Mission-Oriented Configuration Model of Aircraft Carrying Spares and Dynamic Optimization Policy

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Abstract: Spare parts are critical to scheduled maintenance and fault repair, and can directly affect the readiness and combat capability of equipment. Equipment's capacity of carrying spares is influenced by its storage space and scales, so it is necessary to consider economic factors, e.g. spares cost, as well as non-economic ones, such as spares volume, mass and scale, when optimizing spares configuration. Aiming at this problem, the optimization model based on multi-constraints for carrying spares is built by METRIC theory and system analysis. Through the introduction of Lagrange factors, the spares cost is transformed to shadow price, and the optimization method for carrying spares and the dynamic adjustment policy of Lagrange factors are proposed. The result of a given example is analyzed, and demonstrates that the proposed model can be optimized with all constraints, and the research can provide a new way for carrying spares optimization.

Key words: carrying spares project; multi-constrains; optimization; Lagrange factors; operational availability

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0 Introduction

With the rapid development of military affairs revolution, a large number of new types of weapons and equipments, such as surface warship, long-range strategic missile, fourth-generation fighters, etc, are delivered to combat troops. The issue of combat readiness of weapon system becomes obvious, and the equipment support and equipment operations tend to be equal important. Spare parts are supportability material of planed maintenance and fault repair, and directly affect the equipment life-cycle cost, as well as combat capability[1]. When performing combat missions, equipment need to have a strong support capabilities to face the rapidly changing battlefield environment. Therefore, a reasonable planning for carrying spares is critical to improve equipment support ability.

The methods of spares modeling and optimization mainly include single-item modeling, demand oriented modeling, system modeling, availability-centered modeling, and operational readiness based modeling, etc. The basic principle is to meet the precondition of equipment operational availability through cost-effectiveness analysis[2,3]. Spares fill rate[4-6], support delay[7] and mission success probability[8] are always used as support effectiveness targets. Through the given target constraints, spares configuration is optimized to minimize the total investment of spares stock. For mission-oriented carrying spares support project, several important non-economic factors such as spares mass, volume, quantity, scale, etc, are also need to be considered besides spares stock cost. In the fields of military affairs, such as the naval warship fleets, tank regiment, air squadrons, and orbit space station[9], carrying spares optimization has been widely applied and

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become a worldwide hot spot since the 1990s. Wang, et al.[7] established spares inventory optimization model under multi-constraints, and proposed the method of updated Lagrange to solve the problem. Robert and Bachman, et al. studied the aircraft spares inventory optimization model, and analyzed the relationship between spares mass, volume and backorders[10,11]. Wei, et al.[12] constructed a multi-echelon multi-objective optimization model for collaborative supply chain inventory control, and applied genetic algorithm to solve the model. The critical step of optimization model is to determine reasonable constraint factors. During the optimization, values of the factors are repeatedly revised until they meet the given targets when finally the optimal project is obtained[13].

We focus on the issue of aircraft spares optimization. Through the introduction of Lagrange factors, the spares mass and volume are transformed to item shadow price, and a new method to solve the problem of spares optimization model under multi-constraints is proposed.

1 Spares Demand Rate

In order to quickly restore the combat effectiveness of failed equipment, the repair mode that replaces the failure items by its spares is usually used[14]. In the way, spares demand rate equals to its replacement rate, which is an important input parameter for spares optimization model. The main factors to affect spares demand rate include: equipment reliability, maintenance and repair conditions, repair capacity, equipment task intensity, system structure, equipment deployment and the support organizational structure. The influence factors of spares demand rate and its corresponding model parameters are given in Table 1.

According to spares indenture in system, it is divided to line replaceable unit (LRU) and shop replaceable unit (SRU)[15]. Suppose $j=1,2,\cdots,J$, is the item index of spares, then we can obtain the spares demand rate for LRU

Table 1 Influence factors of spares demand rate

Influencing factor	Corresponding model parameter
Equipment reliability	• Mean time between failures
Maintenance and support conditions	• Repair in place rate • Retest OK rate • Repair probability
Equipment task intensity	• Working intensity in a given interval • Duty cycle of equipment components • Spares indenture in the system structure
Equipment structure	• Item installation number in its higher indenture mother component
Equipment deployment	• Deployment number of equipment

$$\lambda_j=\frac{D_j(1-R_j)\cdot H_0\cdot Z_j\cdot N}{\mathrm{MTBF}_j(1-P_j)} \tag{1}$$

where D_j is the duty cycle of item j, R_j repair in place rate, H_0 the mean working time (hour) of each week, Z_j the install number of item j in its higher indenture component, N the equipment deployment amount, MTBF_j the mean time between failures of the jth item, and P_j the retest OK rate for item j.

