sum up:

(i) If provisioning phases are not distinguished and the threshold is equal to the repeated interval, the minimized total cost rate based on the existing optimization model is 20.56% higher than the total cost rate minimized by the proposed model;

(ii) The proposed model can save 32.50% of the total cost rate compared to the airline real case, and can save 40.03% if the period of ongoing spare provisioning is long enough;

(iii) The results of sensitivity analysis show that the proposed model is consistent with the actual situation of aircraft maintenance practice and inventory management.

6. Conclusions

In this study, a joint optimization of maintenance inspection and spare provisioning for aircraft parts is proposed to minimize the total cost rate. In the case study, the proposed model and its optimal results are analyzed and compared with the existing optimization model and the airline engineering method, and then sensitivity analysis of the proposed model is conducted. The distinguishes of this study are as follows: (i) Considering different spare provisioning phases and the varying inspection interval, the proposed joint optimization model is more consistent with the actual situation of aircraft maintenance practices and inventory management than the existing model; (ii) The cheaper total cost rate is obtained by the jointly optimizing inspection interval, maintenance decision and spare provisioning, compared to both the existing optimization model and the airline real case.

In the future, the joint optimization should be extended to consider imperfect PM/CM and different degradation processes, which is of more practical value.

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