For the item of SRU, suppose SRU_k is the subcomponent of LRU_j, and its fault isolation probability is defined as q_{jk}, that is, the probability that failure item j is caused by its subassembly k, and then we can obtain the calculation formula of demand rate for SRU_k

$$\lambda_k=\lambda_j\cdot q_{jk} \tag{2}$$

$$q_{jk}=\frac{D_k\cdot Z_k\cdot \mathrm{MTBF}_j(1-P_j)(1-R_k)}{\mathrm{MTBF}_k(1-P_k)(1-R_j)} \tag{3}$$

where Z_k is the install number of SRU_k in its single parent component LRU_j.

2 Configuration Model of Carrying Spares

Suppose the average repair time of item j is T_j, and its spares stock is s_j, the expected value $E[X_j]$ and variance $\mathrm{Var}[X_j]$ of pipeline of item j are[16]

$$E[X_j]=\lambda_j T_j+\sum_{k\in S(j)}\mathrm{EBO}_k \tag{4}$$

$$\mathrm{Var}[X_j]=\lambda_j T_j+\sum_{k\in S(j)}\mathrm{VBO}_k \tag{5}$$

where EBO_k is the expected backorders of SRU_k and VBO_k the variance of backorders. $k \in S(j)$ means the aggregate of item k which is the sub-components of LRU_j.

Backorders is the state variable of spares stock, recorded as $B(X \mid s)$, X the amount of spares to be received, and s the spares stock

$$B(X \mid s)=\begin{cases} X-s & X>s \\ 0 & X \leqslant s \end{cases} \tag{6}$$

Expected backorders (EBO) and variance of backorders (VBO) is defined as

$$\mathrm{EBO}=p(X=s+1)+\cdots+k \cdot p(X=s+k)+\cdots=\sum_{x=s+1}^{\infty}(x-s) p(X=x) \tag{7}$$

$$\mathrm{VBO}=E[\mathrm{BO}^2]-[\mathrm{EBO}]^2 \tag{8}$$

$$E[\mathrm{BO}^2]=\sum_{X=s+1}^{\infty}(X-s)^2 \cdot p(X) \tag{9}$$

where $p(X)$ is the probability distribution of spares to be received. When variance to mean rate $\mathrm{Var}[X]/E[X]=1$, $p(X)$ obeys poisson probability distribution.

$$p(X)=\frac{(E[X])^X \cdot \mathrm{e}^{-E[X]}}{X!} \tag{10}$$

If $\mathrm{Var}[X]/E[X]>1$, $p(X)$ obeys negative binomial distribution[17]

$$p(X)=\binom{a+X-1}{X} b^X(1-b)^a \tag{11}$$

According to the features of negative binomial distribution, its mean value $E[X]=ab/(1-b)$, the variance $\mathrm{Var}[X]=ab/(1-b)^2$. If we obtain the value of $E[X]$ and $\mathrm{Var}[X]$, the parameters a and b can be determined.

If $\mathrm{Var}[X]/E[X]<1$, $p(X)$ obeys binomial distribution[18]

$$p(X)=\binom{n}{X} p^X(1-p)^{n-X} \tag{12}$$

Similarly, for binomial distribution, its mean value $E[X]=np$, the variance $\mathrm{Var}[X]=np(1-p)$, if the value of $E[X]$ and $\mathrm{Var}[X]$ are determined, the parameters n and p can be obtained.

Based on the expected backorders of spares, we can calculate the equipment availability, and from different perspectives, it is distinguished as operational availability (A_o), supply availability (A_s) and inherent availability (A_i). Different definitions about equipment availability are shown as follows, respectively[3]

$$A_o=\frac{\mathrm{MTBF}}{\mathrm{MTBF}+\mathrm{MTTR}+\mathrm{MLDT}} \tag{13}$$

$$A_s=\frac{\mathrm{MTBF}}{\mathrm{MTBF}+\mathrm{MLDT}} \tag{14}$$

$$A_i=\frac{\mathrm{MTBF}}{\mathrm{MTBF}+\mathrm{MTTR}} \tag{15}$$

where MTBF is the mean time between failure, MTTR the mean time to repair, and MLDT the mean logistic delay time. According to Eqs. (13)—(15), we can obtain another formation about operational availability (A_o)

$$A_o=\frac{A_s A_i}{A_s+A_i-A_s A_i} \tag{16}$$

For series system, any shortage of LRU will cause system breakdown, so the spares supply availability is

$$A_s=\prod_{j \in I(1)}\left[1-\frac{\mathrm{EBO}_j}{(Z_j N)}\right]^{Z_j} \tag{17}$$

where EBO_j is the expected backorders of LRU_j, Z_j the install number of item j in its parent component, N the deployment amount of equipment, and $j \in I(1)$ the first indenture item LRU_j.

For the carrying spares optimization model, the operational availability of system, spares mass and volume need to be considered as the constraints. The basic modeling method is to introduce Lagrange factors based on cost-effectiveness analysis.

$$\min C=\sum_{j=1}^{J} c_j s_j \tag{18}$$

$$A_o=\frac{A_s A_i}{A_s+A_i-A_s A_i} \geqslant A_T \tag{19}$$

$$\sum_{j=1}^{J} s_j m_j \leqslant M_0 \tag{20}$$

$$\sum_{j=1}^{J} s_j v_j \leqslant V_0 \tag{21}$$

where s_j is the spares stock, c_j the spares price. Eq. (19) means the constraint of operational availability, where A_T is the value of setting target. Eq. (20) means the constraint of spares mass, where m_j is the mass of item j, and M_0 the given target of spares total mass. Eq. (21) means constraint of spares volume, where v_j is the volume of item j, and V_0 the given target value of spares total volume.

The spares scale is defined as

$$r_j = \lambda_c c_j + \gamma_m m_j + \mu_v v_j \tag{22}$$

where λ_c is the spares cost factor, γ_m the mass factor, and μ_v the volume factor. If $\gamma_m = \mu_v = 0$, there is only factor of cost in the spares scale. If λ_c, γ_m, $\mu_v \neq 0$, the spares scale includes cost, mass and volume. According Eq. (17), we can obtain its transformation form

$$A_s(r_1, r_2, \cdots, r_j) = \prod_{j \in I(1)} A_s(r_j) = \prod_{j \in I(1)} \left[1 - \frac{\mathrm{EBO}_j(r_j)}{(Z_j N)}\right]^{Z_j} \tag{23}$$

where r_j is the spares scale of item j, $r = (r_1, r_2, \cdots, r_j, \cdots, r_J)$ the current spares project. After increasing a optimal spares of item j, the new project becomes $r' = (r_1, r_2, \cdots, r_j', \cdots, r_J)$. Take a logarithm to Eq. (23), we can obtain[19,20]

$$\begin{aligned}\Delta A_s = \ln A_s(r_1, r_2, \cdots, r_j', \cdots, r_J) - \\ \ln A_s(r_1, r_2, \cdots, r_j, \cdots, r_J) = \\ Z_j \ln\left(1 - \frac{\mathrm{EBO}(r_j')}{Z_j N}\right) + \sum_{j \notin r'} Z_j \ln\left(1 - \frac{\mathrm{EBO}(r_j)}{Z_j N}\right) - \\ Z_j \ln\left(1 - \frac{\mathrm{EBO}(r_j)}{Z_j N}\right) - \sum_{j \notin r'} Z_j \ln\left(1 - \frac{\mathrm{EBO}(r_j)}{Z_j N}\right) = \\ \ln A_s(r_j') - \ln A_s(r_j)\end{aligned} \tag{24}$$

The marginal increment δ_j is defined as

$$\delta_j = \frac{\ln A(r_j') - \ln A(r_j)}{r_j' - r_j} \tag{25}$$

The basic steps of marginal algorithm are shown as follows:

Step 1 Initialize the spares stock, set $s_j = 0$.

Step 2 Calculate equipment operational availability, spares volume and mass.

Step 3 Go to the process of optimization, and calculate the marginal increment δ_j of each spare.

Step 4 Compared with the marginal increment δ of each spare, the maximum value of δ_j is recorded as $\max(\delta_j)$, and the optimal spare item corresponding to $\max(\delta_j)$ is recorded as j^*. Add 1 to the spares stock of item j^*, and keep other spares stock unchanged.

Step 5 If the calculation result meets the given targets, the algorithm ends, otherwise, returns to Step 3 and continue to calculate until meeting the given targets.

3 Determination Method and Dynamic Adjustment Policy of Lagrange Factors

The initial values of the Lagrange factors need to be determined before model calculation. The basic method is:

(1) Set $\gamma_m = \mu_v = 0$. In this case, only the constraint of spares cost is considered. Through marginal algorithm, we can obtain the optimal result $s_0 = (s_1, s_2, \cdots, s_J)$.

(2) Based on the spares configuration s_0, we can obtain the spares total cost $C(s_0)$, spares mass $M(s_0)$ and volume $V(s_0)$.

(3) Determine the initial Lagrange factors, $\gamma_{m0} = C(s_0)/M(s_0)$, $\mu_{v0} = C(s_0)/V(s_0)$. Then, we can obtain another spares project, recorded as s, $s = (s_1, s_2, \cdots, s_J)$. The value of γ_{m0} and μ_{v0} need to be summed up so as to form the penalty factors if the corresponding spares mass or volume exceed the given target. The calculation method of dynamic adjustment for γ_m and μ_v is

$$\Delta\gamma_m = \frac{M(s) - M_0}{M_0} \cdot \gamma_{m0} \tag{26}$$

$$\Delta\mu_v = \frac{V(s) - V_0}{V_0} \cdot \mu_{v0} \tag{27}$$

where M_0 is the mass constraint target, and V_0 the volume constraint target. If the current spares project does not meet the constraint, we can update and adjust the value of Lagrange factors through Eqs. (26), (27).

In practice, a special case may appear. No matter how many times we adjust the value of factors γ_m and μ_v, we cannot obtain a solution to satisfy all constraints. In this case, the constraint target should be reset by reducing the value of A_0, or increasing M_0 and V_0.

4 Application and Results Analysis

Suppose there is an air force combat unit. Each aircraft of the unit is equiped with an airborne navigation device. Suppose the setting target of operational availability $A_T > 0.95$, R and P for each item equal to 0. For airborne navigation device, its mean time to repair MTTR=6 h, and the mean time between failure MTBF =400 h. According to Eq. (15), we can calculate the inherent availability

$$A_i=\frac{\text{MTBF}}{\text{MTBF}+\text{MTTR}}=\frac{400}{400+6}=0.985$$

Then we can obtain the target of spares supply availability

$$A_s=\frac{A_T A_i}{A_i-A_T+A_T A_i}=0.964$$

Spares bill and its parameters are shown in Table 2. Set $\gamma_m=\mu_v=0$, we can obtain a configuration project s_0 without considering the spares mass and volume. Then, spares supply availability $A_s(s_0)=0.968\ 7$, spares cost $C(s_0)=3\ 072\ 000$, spares mass $M(s_0)=257.7$ kg, and spares volume $V(s_0)=0.411\ 2\ \text{m}^3$. The initial mass factor $\gamma_{m0}=C(s_0)/M(s_0)=1.192$, and initial volume factor $\mu_{v0}=C(s_0)/V(s_0)=747.1$.

Table 2 Equipment spares bill and its parameters

Item of spares	Structure code	MTBF_j/h	Duty cycle	Repair time/d	Install number	Item price/yuan	Mass/kg	Volume/10^{-3}m^3	Annual demand
Control module	1	176	1	3	1	433 000	25.3	68.3	310.7
Power module	2	643	1	2	1	678 000	17.7	21.7	85.1
Thermostat	3	685	1	4	1	154 000	7.6	4.6	79.9
Navigation control module	4	330	1	2	1	98 000	37.5	45.5	165.7
Processor	1.1	900	0.9	1	2	98 000	7.2	15.2	109.5
Interface board	1.2	1 200	0.6	3	3	116 000	2.1	9.3	82.1
Program board	1.3	1 050	0.9	1	1	84 000	6.4	4.5	46.9
Storage battery	2.1	2260	1	2	1	265 000	1.8	3.8	24.2
Charging board	2.2	1 800	0.8	1	2	327 000	4.6	6.6	48.7
Platform temperature control board	3.1	1450	1	1	1	96 000	0.9	8.4	37.8
Component temperature control board	3.2	1 300	1	4	1	135 000	2.3	2.8	42.1
Horizontal gyroscope	4.1	1 450	0.5	6	2	35 000	12.8	15.1	37.7
Azimuth gyroscope	4.2	2 330	0.9	3	3	26 000	9.4	7.7	63.4
Accelerometer	4.3	2 780	0.7	2	1	17 000	6.2	5.2	13.8

Suppose the given target of spares mass $M_0=250$ kg, and spares volume $V_0=0.4\ \text{m}^3$, then, $M(s_0)=257.7>M_0$, and $V(s_0)=0.411\ 2>V_0$. That is to say, the setting target of spares mass and volume are not satisfied. Based on the initial constraints γ_{m0} and μ_{v0}, we can obtain another configuration project s, under which, availability $A_s(s)=0.966\ 5$, spares cost $C(s)=3\ 091\ 000$, spares mass $M(s)=226.1$ kg, volume $V(s)=0.390\ 7\ \text{m}^3$. Then, $A(s)>A_s$, $M(s)<M_0$ and $V(s)<V_0$, the result of the project s satisfies the setting constraint targets.

If we change the value of γ_m and μ_v, we can obtain several different spares project, shown in Table 3. If $\gamma_m=\mu_v=0$, it is the cost project. If $\lambda_c=\mu_v=0$, it is the mass project. If $\lambda_c=\gamma_m=0$, it is the volume project. If $\lambda_c\neq 0$, $\gamma_m\neq 0$ and $\mu_v\neq 0$, it is the spares scale project.

Table 3 Optimal spares project under different constraints

Item of spares	Cost project	Mass project	Volume project	Resource project
Control module	3	4	3	3
Power module	1	1	1	1
Thermostat	3	2	3	2
Navigation control module	2	1	1	2
Processor	1	1	1	1
Interface board	1	2	2	2
Program board	1	0	1	1
Storage battery	0	1	1	0
Charging board	0	1	1	0
Platform temperature control board	0	1	0	0
Component temperature control board	0	1	1	1
Horizontal gyroscope	2	1	1	1
Azimuth gyroscope	2	1	2	1
Accelerometer	1	0	1	0

The support effectiveness of different spares projects are shown in Table 4, among which, the volume project and scale project satisfy all of the given targets. For the scale project, the spares total cost $C(R)=3\ 091\ 000$, which is less than that of the volume project ($C(V)=3\ 782\ 000$), therefore, scale project is optimal solution.

Table 4 Spares support effectiveness for different projects

Projects	Result analysis	A	$C/10^4$	M/kg	V/m^3
Cost project	result	0.968 7	307.2	257.7	0.411 2
	Condition satisfied	Y	—	N	N
Mass project	Calculation value	0.967 2	403	214.8	0.427 8
	Condition satisfied	Y	—	Y	N
Volume project	Calculation value	0.965 5	378.2	218.2	0.373 1
	Condition satisfied	Y	—	Y	Y
Scale project	Calculation value	0.966 5	309.1	226.1	0.390 7
	Condition satisfied	Y	—	Y	Y

The result comparisons of support effectiveness are shown in Fig. 1, and optimal cost-effectiveness curves of spares project are shown in Fig. 2, where the values of cost, mass and volume are normalized.

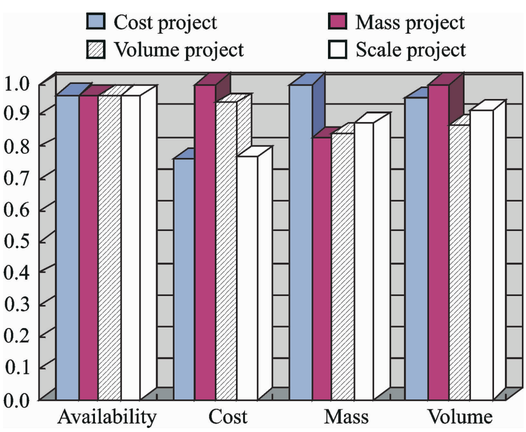

Fig. 1 Support effectiveness for different project

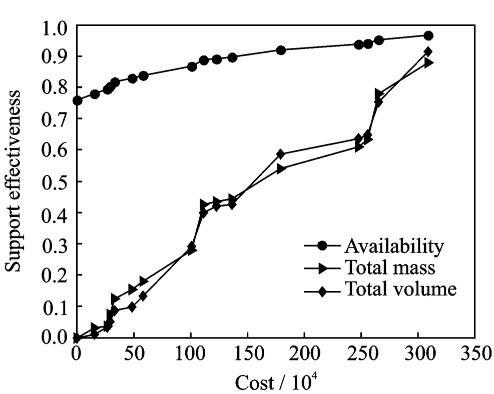

Fig. 2 Optimal curves of effectiveness v. s. cost

5 Conclusions

Modeling of carrying spares configuration and its optimization method is researched. The airborne navigation device is taken as example for calculation and simulation analysis. Several conclusions are obtained.

(1) The proposed optimization method is feasible to the application of spares configuration modeling under multi-constraints. Our research conclusions can provide decision-making for spares optimization.

(2) The value of Lagrange factors may affect the calculation result, and is important to multi-constraint modeling. Therefore, reasonable Lagrange factors should be determined.

(3) In the given example, calculation result is reasonable. The spares project satisfies all of the given targets, and can improve the equipment support effectiveness.

Our research is significant for equipment logistics support. It can provide analysis method for spares demand during equipment design, and decision-making for spares configuration optimization and effectiveness evaluation in practice.

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